Structured to Succeed?: Strategy Dynamics in Engineering Systems Design and their Effect on Collective Performance

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Strategy dynamics are hypothesized to be a structural factor of interactive multi-actor design problems that influence collective performance and behaviors of design actors. Using a bi-level model of collective decision processes based on design optimization and strategy selection, we formulate a series of two-actor parameter design tasks that exhibit four strategy dynamics (harmony, coexistence, bistability, and defection) associated with low and high levels of structural fear and greed. In these tasks, design actor pairs work collectively to maximize their individual values while managing the trade-offs between aligning with or deviating from a mutually-beneficial collective strategy. Results from a human-subject design experiment indicate cognizant actors generally follow normative predictions for some strategy dynamics (harmony and coexistence) but not strictly for others (bistability and defection). Cumulative link model regression analysis shows a greed factor contributing to strategy dynamics has a stronger effect on collective efficiency and equality of individual outcomes compared to a fear factor. Results of this study provide an initial description of strategy dynamics in engineering design and help to frame future work to mitigate potential unfavorable effects of their underlying strategy dynamics through social constructs or mechanism design.

Keywords: design decision-making, strategy dynamics, game theory, systems engineering, human-subject experimentation.

1 Introduction

Design of engineering systems involves the collective efforts of a diverse set of actors representing multiple firms, organizations, and agencies, each pursuing individual objectives. Achieving broader objectives such as sustainability or resource efficiency requires an integrated perspective to understand inter-dependencies at multiple levels of abstraction [1]. This type of distributed authority does not align well with existing system engineering approaches which assume a strong central actor. Rather, it resembles a systems-of-systems architecting process emphasizing design stability, component interfaces, and coordination mechanisms [2]. Cooperation among entities is often desired [3] but also proves expensive and risky to overcome associated challenges from navigating different goals, requirements, and policies [4].

Collective design problems can exhibit social dilemma from conflicts between self-interest and collective benefit. In extreme cases, free-riding actions provide individual benefit but collective harm [5]. Less extreme dilemma struggle to gain or retain control over decisions [6, 7] or balance the potential reward of collaboration with downside risk of coordination failures [8].

While there has been progress in the systems engineering community to characterize and study systems-of-systems [9, 10] including model-based approaches to coordinate constituent systems [11, 12], this approach alone is not sufficient to capture how local incentives of independent actors influence joint design activities. Research on collective design decision-making highlights fundamental challenges in forming consistent group preferences [13], proposes frameworks and methods to build on negotiation mechanisms to resolve conflicts [14, 15], and applies game theoretic solutions such as Nash equilibria [16–18]. While existing research focuses on general processes to administer collective design or identify stable solutions, there is a gap to understand the dynamical relationship (from a set of dynamical domains) between design actors and connect with actions known to stabilize or mitigate any associated social dilemma. This perspective appears to be unique in design literature and has the potential to accelerate transfer of knowledge from economic theory to engineering design.

This paper investigates how the fundamental structure of a design problem facilitates or inhibits collective action through a factor described as *strategy dynamics*. The intent is not to optimize or otherwise prescribe solutions to multi-actor design problems but to understand inherent trade-offs and relationships between individual actors generalizable across several dynamical domains. While problems in favorable dynamical domains naturally facilitate desirable design outcomes, others may need enhanced communication, enforced role responsibilities, or multi-stage decisions to overcome social dilemma. Improved understanding of how technical and organizational factors influence design behaviors through strategy dynamics will help improve design processes, mechanisms, and incentives to achieve desired collective results.

This paper addresses central questions about how strategy dynamics manifest in socio-technical problems and how they influence design decisions. Building on foundations of game theory and value-driven design, this paper elaborates a bi-level model of collective systems design to differentiate lower-level design decisions and upper-level strategy decisions, constructs parameter design tasks with strategy dynamics drawn from four canonical social dilemma problems, and conducts a human designer experiment to study the effect of strategy dynamics on design outcomes. Discussion compares observations with results of game theory to explain important factors for human decisions in design. Key contributions formulate and characterize strategy dynamics in the collective design of engineering systems and generate insights about their effect on collective performance in parameter design tasks.

