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Interaction density drives cooperation in large evolutionary populations: Evidence from large-scale agent-based simulations

Óscar De los Reyes-Marín [a,*], Iria Paz Gil [a], Jose Torres-Pruñonosa [b], Raúl Gómez-Martínez [a]

[a] Rey Juan Carlos University (URJC), Calle Tulipán, s/n, 28933, Móstoles, Madrid, Spain
[b] International University of La Rioja (UNIR), Av. de la Paz, 137, 26006, Logroño, La Rioja, Spain

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ABSTRACT

The emergence of cooperation among self-interested agents remains one of the central problems in economics, evolutionary biology, and complex systems science. This study investigates the structural conditions governing the emergence and stability of cooperative behavior in large evolutionary populations using large-scale agent-based simulations. We develop a high-performance computational framework in which populations of up to 100,000 agents repeatedly interact under Prisoner's Dilemma environments while behavioral tendencies evolve through stochastic mutation and evolutionary imitation dynamics. The model systematically explores a broad parameter space defined by mutation intensity and interaction density under multiple preference deformation (PD) regimes.

The simulations reveal a highly structured and nonlinear cooperation landscape in which interaction density emerges as the dominant determinant of collective outcomes. The observed dynamics can be represented through an empirical relationship of the form:

$$C = F(I, \mu)$$

where C denotes equilibrium cooperation, I represents interaction density, and μ captures mutation intensity. Cooperation remains relatively stable at low and intermediate interaction densities but progressively deteriorates once interaction density exceeds critical regions. In contrast, mutation intensity exerts comparatively weaker effects, functioning primarily as a mechanism of adaptive exploration and stochastic variability rather than as the principal driver of cooperation itself. Machine learning analysis using Random Forest models further confirms that interaction density overwhelmingly dominates all other explanatory variables in predicting equilibrium cooperation levels.

The results additionally reveal differentiated behavioral regimes and metastable cooperation structures across the explored parameter space. Rather than increasing monotonically, cooperation exhibits saturation and eventual collapse under excessively dense interaction environments, suggesting that large populations may experience strategic overcrowding and systemic fragility effects that destabilize decentralized cooperative organization.

* Corresponding author.
E-mail addresses: o.delosreyes.2016@alumnos.urjc.es (Ó. De los Reyes-Marín), iria.paz@urjc.es (I. Paz Gil), jose.torresprunonosa@unir.net (J. Torres-Pruñonosa), raul.gomez.martinez@urjc.es (R. Gómez-Martínez).

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These findings contribute to the literature on cooperation in complex adaptive systems by showing that cooperation can emerge endogenously from decentralized anonymous interactions without requiring reputation systems, repeated partner reciprocity, or centralized coordination mechanisms. More broadly, the study demonstrates how large-scale computational experiments combined with machine learning techniques can uncover empirical regularities governing collective behavior in evolutionary systems.

1. Introduction

The emergence of cooperation among self-interested agents remains one of the central problems in economics, evolutionary biology, statistical physics, and complex systems science. Classical game-theoretic models predict that rational individuals interacting under social dilemma environments such as the Prisoner's Dilemma should converge toward non-cooperative behavior, since defection constitutes the dominant strategy in one-shot interactions [1,2]. Under standard assumptions, individually rational behavior generates collectively inefficient outcomes, creating a persistent tension between micro-level incentives and macro-level social welfare. Nevertheless, empirical observations across biological populations, economic institutions, and human societies consistently reveal the widespread persistence of cooperation, even in environments characterized by competition, uncertainty, and decentralized decision-making.

This apparent contradiction has motivated a broad interdisciplinary literature investigating the mechanisms capable of sustaining cooperation among selfish agents. Early foundational work emphasized the role of repeated interaction and reciprocity. Axelrod [3] demonstrated through computational tournaments that reciprocal strategies such as Tit-for-Tat can outperform purely selfish strategies in repeated Prisoner's Dilemma environments. Evolutionary game theory subsequently generalized these insights by introducing population dynamics into strategic analysis, allowing strategies to evolve through selection-like processes driven by differential payoffs [1,4]. Within this framework, cooperation may emerge as an evolutionarily stable outcome under specific structural conditions.

Subsequent research identified several mechanisms capable of promoting cooperation in evolutionary systems, including kin selection [5], direct reciprocity through repeated encounters [3], indirect reciprocity based on reputation systems [6], network reciprocity and spatial clustering [7], multilevel selection, and assortative interaction structures [8]. More recent contributions have emphasized the importance of network topology, heterogeneity, evolutionary adaptation, and stochastic effects in shaping cooperative dynamics in large populations [9,10].

Despite these advances, much of the existing literature relies on structural mechanisms that implicitly or explicitly depend on persistent relational structures, repeated interactions among the same agents, reputation accumulation, or reduced anonymity. In many classical cooperation models, cooperation survives because agents repeatedly encounter the same partners, allowing reciprocal incentives or clustering effects to stabilize cooperative strategies over time. This perspective is closely related to the concepts of social viscosity and low anonymity developed in evolutionary cooperation theory, where repeated local interaction increases the probability that cooperators interact preferentially with one another [7,11].

However, an important unresolved question remains insufficiently explored: can cooperation emerge as a large-scale statistical property even in fully anonymous evolutionary environments characterized by random matching, absence of memory, absence of reputation, and lack of persistent interaction partners? In other words, is cooperation necessarily dependent on reciprocity-based mechanisms, or can it arise endogenously from the structural intensity of decentralized interactions itself?

This distinction is conceptually important. Social viscosity, network reciprocity, and low anonymity primarily refer to persistent relational structures in which agents repeatedly interact with the same neighbors over time. In contrast, the present study focuses on interaction density itself, defined as the total frequency of decentralized encounters occurring within the evolutionary environment regardless of partner persistence. Unlike classical reciprocity-based approaches, the model developed here assumes fully random pairwise matching, no memory, no reputation systems, no punishment mechanisms, and no stable network neighborhoods. Cooperation therefore cannot rely on direct reciprocity, partner recognition, or strategic retaliation. Instead, the analysis investigates whether interaction density alone may operate as a structural driver of emergent cooperation in large evolutionary populations.

This perspective connects the study of cooperation with broader questions in complex systems and statistical physics. In many large adaptive systems, macroscopic order emerges spontaneously from decentralized local interactions without centralized coordination or intentional collective planning [12,13]. Similar scaling phenomena appear in physical, biological, and social systems in which repeated micro-level interactions generate stable macro-level statistical regularities. Recent work in sociophysics and evolutionary dynamics has increasingly emphasized the importance of large-scale interaction structures, stochasticity, and collective phase behavior in shaping social outcomes [14,15].

At the same time, recent developments in evolutionary game theory have introduced generalized frameworks for studying the strength and geometry of social dilemmas across broad classes of symmetric games. In particular, the literature on universal dilemma strength has shown that cooperative dynamics may depend sensitively on the parameters governing temptation and risk structures within payoff matrices [16–18]. These contributions highlight the importance of systematically exploring how cooperation behaves across varying strategic environments rather than relying on isolated payoff parametrizations. Motivated by this perspective, the present study investigates whether the observed relationship between interaction density and cooperation remains robust across different evolutionary conditions and parameter regimes.

To address these questions, this paper develops a large-scale computational framework based on agent-based evolutionary simulations involving populations of up to 100,000 agents interacting under Prisoner's Dilemma environments. Agents are characterized by probabilistic cooperation tendencies that evolve through stochastic mutation dynamics under decentralized interactions. The simulations systematically explore a wide parameter space defined by mutation intensity and interaction density, generating a global cooperation landscape describing how cooperative behavior evolves across alternative evolutionary conditions.