2 Background

From requirements-based to value-driven approaches, engineering design and systems engineering traditionally relies on a central

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authority to decompose and allocate objective functions among designers [19]. This perspective is inherently optimistic of the willingness for independent design actors to strategically share resources and align decisions with top-down goals. The need for collaboration between design actors across disciplines and organizations becomes more important as large engineering projects demand technologically-complex solutions. Game theory provides a means to study and treat these collective settings by abstracting designers' decisions and interrelated objectives as strategies to model and understand collectively-efficient courses of action.

Game theory has two main branches: non-cooperative game theory studies player decisions to maximize individual value in the absence of binding agreements ("strategy-oriented") and cooperative game theory investigates how value can be improved by forming or joining a coalition with others ("outcome-oriented") [20]. Both non-cooperative and cooperative game theory offer methods to study multi-actor interactions ranging from extreme competition to cooperation with and without communication [21].

Yet, most game-theoretical models in engineering systems design focus on analysis of design problems with a single decision-making authority. Contributions on this line of work use game theory for multidisciplinary systems design optimization [16, 22, 23]. Design decisions treated as strategies in these applications largely relate to the system's functional properties and short-term objectives. However, true strategic design decisions should be large in degree of commitment and scope of potential impact to meet designers' long-term interests [24].

Moreover, it is a common misunderstanding that non-cooperative game theory assumes no communication between actors. Popular applications of game theory make this assumption to limit influence of more complex factors such as trust, threat of retaliation, and reputation effects. Nonetheless, non-cooperative games are useful in circumstances where players exchange information strategically or engage in "pre-play" negotiations that could (but do not necessarily) lead to coalitions or "self-enforcing" agreements among actors [25, 26].

Engineering systems design needs methods like those provided by game theory to assess the effects of strategy-related uncertainty on system's performance but also to understand designers' individual trade-offs and collective decision-making processes. This paper examines how the strategy dynamics that characterize collective decision-making settings apply to multi-actor design problems and impact collective performance. The following sections discuss background in game theory, applications in engineering systems design, and specific objectives of this work. The Nomenclature section describes all symbols and acronyms used in this work.

2.1 Strategy Dynamics: Definition. The notion of *strategy* encapsulates the general principles that govern an actor's decision-making process as the most important concept in non-cooperative game theory [27]. A strategy is a complete contingency plan of actions developed and executed by a player to meet individual objectives in a game. A *normal-form game* is a triple

$$\mathcal{G} = \left(\mathcal{N}, \langle \mathcal{S}_i \rangle, \langle U_i \rangle\right) \tag{1}$$

where

- $\mathcal{N} = \{1, \ldots, n\}$ is a finite set of players.
- $\mathcal{S}_i$ is a finite set of strategies for each player $i \in \mathcal{N}$. The set of all collective strategies is $\mathcal{S} = \mathcal{S}_i \times \cdots \times \mathcal{S}_n$.
- $U_i : \mathcal{S} \mapsto \mathbb{R}$ is a function that associates each strategy vector $s \in \mathcal{S}$ with the utility (or *payoff*) to player i.

Representing a strategic setting of collective action as a normal-form game facilitates the analysis and interpretation of its actors' decision-making process and outcomes [28]. The simplest normal-form game is represented as a 2×2 bimatrix (one payoff matrix per player) where rows and columns list a binary strategy space $\mathcal{S}_i = \{0, 1\}$. Figure 1(*a*) shows the general form of a payoff matrix

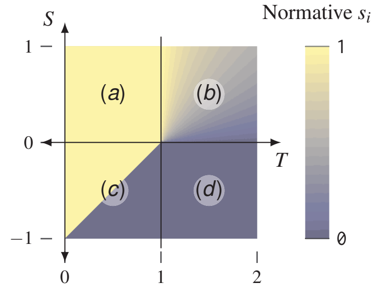
(*a*)

$U_i(s_i, s_j)$	Player j: $s_j = 0$	Player j: $s_j = 1$
$s_i = 0$	$U_i(0,0)$	$U_i(0,1)$
$s_i = 1$	$U_i(1,0)$	$U_i(1,1)$

(*b*)

$u_i(s_i, s_j)$	Player j: Defect	Player j: Cooperate
Defect	0	T
Cooperate	S	1

Fig. 1 Normal-form game: (*a*) player *i*'s payoff matrix; (*b*) normalized payoffs as a social dilemma game



	S	T	F	G
(*a*)	≥ 0	< 1	L	L
(*b*)	> 0	≥ 1	L	H
(*c*)	< 0	≤ 1	H	L
(*d*)	≤ 0	> 1	H	H

L: Low; H: High.

Fig. 2 Normative s_i across S–T plane: (*a*) harmony; (*b*) coexistence; (*c*) bistability; and (*d*) defection dynamics [30]

for any player i where elements show the payoff $U_i(s) = U_i(s_i, s_j)$ that player i would obtain if the corresponding row and column strategies, s_i and s_j, are selected.

In 2×2 social dilemmas (also known as *mixed motives* games), strategy labels indicate whether a player chooses to *cooperate* ($s_i = 1$) or *defect* ($s_i = 0$) and it is assumed that unanimous cooperation is always preferred to mutual defection; i.e.

$$U_i(1, 1) > U_i(0, 0), \quad \forall\, i \in \mathcal{N}. \tag{2}$$

Although often aligning with semantics, *cooperate* and *defect* are only labels and may correspond to any strategic action yielding the corresponding dynamics. In general, the diagonal collective strategies $s = \langle 0, 0 \rangle$ and $s = \langle 1, 1 \rangle$ can be described, respectively, as the *status quo* and the *desired outcome*.

Any normal-form game in which Eq. (2) holds can be characterized as a social dilemma by normalizing payoffs $U_i(s_i, s_j)$ via the positive affine transformation

$$u_i(s_i, s_j) = \frac{U_i(s_i, s_j) - U_i(0, 0)}{U_i(1, 1) - U_i(0, 0)}, \tag{3}$$

which yields $u_i(0, 0) = 0$ and $u_j(1, 1) = 1$. The off-diagonal normalized payoffs obtained with Eq. (3),

$$S = u_i(1, 0) \quad \text{and} \quad T = u_i(0, 1). \tag{4}$$

are referred to as the *sucker's* (S) and *temptation* (T) payoffs in symmetric social dilemma games, respectively.

A normal-form game with normalized payoffs is shown in Fig. 1(*b*). The payoffs in Eq. (4) owe their nickname to the *Prisoner's Dilemma* game where S represents a discouragement to cooperate due to fear and T is an incentive to defect due to greed [29]. More generally, strategy-induced fear is related to a player's expected loss of choosing to cooperate when some or all of the other players defect. Greed is induced by the expected gain of unilaterally deviating from a cooperative collective strategy.

A measure of relative fear (F) and greed (G) can be obtained by dividing the total loss or gain of deviating from a diagonal strategy by the difference between maximum and minimum payoffs [32]. For a symmetric two-player game,

$$F \equiv \frac{U_i(0, 0) - U_i(1, 0)}{\max U_i - \min U_i} \equiv \frac{-S}{\max u_i - \min u_i}, \tag{5}$$

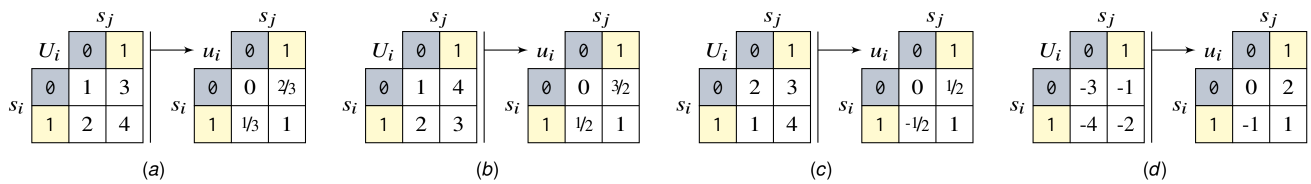


Fig. 3 Strategy dynamics, representative normal-form social dilemma games and their normalized payoffs [30, 31]: *(a)* harmony: *Concord* game, *(b)* coexistence: *Chicken* game, *(c)* bistability: *Stag Hunt*, and *(d)* defection: *Prisoner's Dilemma*

$$G \equiv \frac{U_i(0,1) - U_i(1,1)}{\max U_i - \min U_i} \equiv \frac{T-1}{\max u_i - \min u_i}. \quad (6)$$