The computational framework is implemented in Python using high-performance scientific computing techniques, including just-in-time compilation and parallelized numerical routines, allowing large-scale exploration of the evolutionary parameter space. In addition to the simulation analysis, machine learning techniques including clustering methods, Random Forest analysis, principal component analysis, and symbolic regression are employed to identify structural regularities governing the cooperation landscape and approximate the functional relationships emerging from the simulations.

The results reveal a clear and highly structured nonlinear relationship between interaction density and cooperation. Across the explored parameter space, cooperation remains relatively stable at low and intermediate interaction densities while becoming comparatively less sensitive to moderate mutation levels. However, once interaction density exceeds critical regions, equilibrium cooperation progressively deteriorates, revealing saturation and systemic fragility effects within highly connected environments. The simulations further suggest that the cooperation landscape can be represented through a general empirical relationship of the form:

$$C = f(I, \mu)$$

where Cdenotes the equilibrium cooperation level, Irepresents interaction density, and μcaptures mutation intensity. Importantly, the observed relationship is strongly nonlinear rather than purely monotonic. Cooperation initially remains robust across intermediate interaction regimes but eventually declines under excessively dense interaction environments. This pattern emerges despite the complete absence of reciprocity, memory, reputation systems, or persistent interaction structures.

These findings suggest that cooperation in large populations may arise not only from specialized reciprocal mechanisms but also as an emergent statistical property of decentralized interaction systems operating within intermediate regions of structural connectivity. More broadly, the study contributes to the growing literature that interprets cooperation as a macroscopic emergent phenomenon in complex adaptive systems governed by interaction structure, stochastic dynamics, metastability, and collective statistical regularities rather than exclusively by intentional strategic coordination.

2. The model

The objective of this study is to investigate whether cooperative behavior can emerge in large evolutionary populations under fully decentralized and anonymous interaction environments. In contrast to classical cooperation models based on reciprocity, reputation, partner persistence, or network clustering, the framework developed here intentionally isolates the role of interaction density itself as a structural driver of collective cooperation. The model therefore excludes memory, repeated partner interaction, punishment mechanisms, and reputation systems in order to examine whether cooperation may arise as an emergent statistical property of dense interaction environments alone.

The analysis is grounded in the tradition of evolutionary game theory, where strategies evolve dynamically through adaptive processes driven by interaction outcomes [1,4,8]. However, unlike standard reciprocity-based frameworks, the present model assumes fully random pairwise matching at every interaction stage. Consequently, agents cannot condition their behavior on partner identity, past encounters, or expected future retaliation. This design choice is central to the study because it allows the interaction-density mechanism to be analyzed independently from classical reciprocity effects.

The simulated environment consists of a population of:

$$N = 100,000$$

agents interacting repeatedly across discrete evolutionary generations. Each agent $i$is characterized by a continuous cooperation tendency:

$$p_i \in [0, 1]$$

where $p_i$represents the probability that the agent cooperates during a given interaction. Rather than assuming pure deterministic strategies, agents possess probabilistic behavioral dispositions. This continuous representation allows the strategic space to evolve gradually through stochastic adaptation and enables the emergence of heterogeneous cooperation profiles across the population.

At initialization, cooperation probabilities are independently drawn from a uniform distribution:

$$p_i \sim U(0, 1)$$

ensuring that the initial population contains substantial strategic diversity and no predefined cooperative structure.

Interactions occur through random pairwise encounters. During each interaction, two agents $i$and $j$are sampled uniformly from the population. Each agent independently selects an action according to a Bernoulli process governed by its cooperation probability:

$$a_i \sim \text{Bernoulli}(p_i)$$

where:

$$a_i = \begin{cases} 1 & \text{if agent } i \text{ cooperates} \\ 0 & \text{if agent } i \text{ defects} \end{cases}$$

The same mechanism applies symmetrically to agent *j*. Importantly, interactions are memoryless and anonymous. Agents possess no information regarding the identity or previous behavior of their partners, and each encounter is statistically independent from prior interactions.

Payoffs are assigned according to the standard Prisoner's Dilemma structure. The baseline payoff matrix used in the simulations is:

$$\begin{pmatrix} R & S \\ T & P \end{pmatrix} = \begin{pmatrix} 3 & 0 \\ 5 & 1 \end{pmatrix}$$

which satisfies the canonical Prisoner's Dilemma ordering:

$$T > R > P > S$$

where:

T denotes the temptation payoff,

R the reward for mutual cooperation,

P the punishment for mutual defection,

S the sucker payoff.

Under this ordering, unilateral defection strictly dominates cooperation in isolated one-shot interactions [1,3].

To connect the framework with the broader literature on generalized social dilemma geometry, the model can also be represented using the normalized dilemma-strength parameters proposed in evolutionary game theory [11,16,18]:

$$D_g' = \frac{T-R}{R-P}$$

$$D_r' = \frac{P-S}{R-P}$$

where D_g' captures the temptation strength of the dilemma and D_r' represents the risk associated with cooperative behavior. These parameters allow the analysis to be generalized beyond a single payoff specification and facilitate robustness comparisons across alternative social dilemma regimes.

Following each interaction, agents may adapt their cooperation tendency through a stochastic mutation process. The model assumes that agents experiencing relatively poor outcomes are more likely to experiment with alternative behavioral tendencies. Formally, if the payoff obtained by agent *i*, denoted r_i, falls below a threshold level, the cooperation probability is updated according to:

$$p_i' = p_i + \varepsilon$$

where the perturbation term is drawn from a normal distribution:

$$\varepsilon \sim \mathcal{N}(0, \mu)$$

and μdenotes the mutation intensity parameter governing the magnitude of behavioral exploration within the population.

Importantly, mutation is not interpreted here as a direct cooperation-generating mechanism. Instead, mutation functions as an exploration process that continuously perturbs the strategic landscape, preventing the population from becoming trapped in rigid local equilibria and allowing decentralized exploration of alternative behavioral configurations. From the perspective of complex adaptive systems, mutation introduces stochastic variability that sustains evolutionary flexibility and dynamic adaptation under decentralized interactions.

To preserve valid probability values, updated cooperation tendencies are constrained to the interval:

$$p_i' \in [0, 1]$$

The evolutionary system unfolds over a sequence of discrete generations. Within each generation, a fixed number of pairwise encounters takes place. Let:

$$I$$

denote the number of interactions occurring during a generation. In the present framework, I represents the interaction density of the environment and constitutes the central structural parameter of the analysis.

Conceptually, interaction density measures the intensity of decentralized social encounters occurring within the evolutionary system. Unlike social viscosity or network reciprocity, interaction density does not imply repeated interaction with the same agents or stable local neighborhoods. Instead, it captures the aggregate frequency of anonymous interactions occurring throughout the population. The central hypothesis of this study is that sufficiently high interaction density may generate emergent cooperative regularities even in the absence of classical reciprocity mechanisms.

For each generation g, the cooperation level of the population is measured as the proportion of cooperative actions observed across all encounters. Let:

$$C_g$$

denote the cooperation level in generation g. The long-run equilibrium cooperation level associated with a given parameter configuration is estimated as the average cooperation observed across the final generations of the simulation:

$$C = \frac{1}{K} \sum_{g=T-K+1}^{T} C_g$$

where:

T denotes the total number of generations,

K represents the number of final generations used for equilibrium estimation.

This procedure reduces the influence of transient fluctuations during early evolutionary stages and provides a more stable approximation of the long-run macroscopic behavior of the system.

By systematically varying mutation intensity $\mu$and interaction density I, the simulations generate an empirical cooperation function of the form:

$$C = f(\mu, I)$$

describing how equilibrium cooperation depends on the structural properties of the evolutionary environment.