The levels of structural fear and greed and their associated values of S and T in the normal-form game in Fig. 1(*b*) describe four different strategy dynamics in Fig. 2 [30]. Each domain exhibits different payoff dominance conditions with respect to the normative (or "rational") Nash equilibrium solution concept for a single-shot, non-cooperative game:

- *Harmony*. Also known as cooperation dynamics, the socially-efficient strategy is also a pure-strategy Nash equilibrium, i.e. unilaterally deviating from such collective strategy is detrimental (and thus irrational) for either player. For instance, in the *Concord* game in Fig. 3(*a*) (positioned within the $s_i = 1$ region of Fig. 2(*a*)), player i is always better off by choosing $s_i = 1$ regardless of the value of s_j. All players naturally concur on the same collective strategy, which also happens to yield the highest available payoff.
- *Coexistence*. In mixed motives games with coexistence dynamics, players drift between two strict equilibrium points by coordinating between conflicting interests described by $s_i \neq s_j$. Also known as *anti-coordination* games, they include *Battle of the Sexes*, *Leader* and, most notably, the game of *Chicken* (Fig. 3(*b*)). A popular example of a Chicken game features two drivers that compete to demonstrate bravery by racing cars toward each other on a single-lane road ($s_i = 0$) hoping for their opponent to "chicken out" and veer off ($s_j = 1$) to avoid collision. The corresponding point in Fig. 2(*b*) shows a mix of normative strategies corresponding to $s_i \neq s_j$ with an implicit power struggle for the upper hand.
- *Bistability*. In two-player bistable or *bipolar* games, such as *Stag Hunt* (Fig. 3(*c*)), the diagonal collective strategies are pure-strategy Nash equilibria. Both players are better off coinciding on $s_i = s_j$, but they might perceive differently which strategy is more favorable. In the absence of complete information about their counterpart's preferences, a player's choice of strategy becomes a matter of balancing intuition, deliberation, and trust [35, 36]. Strategy selection in bipolar games requires further assessment of risk dominance [37] which segments the normative strategy between $s_i = 1$ and $s_i = 0$ regions illustrated in Fig. 2(*c*).
- *Defection*. In defection games, the intersection of the players' equilibrium strategies is a socially-inefficient outcome. For example, the Prisoner's Dilemma game in Fig. 3(*d*) (positioned within the $s_i = 0$ region of Fig. 2(*d*)) demonstrates defection dynamics: two perpetrators of a crime are separately promised a lighter jail sentence if they confess ($s_i = 0$) instead of remaining silent ($s_i = 1$). For either player, confessing the crime and blaming it on their partner is the utility-maximizing course of action, even though refusing to talk is mutually beneficial. Games with defection dynamics are common templates for the study of the evolution of cooperative behaviors in conflict situations [38].

2.2 Strategy Dynamics in Engineering Design. Every decision-making process that involves two or more actors can be described in terms of one or more strategy dynamics regardless of its underlying organizational and incentive structures, multidisciplinarity, or geographic distribution of actors. Likewise, the strategy dynamics introduced in the previous section can be traced to cases in existing engineering design and systems engineering literature; however, no existing work synthesizes design activities across dynamical domains, a necessary step to enable interventions to mitigate or even augment the natural strategy dynamics. This section discusses several such collective settings, one per strategy dynamic, and presents them as normal-form games (Fig. 4).

2.2.1 Harmony. Sustainable consensus between decision-makers is a desired property in any distributed design process and is a natural, although optimistic, dynamic for engineering design. The harmony dynamic is often characterized by a purely cooperative design problem where all actors have aligned objectives and will naturally achieve a collectively efficient outcome. In general, any design problem in which the combination of individual strategies preferred by each actor also yields the highest utility to all of them can be described as a game with harmony dynamics.

An example of these dynamics in engineering design is observed in a behavioral study in Ref. [33] that assessed performance in team-based conceptual design tasks using three team configurations: 1) all designers work together to generate a design concept; 2) one designer assumes a manager role and assists the design process; and 3) all designers work alone on the task (viz. nominal team) and the best design concept is chosen as the team's solution. This problem can be reduced to two strategies: "work together" to pursue a joint effort (or manage) or "work alone" to pursue an independent effort (or serve as managed worker).

Symmetric payoffs assume all team members receive the same reward proportional to the quality of the team's solution. Results in Ref. [33] suggest that unmanaged teams provide worse design quality than managed teams in conceptual design tasks, while the latter were slightly outperformed by nominal teams. Translating results into a hypothetical normal-form game in Fig. 4(*a*) by multiplying quality rating by frequency shows "work alone" is both the payoff-dominant and the only strict equilibrium. In other words, there is no individual or collective incentive in this type of problem to choose other than the "work alone" strategy. Note the "cooperative" strategy is not a semantically correct label in this case: the strategic action to work alone is both preferred by and mutually beneficial for both actors, regardless of the other's decision.

2.2.2 Coexistence. Achieving disciplinary autonomy is yet another goal in the design of complex systems that carries practical difficulties. Although collaborative approaches boost agile subsystem development, system-level evaluation of consistency constraints mitigates their benefits [39]. Integrating some constraints at the discipline level and allowing for a hierarchy of subsystem analyses helps engineers preserve some of the advantages of distributed design without sacrificing robustness.

Choosing between a collaborative, an independent, or a sequential multi-actor decision-making approach can be modeled as a game with coexistence dynamics where the strategy set refers to different levels of autonomy. Consider the design of a passenger aircraft in Ref. [6, 7] with two disciplinary teams (Weights and

$U_i(s_i, s_j)$	The other designer(s): Work together	Work alone
Work together	14	23
Work alone	23	28*

∗ Nominal team's performance.

(*a*)

$U_i(s_i, s_j)$	Aerodynamics team: Lead	Collaborate
Lead	$1 - 0.262^*$	$1 - 0.201$
Collaborate	$1 - 0.255$	$1 - 0.213$

∗ Non-cooperative/isolated actors solution.

(*b*)

$U_i(s_i, s_j)$	NOAA: Independent	Joint System
Independent	0.680	0.680
Joint System	0.434	0.719

∗ Risk-dominant, perfectly-limited strategy.

(*c*)

$U_i(s_i, s_j)$	Materials Engineer: Free-ride	Commit
Free-ride	2.00	4.01*
Commit	0.98*	3.74

∗ Non-substitutable roles (zero efficiency).

(*d*)

Fig. 4 Strategy dynamics: examples from engineering design and systems engineering literature: *(a)* harmony: cumulative quality ratings of concepts generated by members of a design team [33]; *(b)* coexistence: Weights team performance in various aircraft design approaches [6, 7]; *(c)* bistability: DoD's payoffs from a risk dominance analysis of distributed satellite systems [34]; and *(d)* defection: design engineer's payoffs in team-based product development model [5].

Aerodynamics) poised to either lead the design process or cooperate with the other. There are three possible scenarios:

i. Both teams pursue leadership of the design process and the lack of cooperation results in low-performing subsystems with respect to system-level integrability.
ii. Both teams are willing to collaborate to improve integrability but unwilling to lead. Such concurrency of design decisions is limited by complexity and practicality issues.
iii. One team leads the design process and initiates the search for feasible solutions within their domain. The other team carries on the search at the discipline level constrained by the leading team's outcomes.

In the first scenario, actors make decisions in isolation, either intentionally or involuntarily, while making assumptions about the preferences of their counterparts. This scenario is modeled as an isolated decision support problem. The second scenario encompasses the main principles of concurrent engineering. In practice, this paradigm can be modeled as approximate cooperation [7]. Finally, the third scenario describes a Stackelberg/leader–follower protocol [40].

The normal-form game in Fig. 4(*b*) shows the performance of the Weights team in each scenario measured as 1 minus a deviation function—or the difference between what the design team wants and what they achieve [6, 7]—for each strategic scenario. (The payoff matrix for the Aerodynamics team, not shown, is estimated in a similar fashion and has the same payoff ordering). The individual performance of either team is maximized when they lead the process and the other team follows.

This scenario resembles a variant of the Chicken game called *Hawk–Dove* where two actors compete for access to limited common-pool resources and are better off letting the other take the advantage and avoid confrontations. As an example, for the completion of a large project within an engineering organization, disciplinary teams competing for limited resources such as personnel, facilities, and equipment, need to agree on the assignment of roles—which teams are hawks (leaders) and which ones are doves (followers)—that generates the most positive externalities for the organization [41].