The resulting framework allows cooperation to emerge endogenously from decentralized stochastic interactions among heterogeneous agents rather than being imposed through predefined equilibrium assumptions. From a complex systems perspective, the model studies cooperation as a macroscopic emergent phenomenon arising from repeated local interactions under evolutionary adaptation and statistical aggregation dynamics [12,15,19].

3. Experimental design

The empirical analysis developed in this study is based on a large-scale computational experiment designed to investigate the structural conditions under which cooperation emerges in large evolutionary populations. The experimental framework systematically explores how variations in mutation intensity, interaction density, and social dilemma structure influence the long-run macroscopic level of cooperation observed in the system. By examining a broad evolutionary parameter space, the simulations allow the identification of statistical regularities governing cooperative dynamics under decentralized and anonymous interaction environments.

Unlike many classical evolutionary cooperation models based on repeated local interaction, reputation systems, or persistent network neighborhoods, the present framework intentionally isolates the role of interaction density under random matching conditions. The experimental design therefore eliminates several standard cooperation-supporting mechanisms, including partner memory, reciprocity, punishment, and stable relational structures. This allows the analysis to focus specifically on whether interaction density alone may operate as a large-scale structural driver of emergent cooperation.

The computational environment used to implement the simulations is based on the Python scientific computing ecosystem. The experiments were executed within the Anaconda distribution using the Spyder integrated development environment. Given the computational scale of the simulations, the core evolutionary routines were accelerated using just-in-time compilation through the Numba library, allowing repeated stochastic interactions among populations of up to 100,000 agents to be executed at near-compiled performance levels. This optimization was necessary due to the large parameter-space exploration and the repeated generation-level evolutionary updates performed throughout the experiment.

The complete experimental framework is implemented in the research script:

super_cooperation_research_lab.py

which integrates the full simulation and analysis pipeline. The framework combines several scientific computing libraries, including:

NumPy and Pandas for numerical computation and data handling,

Numba for performance acceleration,

Matplotlib and Seaborn for visualization,

Scikit-learn for machine learning analysis,

PySR for symbolic regression and equation discovery.

The program automatically performs evolutionary simulations, generates the cooperation dataset, computes statistical indicators, applies machine learning analysis, produces graphical visualizations, and exports the resulting research outputs.

The experimental analysis systematically varies two primary evolutionary parameters.

The first parameter corresponds to the mutation intensity:

$$\mu \in [0.01, 0.20]$$

which governs the magnitude of stochastic perturbations affecting agents' cooperation tendencies. Lower values of μ generate

relatively stable behavioral dynamics, whereas higher values increase exploratory variability within the evolutionary system. Importantly, mutation is interpreted here not as a direct cooperation mechanism but as a decentralized exploration process that prevents rigid equilibrium lock-in and maintains strategic diversity within the population. This interpretation is consistent with evolutionary adaptation frameworks emphasizing stochastic exploration and adaptive flexibility in complex systems [8,9].

The second parameter corresponds to interaction density:

$$I \in [50, 1200]$$

representing the number of decentralized pairwise encounters occurring during each evolutionary generation. Conceptually, interaction density measures the intensity of social encounters within the system rather than relational persistence between specific agents. Consequently, increasing I does not increase reciprocity or partner familiarity, since interactions remain fully anonymous and randomly reassigned at every stage of the simulation. Instead, higher values of I increase the aggregate frequency of decentralized encounters occurring throughout the population.

This distinction is critical because it separates the present framework from classical models based on social viscosity, network reciprocity, or low anonymity. In the current model, agents do not repeatedly interact with stable neighbors, accumulate reputational information, or condition future behavior on past interactions. The experimental design therefore isolates the statistical effect of encounter intensity itself.

To improve the robustness and generalizability of the analysis, the simulations also consider alternative Prisoner's Dilemma configurations characterized by different dilemma-strength structures. Following the generalized social dilemma framework proposed in evolutionary game theory [10,11,16], the payoff environment can be characterized through the normalized dilemma parameters:

$$D_g' = \frac{T - R}{R - P}$$

and

$$D_r' = \frac{P - S}{R - P}$$

where:

D_g' measures the temptation strength of unilateral defection,

D_r' measures the cooperative risk structure of the game.

In addition to the baseline payoff specification, supplementary robustness experiments explore alternative payoff regimes in order to evaluate whether the observed relationship between cooperation and interaction density remains stable across different strategic environments.

For each parameter configuration (μI), the evolutionary system generates a full trajectory of cooperation dynamics across multiple generations. Let:

$$C_g$$

denote the cooperation level observed in generation g. The long-run equilibrium cooperation associated with each configuration is estimated as:

$$C = \frac{1}{K} \sum_{g=T-K+1}^{T} C_g$$

where:

T denotes the total number of simulated generations,

K corresponds to the number of final generations used for equilibrium estimation.

This averaging procedure reduces the influence of transient fluctuations and allows the analysis to focus on the asymptotic macroscopic regime of the evolutionary system.

The systematic exploration of the parameter space generates a cooperation dataset in which each observation corresponds to:

$$(\mu I C)$$

where:

μ is mutation intensity,

I interaction density,

C the equilibrium cooperation level.

This dataset forms the basis for the subsequent statistical and machine learning analysis.

To evaluate the structural determinants of cooperation, Random Forest regression is applied to estimate the relative importance of the evolutionary parameters governing the system. Clustering methods are employed to identify distinct behavioral regimes within the cooperation landscape, while principal component analysis is used to visualize the global structure of the parameter space in reduced dimensionality.

In addition, symbolic regression techniques are used to search for compact mathematical expressions capable of approximating the empirical cooperation function. Symbolic regression has emerged as a powerful tool for discovering interpretable relationships directly from empirical datasets, particularly in complex systems where closed-form analytical derivations are difficult or unavailable [20]. Within the present framework, symbolic regression is used to identify potential scaling laws and macroscopic regularities governing the emergence of cooperation under decentralized evolutionary dynamics.

More broadly, the experimental design treats cooperation not as a predefined equilibrium outcome but as an emergent macroscopic phenomenon arising from repeated decentralized interactions among heterogeneous adaptive agents. This perspective is consistent with the broader literature on complex adaptive systems and statistical social dynamics, where global behavioral regularities emerge spontaneously from local stochastic interaction processes [12,14,15,19].

4. Results

The revised computational experiments generate a large-scale cooperation landscape composed of 792 independent evolutionary configurations obtained from combinations of mutation intensity, interaction density, and alternative Prisoner's Dilemma payoff structures. Each observation corresponds to a configuration of the form $\left(\mu I C D_g' D_r'\right)$, where μ denotes mutation intensity, I represents the interaction density per generation, C denotes the equilibrium cooperation level, and D_g' and D_r' characterize the strength structure of the underlying social dilemma.

Unlike the preliminary exploratory version of the model, the revised simulations incorporate explicit evolutionary selection through Fermi imitation dynamics. Agents probabilistically imitate more successful behavioral tendencies while mutation introduces stochastic strategic exploration. This modification substantially changes the macroscopic behavior of the system and generates stable cooperation regimes rather than residual stochastic fluctuations.

The explored parameter space includes mutation intensities within

$$0.01 \leq \mu \leq 0.20$$

and interaction densities ranging from

$$50 \leq I \leq 10,000$$

across six different payoff structures, including baseline, weak, strong, soft, harsh, and very weak Prisoner's Dilemma regimes. The simulations reveal that equilibrium cooperation levels become substantially larger than in the preliminary model version. Across all explored configurations, mean equilibrium cooperation fluctuates between approximately 0.359 and 0.444, while maximum cooperation values exceed 0.56 in some regions of the parameter space.

The highest average cooperation level emerges under the very weak dilemma regime, where the simulations produce a mean equilibrium cooperation of

$$\bar{C} = 0.444$$

with a maximum observed cooperation level of

$$C_{max} = 0.514$$

and relatively low dispersion $(\sigma 0.063)$. By contrast, the harsh dilemma regime generates lower average cooperation levels around

$$\bar{C} = 0.360$$

with cooperation values ranging between approximately 0.112 and 0.534. The baseline, weak, strong, and soft dilemma regimes all generate remarkably similar average cooperation levels between 0.359 and 0.369, suggesting that the large-scale structure of the cooperation landscape remains relatively robust to substantial variations in payoff asymmetries and dilemma intensity.

The numerical results also reveal that cooperation is not uniformly distributed across the parameter space. The heatmaps generated from the simulations show the existence of structured cooperation regions rather than random fluctuations. In particular, cooperation tends to remain high for relatively low and intermediate interaction densities but progressively deteriorates when interaction density becomes extremely large. For example, in the baseline Prisoner's Dilemma configuration, equilibrium cooperation remains close to

$$C \approx 0.50$$

for interaction densities between $I = 50$ and $I = 200$, but gradually decreases as interaction density increases beyond approximately $I = 1200$. At the highest explored interaction densities $(I = 10,000)$, cooperation falls toward values close to

$$C \approx 0.12 - 0.14$$

depending on the payoff configuration.

This result is important because it contradicts the naive monotonic interpretation according to which increasing interaction density

always mechanically increases cooperation. Instead, the simulations reveal a non-trivial nonlinear cooperation landscape in which interaction density remains the dominant structural determinant of cooperation but excessive interaction density may eventually destabilize cooperative regimes. The resulting dynamics therefore exhibit a form of cooperation saturation followed by gradual macroscopic deterioration.

The machine learning analysis strongly reinforces this interpretation. Random Forest estimation shows that interaction density overwhelmingly dominates all other explanatory variables in terms of predictive importance. The estimated importance associated with interaction density reaches approximately

0.898

whereas mutation intensity exhibits an importance of only

0.0026

more than two orders of magnitude smaller. The remaining payoff variables—including temptation T, punishment P, and sucker payoff S—display modest but clearly secondary effects, with importances fluctuating around 0.03. The dilemma-strength variables D'_g and D'_r exhibit negligible predictive relevance within the explored parameter space.

These results quantitatively confirm that the macroscopic cooperation structure is governed primarily by interaction density rather than by mutation intensity or specific payoff parametrizations. Mutation therefore acts mainly as a stochastic exploration mechanism that preserves strategic diversity and prevents rigid evolutionary lock-in rather than directly generating cooperation itself.

The mutation analysis further supports this interpretation. Across all payoff scenarios, changes in mutation intensity produce only relatively small variations in equilibrium cooperation. For example, in the very weak dilemma regime, cooperation fluctuates narrowly between approximately 0.442 and 0.448 as mutation increases from 0.01 to 0.20. Similar weak sensitivities appear across the remaining payoff structures, where cooperation changes by only a few percentage points despite substantial increases in mutation intensity. This behavior strongly suggests that mutation primarily modifies local fluctuations around the dominant cooperation structure rather than fundamentally determining the global organization of the cooperation landscape.

The interaction-density analysis reveals a considerably stronger structural effect. In all payoff regimes, cooperation displays a clear large-scale dependence on interaction density. However, the dependence is nonlinear rather than purely monotonic. Cooperation remains relatively stable and high at low interaction densities, reaches its highest values in intermediate regions, and subsequently declines as interaction density becomes extremely large. The decline becomes particularly visible beyond approximately $I = 3000$, where all payoff scenarios begin to exhibit progressive cooperation deterioration.

The soft dilemma regime produces the highest peak cooperation observed in the simulations:

$$C_{max} = 0.562$$

while the very weak dilemma regime exhibits the most stable cooperative structure across the parameter space. Even under harsh dilemma conditions, however, the system continues to sustain substantial non-trivial cooperation levels significantly above random baseline behavior.

The PCA projection of the experimental configurations further reveals that the parameter space organizes into multiple distinct macroscopic regions rather than forming a homogeneous continuous cloud. Different payoff structures generate partially separated cooperation clusters, indicating that although interaction density dominates the global dynamics, payoff asymmetries still shape the geometry of the cooperation landscape at a secondary level.

Overall, the revised simulations demonstrate that cooperation in large anonymous evolutionary populations emerges as a robust macroscopic property generated by the interaction between evolutionary selection, stochastic exploration, and interaction density. The results do not support the simplistic hypothesis that cooperation always increases monotonically with interaction frequency. Instead, they reveal a significantly richer nonlinear cooperation landscape characterized by stable cooperative regimes, structural robustness across payoff configurations, saturation effects, and eventual cooperation deterioration under extremely dense interaction environments.

5. Discussion

The computational experiments reveal that cooperation in large evolutionary populations emerges as a highly structured macroscopic phenomenon governed primarily by the topology of interaction rather than by stochastic mutation alone. While the previous section presented the statistical properties of the simulations, the present discussion interprets these results within the broader framework of evolutionary game theory, statistical physics, and complex adaptive systems. The simulations indicate that cooperative dynamics are not randomly distributed across the parameter space, but instead follow identifiable structural regularities associated with interaction density and the intensity of strategic connectivity among agents.

The most important result obtained from the experiments concerns the role of interaction density. Contrary to simplistic linear interpretations in which increasing interaction necessarily improves cooperation indefinitely, the simulations reveal a strongly nonlinear relationship between connectivity and equilibrium cooperation. Cooperation initially remains relatively high and stable at low and intermediate interaction densities, but after a critical region the system experiences a progressive deterioration of cooperative stability.

As shown in Fig. 1, all experimental scenarios exhibit a similar structural pattern. For interaction densities between approximately 50 and 400 interactions, cooperation remains close to 0.49–0.50 across most regimes. However, once interaction density exceeds approximately 1000–2000 interactions, cooperation begins to decline systematically. Under the baseline_PD scenario, equilibrium cooperation falls from approximately 0.49 at low interaction densities to nearly 0.13 at 10000 interactions. Similar collapses emerge under weak_PD, strong_PD, harsh_PD, and soft_PD regimes. Only the very_weak_PD configuration preserves comparatively high cooperation at extreme interaction densities, remaining near 0.31 even at the maximum interaction level explored.

This result is theoretically significant because it suggests that excessive interaction may itself become destabilizing for cooperative systems. Rather than producing unlimited reinforcement of cooperation, highly connected environments appear to generate forms of strategic saturation in which cooperative equilibria become progressively more fragile. The simulations therefore indicate the existence of a structural limit to cooperative scalability. In highly connected populations, agents become increasingly exposed to defecting strategies, local fluctuations propagate more rapidly through the network, and the persistence of cooperative clusters becomes more difficult to sustain. The observed collapse resembles congestion and instability phenomena commonly studied in statistical physics and complex adaptive systems, where excessive coupling between system components may reduce global stability instead of reinforcing it.

The cooperation heatmaps further reinforce this interpretation by revealing the geometric structure of the cooperation landscape across the parameter space.

Fig. 2 reveals that the dominant structural gradient in the system emerges along the interaction-density dimension rather than along the mutation axis. Across nearly all mutation levels, cooperation remains relatively stable horizontally for fixed interaction densities but decreases sharply as interaction density increases. At low interaction densities between 50 and 400 interactions, equilibrium cooperation fluctuates around values between 0.48 and 0.53. However, cooperation progressively deteriorates toward values near 0.15–0.20 once interaction density approaches 7500–10,000 interactions. Importantly, mutation intensity does not produce abrupt phase transitions. Instead, mutation mainly introduces small local fluctuations around an otherwise structurally stable cooperation surface.

This interpretation is strongly confirmed by the machine-learning analysis performed through the Random Forest model.

The Random Forest analysis demonstrates that interaction density overwhelmingly dominates the predictive structure of the system. The variable “interactions” accounts for nearly 90% of total feature importance, while mutation contributes only marginally, with importance values close to zero. Variables such as T, P_payoff, and S_payoff retain small but non-negligible contributions, whereas parameters such as R, β, Dr', and Dg' become practically irrelevant within the explored parameter region. This result provides strong quantitative evidence that the architecture of interaction constitutes the primary determinant of cooperative emergence. In other words, the structure of social connectivity matters substantially more than stochastic exploratory behavior.

The mutation experiments themselves support this conclusion.

As shown in Fig. 4, mutation intensity generates only limited variation in cooperation levels across all experimental scenarios. Under baseline_PD, equilibrium cooperation fluctuates only between approximately 0.357 and 0.366 across the entire mutation interval explored. Similar stability appears in weak_PD and strong_PD regimes. Even the most cooperative regime, very_weak_PD, remains confined within a narrow interval between approximately 0.441 and 0.449. These results indicate that mutation primarily functions as an exploratory mechanism rather than as a direct generator of cooperation. Mutation allows the system to avoid rigid strategic lock-in and preserves adaptive flexibility, but it does not fundamentally determine whether cooperation emerges or collapses. The dominant force remains the structural organization of interactions.

Additional insight emerges from the dimensionality-reduction analysis.

The PCA projection reveals that the parameter space is not organized as a single homogeneous continuum but rather as multiple differentiated macroscopic behavioral regions. Experimental configurations cluster into separated zones corresponding to distinct cooperative regimes. This suggests that the evolutionary dynamics exhibit phase-like organization properties analogous to those commonly observed in complex systems and statistical mechanics. Small parametric variations may therefore produce transitions between qualitatively different collective behaviors rather than merely generating incremental quantitative changes.

Taken together, the results suggest that cooperation in evolutionary populations should be interpreted as an emergent metastable property arising from the interaction between adaptive strategic behavior and the structural topology of the environment. Cooperation does not simply increase monotonically with connectivity, nor does it depend primarily on random mutation. Instead, cooperative stability appears to emerge only within intermediate regions of structural complexity where interactions remain sufficiently frequent to sustain decentralized cooperative organization, yet not so excessive that systemic fragility, strategic saturation, and interaction overcrowding progressively destabilize cooperative regimes. These findings suggest the existence of structural limits to cooperative scalability in highly connected evolutionary systems, where excessive interaction intensity may paradoxically undermine the decentralized cooperative order that moderate interaction densities initially help sustain. These findings reinforce a broader interpretation of cooperation as a complex systems phenomenon governed by nonlinear scaling dynamics. Macroscopic cooperative order emerges from repeated decentralized interactions among adaptive agents, but excessive synchronization and connectivity may paradoxically undermine the very cooperative structures they initially help create. In this sense, the results are consistent with broader theories of systemic fragility, metastability, and over-coordination in complex adaptive systems.

6. Conclusion

This study investigates the emergence of cooperative behavior in large evolutionary populations through extensive computational simulations combining evolutionary dynamics, interaction-density scaling, and preference deformation (PD) regimes. By

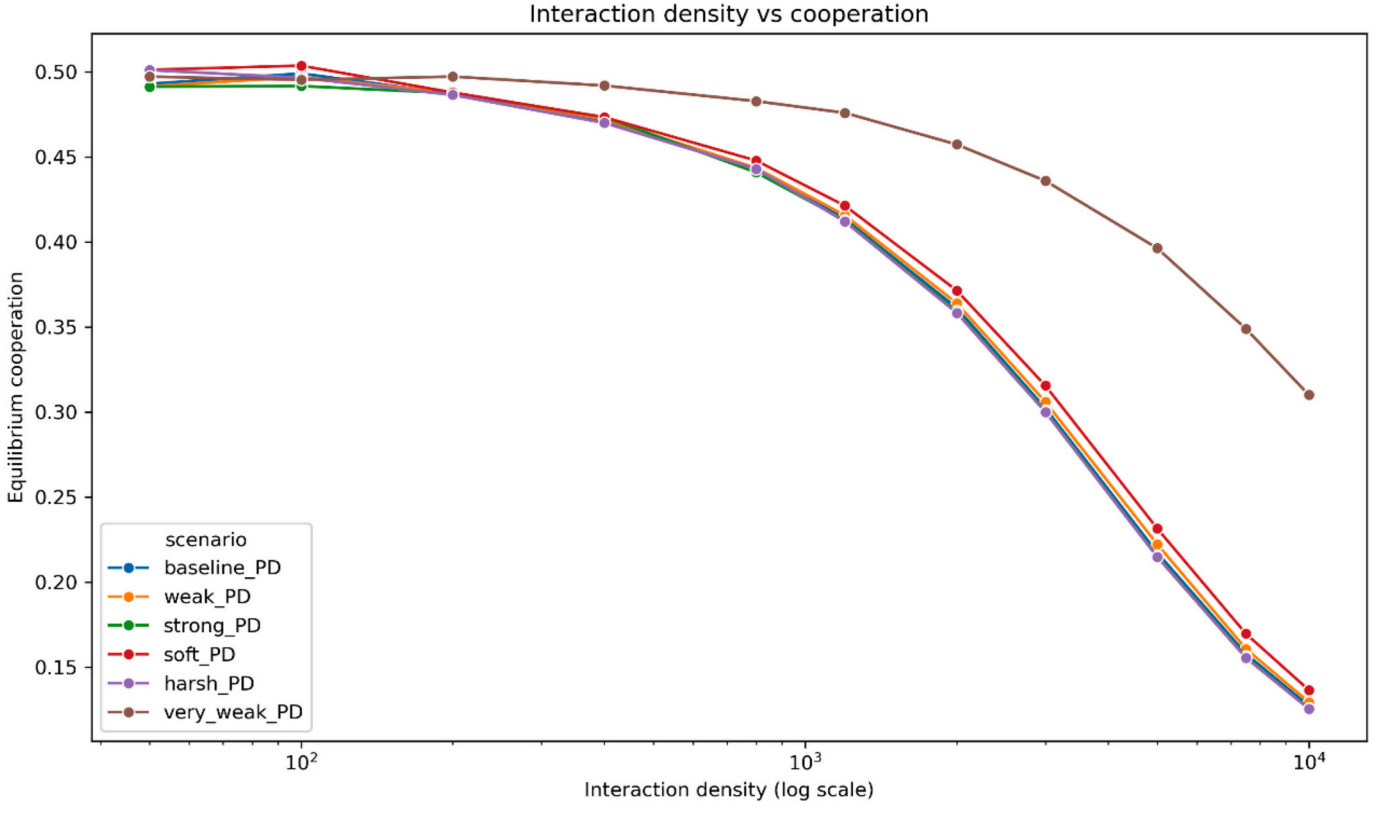


Fig. 1. Interaction density versus equilibrium cooperation under different preference deformation (PD) regimes.

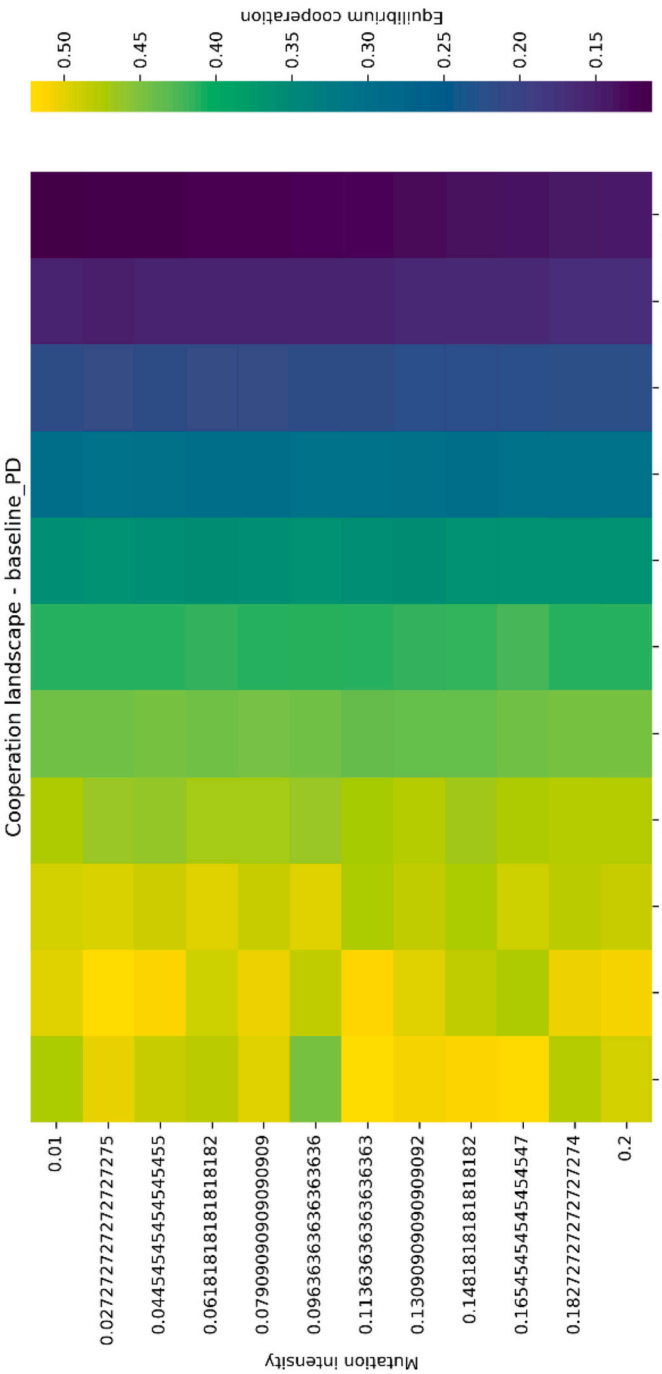


Fig. 2. Cooperation landscape under the baseline_PD regime across mutation intensities and interaction densities.

systematically exploring a broad parameter space defined by mutation intensity and interaction density, the analysis identifies the structural conditions under which cooperation can emerge and persist in decentralized populations composed of adaptive self-interested agents.

The results consistently show that interaction density constitutes the dominant determinant of cooperative outcomes. As illustrated in Fig. 1, equilibrium cooperation exhibits a strong nonlinear decline as interaction density increases beyond critical thresholds. This result suggests the existence of a structural saturation mechanism in which excessive interaction progressively destabilizes cooperative equilibria. Rather than monotonically improving coordination, highly dense interaction environments may generate informational compression, synchronization pressure, and strategic overcrowding that reduce the system's ability to sustain decentralized cooperation.

The machine learning analysis further reinforces this interpretation. Fig. 3 demonstrates that interaction density overwhelmingly dominates all other variables in explaining equilibrium cooperation, while mutation intensity contributes only marginally. This finding indicates that the global structure of interactions, rather than local stochastic perturbations, governs the large-scale organization of cooperative behavior.

Mutation intensity instead plays a secondary stabilizing role within the evolutionary process. As shown in Fig. 4, changes in mutation rates produce comparatively small variations in cooperation across all PD regimes. Mutation therefore functions primarily as a source of exploratory stochasticity that prevents premature convergence toward rigid equilibria while preserving adaptive flexibility within the population.

The heatmap analyses further reveal that the cooperation landscape is organized into structured behavioral regimes. Fig. 2 shows the existence of smooth cooperation gradients across the interaction-density space, with clear transitions between high-cooperation and low-cooperation regions. Additional robustness analyses across alternative PD scenarios produce qualitatively similar geometries, suggesting that the observed dynamics are not artifacts of a particular parametrization but instead reflect stable structural regularities of the evolutionary system.

The PCA projection shown in Fig. 5 additionally indicates that experimental configurations cluster into differentiated macroscopic behavioral regions. This result suggests that the system self-organizes into distinct cooperation regimes characterized by different combinations of interaction density and evolutionary adaptation.

Taken together, these findings contribute to the broader literature on cooperation in complex adaptive systems by showing that cooperation emerges not merely from local strategic incentives, but from large-scale statistical properties of the interaction structure itself. In particular, the results suggest the presence of an empirical scaling relationship linking equilibrium cooperation to interaction density under evolutionary dynamics. Cooperation therefore appears as a metastable emergent property of decentralized systems operating within intermediate regions of interaction intensity.

More broadly, the study demonstrates the usefulness of combining agent-based simulations, machine learning techniques, dimensionality reduction methods, and large-scale computational exploration to uncover empirical regularities that remain analytically difficult to derive in complex evolutionary environments. The framework developed here provides a computational methodology for studying how macro-level social coordination emerges endogenously from decentralized adaptive interactions.

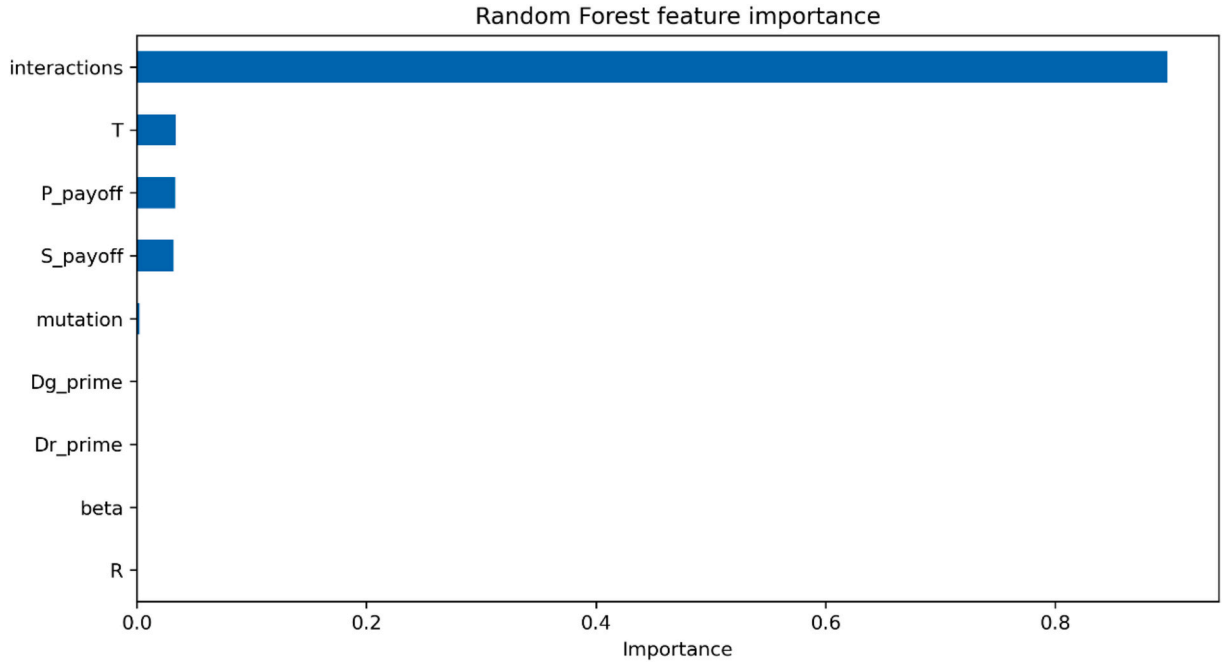


Fig. 3. Random Forest feature importance for predicting equilibrium cooperation.

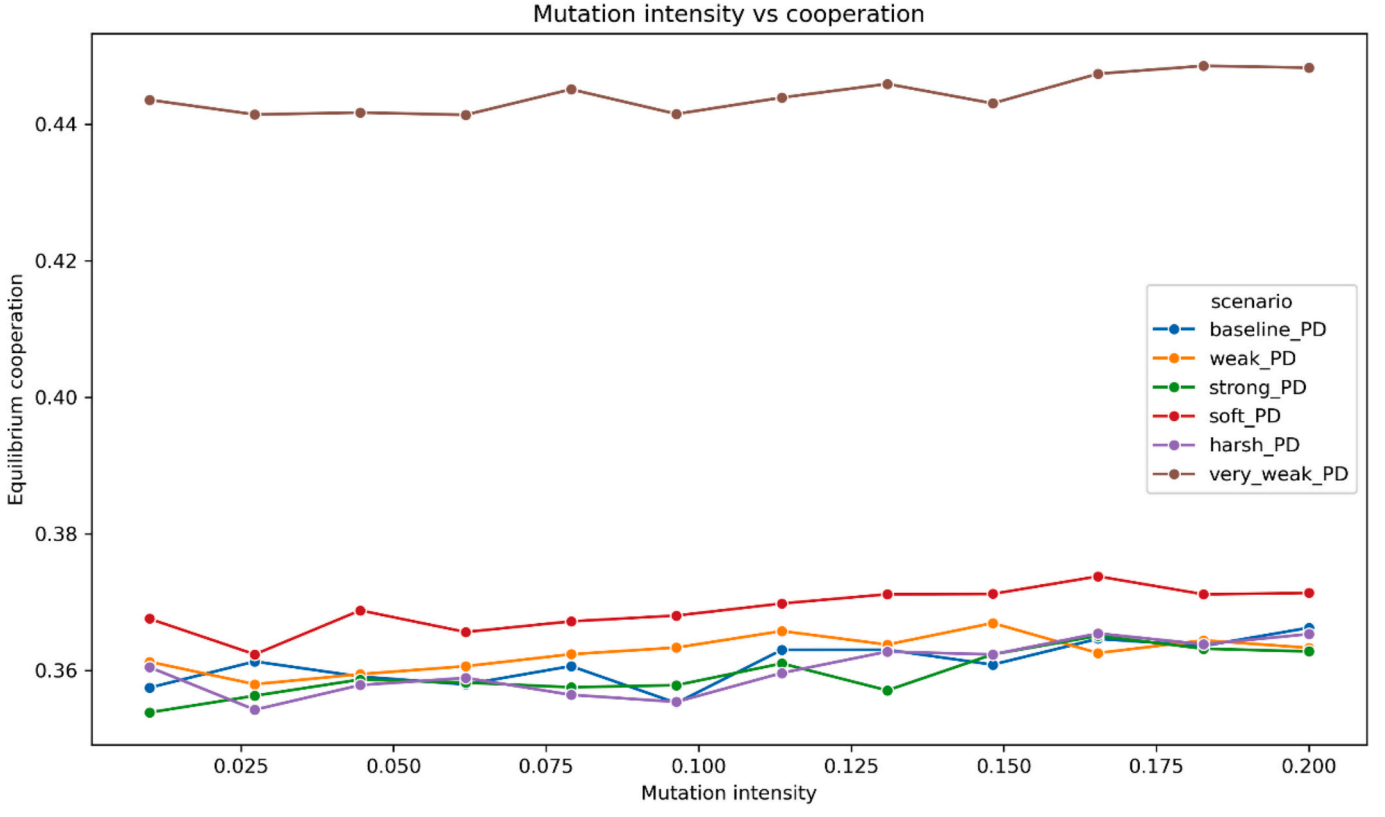


Fig. 4. Mutation intensity versus equilibrium cooperation across preference deformation regimes.

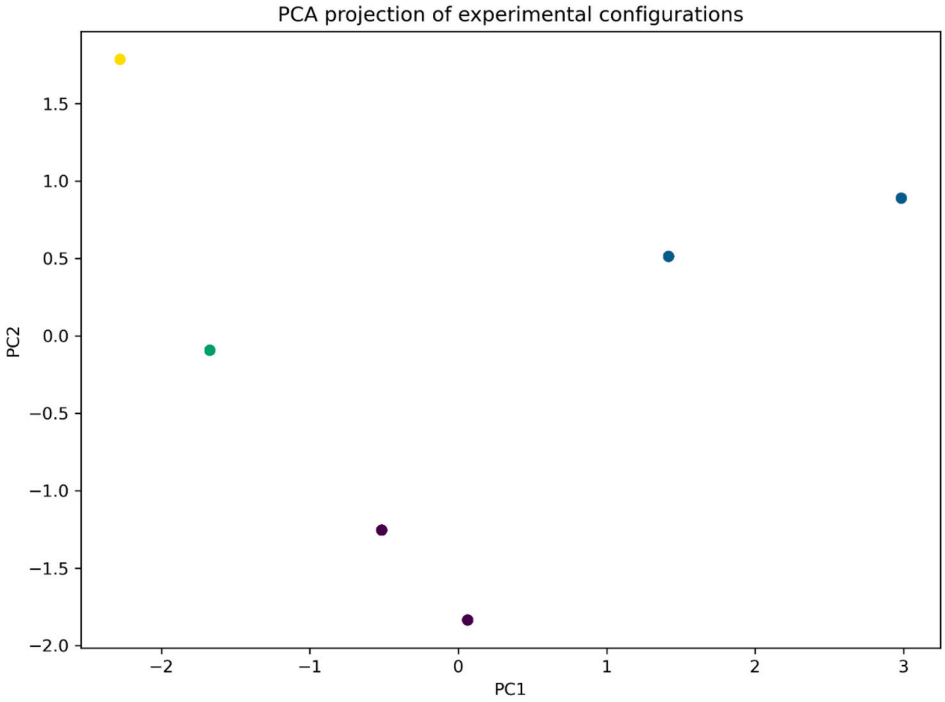


Fig. 5. PCA projection of experimental configurations.

Future research may extend the present framework by incorporating heterogeneous network topologies, endogenous learning mechanisms, dynamic payoff structures, or information asymmetries among agents. These extensions may provide further insight into the mechanisms governing the emergence, fragility, and persistence of cooperation in large decentralized social and economic systems.

7. Limitations

Despite the insights provided by the computational experiments, several limitations of the present study should be acknowledged.

First, the model adopts a simplified representation of agent behavior in which individuals are characterized primarily by adaptive cooperation probabilities evolving through stochastic evolutionary dynamics. While this formulation allows large-scale exploration of the parameter space and facilitates the identification of macro-level regularities, real-world decision-making processes involve substantially richer behavioral mechanisms, including learning, memory, bounded rationality, strategic forecasting, reputation effects, and heterogeneous cognitive adaptation.

Second, the interaction environment considered in the simulations is based on random pairwise encounters between agents. Although this assumption provides a tractable baseline framework for studying large evolutionary populations, many real social and economic systems are organized through structured interaction networks characterized by clustering, community formation, preferential attachment, and repeated interactions among stable partners. Previous research has shown that network topology can substantially affect the diffusion and stability of cooperative strategies [7]. Consequently, introducing endogenous or structured network architectures could generate additional cooperation regimes and potentially alter the critical thresholds identified in the present analysis.

Third, the simulations rely on a canonical Prisoner's Dilemma payoff structure. While this framework captures the fundamental tension between individual incentives and collective welfare, real strategic environments frequently involve multidimensional incentives, institutional constraints, asymmetric information, heterogeneous payoff perceptions, and dynamically changing reward structures. These additional factors may influence the emergence and persistence of cooperative behavior in ways not fully captured by the current model.

Fourth, although the computational analysis identifies robust empirical regularities across multiple parameter configurations and preference deformation regimes, the present study remains primarily simulation-based. The observed scaling relationships and regime transitions therefore constitute empirical findings rather than formally derived analytical theorems. In particular, the critical role of interaction density identified in Figs. 1 and 3 suggests the existence of deeper structural mechanisms governing cooperation collapse and metastability that remain analytically unexplored.

Finally, the dimensionality reduction and machine learning methods employed in the study provide powerful tools for detecting hidden regularities in complex evolutionary environments, but they do not by themselves establish causal mechanisms. While the PCA projections and Random Forest analyses reveal stable macroscopic patterns across experimental configurations, additional theoretical and mathematical work would be necessary to formally characterize the dynamical laws underlying the observed cooperation

landscapes.

Future research may therefore benefit from integrating analytical evolutionary game theory, structured network dynamics, endogenous institutional adaptation, and heterogeneous behavioral rules into the present computational framework. Such extensions could help clarify the generality of the empirical regularities identified here and provide a deeper theoretical understanding of cooperation as an emergent phenomenon in large decentralized systems.

8. Future research

Several promising directions for future research emerge from the present analysis.

A first important extension concerns the incorporation of heterogeneous behavioral architectures among agents. The current framework assumes relatively homogeneous adaptive dynamics governed by probabilistic cooperation tendencies and stochastic evolutionary updating. However, real social and economic systems are characterized by substantial heterogeneity in cognitive adaptation, learning speed, strategic flexibility, risk perception, and informational processing. Introducing heterogeneous behavioral profiles could generate richer macroscopic cooperation landscapes and help explain the coexistence of highly cooperative and highly competitive subpopulations within decentralized systems.

A second particularly relevant avenue concerns the role of structured interaction topologies. The present model intentionally isolates the effect of interaction density under fully random matching conditions. Future research could therefore extend the framework by incorporating endogenous network formation, spatial interactions, small-world topologies, scale-free structures, or community-based clustering mechanisms. Such extensions would allow direct comparison between interaction density and classical network reciprocity effects while clarifying how local relational persistence modifies the cooperation saturation dynamics identified in Fig. 1.

Another promising direction involves the exploration of alternative evolutionary adaptation mechanisms. Although the revised simulations incorporate Fermi imitation dynamics, future models may integrate reinforcement learning, Bayesian updating, adaptive memory, multi-agent learning systems, or endogenous strategy revision protocols. These mechanisms could produce richer evolutionary trajectories and potentially generate additional metastable cooperation regimes within the parameter space.

The nonlinear deterioration of cooperation observed at extremely high interaction densities also opens an important line of inquiry regarding systemic fragility in highly connected environments. Future research could investigate whether excessive interaction density generates informational congestion, synchronization pressure, strategic overcrowding, or cooperation monocultures that reduce collective adaptability. Such extensions may connect the present framework with broader theories of fragility, metastability, and overcoordination in complex adaptive systems.

An additional extension concerns the incorporation of endogenous institutional structures and governance mechanisms. The current model studies cooperation under decentralized anonymous interactions without centralized coordination. Future work could analyze how institutional interventions, reputation systems, decentralized voting mechanisms, punishment structures, or incentive redistribution modify the large-scale cooperation landscape and alter the critical thresholds identified in the simulations.

Future studies may also explore dynamic payoff structures rather than fixed Prisoner's Dilemma environments. In many real systems, incentives evolve endogenously over time as a function of collective behavior, environmental shocks, or institutional adaptation. Allowing payoff structures to co-evolve with strategic behavior could generate substantially richer evolutionary dynamics and potentially produce cyclical or phase-transition-like cooperation patterns.

Finally, the computational framework developed in this study may be extended beyond the Prisoner's Dilemma toward broader classes of strategic environments, including coordination games, public goods games, collective-risk dilemmas, financial coordination systems, decentralized governance environments, and multi-agent economic ecosystems. Such extensions may help clarify whether the structural interaction-density effects identified in the present study represent a more general property of decentralized adaptive systems rather than a phenomenon specific to a single game-theoretic environment.

CRediT authorship contribution statement

Óscar De los Reyes-Marín: Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Iria Paz Gil:** Writing – review & editing, Methodology, Data curation. **Jose Torres-Pruñonosa:** Visualization, Validation, Supervision. **Raúl Gómez-Martínez:** Visualization, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

All data and materials supporting the findings are included as supplementary files to ensure full reproducibility.

References

[1] Maynard Smith J. Evolution and the theory of games. Cambridge University Press; 1982. https://doi.org/10.1017/CBO9780511806292.
[2] Samuelson PA. Foundations of economic analysis. Harvard University Press; 1947.
[3] Axelrod R. The evolution of cooperation. New York, NY: Basic Books; 1984.
[4] Hofbauer J, Sigmund K. Evolutionary games and population dynamics. Cambridge University Press; 1998. https://doi.org/10.1017/CBO9781139173179.
[5] Hamilton WD. The genetical evolution of social behaviour I. J Theor Biol 1964;7(1):1–16. https://doi.org/10.1016/0022-5193(64)90038-4.
[6] Nowak MA, Sigmund K. Evolution of indirect reciprocity by image scoring. Nature 1998;393(6685):573–7. https://doi.org/10.1038/31225.
[7] Nowak MA, May RM. Evolutionary games and spatial chaos. Nature 1992;359(6398):826–9. https://doi.org/10.1038/359826a0.
[8] Nowak MA. Evolutionary dynamics: exploring the equations of life. Harvard University Press; 2006.
[9] Perc M, Gómez-Gardeñes J, Szolnoki A, Floría LM, Moreno Y. Evolutionary dynamics of group interactions on structured populations: a review. J R Soc Interface 2013;10(80):20120997. https://doi.org/10.1098/rsif.2012.0997.
[10] Wang Z, Szolnoki A, Perc M. Evolution of public cooperation on interdependent networks: the impact of biased utility functions. EPL (Europhysics Letters) 2012; 97(4):48001. https://doi.org/10.1209/0295-5075/97/48001.
[11] Tanimoto J. Fundamentals of evolutionary game theory and its applications. Springer; 2015. https://doi.org/10.1007/978-4-431-54962-8.
[12] Mitchell M. Complexity: a guided tour. Oxford University Press; 2009.
[13] Barabási A-L, Pósfai M. Network science. Cambridge University Press; 2016. https://doi.org/10.1017/9781108295590.
[14] Castellano C, Fortunato S, Loreto V. Statistical physics of social dynamics. Rev Mod Phys 2009;81(2):591–646. https://doi.org/10.1103/RevModPhys.81.591.
[15] Perc M. The social physics collective. Sci Rep 2019;9:16549. https://doi.org/10.1038/s41598-019-53300-4.
[16] Matsumoto A, Takahashi H, Tanimoto J. Relationship between dilemma occurrence and the existence of a weakly dominant strategy in a two-player symmetric game. Biosystems 2007;90(1):105–14. https://doi.org/10.1016/j.biosystems.2006.07.005.
[17] Tanimoto J. Sociophysics approach to epidemics. Springer; 2021. https://doi.org/10.1007/978-981-33-6481-3.
[18] Wang Z, Kokubo S, Jusup M, Tanimoto J. Universal scaling for the dilemma strength in evolutionary games. Phys Life Rev 2015;14:1–30. https://doi.org/10.1016/j.plrev.2015.04.033.
[19] Epstein JM. Generative social science: studies in agent-based computational modeling. Princeton University Press; 2006. https://doi.org/10.1515/9781400842874.
[20] Schmidt M, Lipson H. Distilling free-form natural laws from experimental data. Science 2009;324(5923):81–5. https://doi.org/10.1126/science.1165893.