2.2.3 Bistability. Strategic sharing of information and resources by and between actors in a design process is governed by autonomy and pursuit of individual gains. This is especially relevant in the design of federated systems and systems-of-systems where there is a lack of centralized control and adherence to a common strategy is voluntary [2]. This scenario can me modeled as a Stag Hunt game where players weigh the upside potential of cooperative joint action and the downside risk of coordination failure [8]. The alternative—and *safer*—strategy chooses independent action, analogous to chasing hares instead of collaborating on hunting a stag, the Pareto-dominant equilibrium [42].

Figure 4(*c*) shows the payoff matrix for United States government agencies directed to coordinate efforts to develop a distributed satellite system [34]. The directive, known as National Polar-orbiting Operational Environmental Satellite System (NPOESS), was a joint endeavor between the U.S. Department of Defense (DoD) and the National Oceanic and Atmospheric Administration (NOAA) to replace and unify existing independent missions, combine capabilities, and save resources [43]. NPOESS consolidation presents some upside benefits to the DoD (e.g. 0.719 for a joint system vs. 0.680 for an independent system); however, joint operations carry additional risk of coordination failures if other partners drop out (e.g. falling to 0.434). Similar strategic dynamics exist for NOAA, but with greater upside potential. Lack of alignment between strategic sources of risk may have contributed to disagreements along the program and its eventual dissolution [34].

2.2.4 Defection. From mathematics and the social sciences to biology and systems theory, the Prisoner's Dilemma game is widely used to represent a bargaining problem between self-interested agents that might pass on pursuing a mutual benefit. Similar applications in engineering design also use it as a model to study collaboration [14]. One example is provided by Takai [5] and presented in Fig. 4(*d*). This model represents a dilemma between two disciplinary engineers in a team-based product development process that choose between committing time to teamwork or focusing exclusively on individual projects.

The payoffs for the design and materials engineers combine the value obtained from individual project performances and contributions to the team project performance. Allocating time to the team project negatively affects one's individual project performance. Meanwhile, allocating time to an individual project produces benefits from both individual and team outcomes [44]. In cases with a free-rider, the team project success depends on how effective one role is for the other. In cases with low effectiveness in Fig. 4(*d*), free-riding is a payoff-dominant strategy for both engineers, i.e. Nash equilibrium. Although the collective efficient solution commits to the team project, the underlying dynamics in this problem promote free-riding as a dominant strategy.

2.3 Research Objectives. Literature in engineering design shows two main limitations with adopting game-theoretic concepts to explain strategy dynamics in multi-actor design problems. First, some existing work equates strategies with design decisions following an optimization perspective [16, 22, 23], yielding a large number of alternative strategies and limited ability to characterize the strategy dynamics. Second, existing work that implicitly or explicitly adopts a more abstract strategic decision [5–7, 33, 34] focuses on one dynamical domain at a time, rather than understanding how the underlying problem structure contributes to the resulting actor dynamics. As a result, there is limited knowledge about how strategy dynamics influence engineering design decision-making.

This study works towards a theory of collective systems design by establishing a body of evidence based on analytical and behavioral experiments to address the research question:

> *How do the strategic components characteristic of the structure of a design problem affect collective action?*

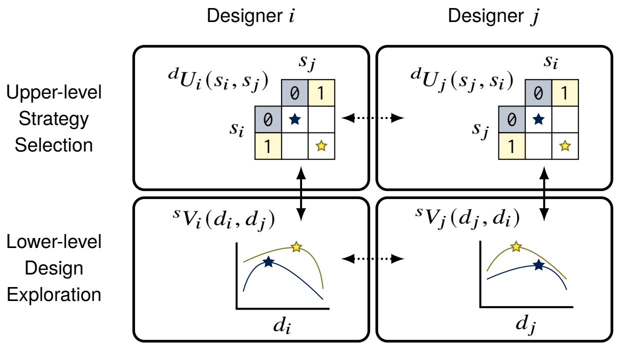


Fig. 5 Two-actor bi-level model of collective systems design with lower-level design exploration and upper-level strategy selection under interactive effects

Owing to the broadness of this goal, this paper focuses on the modeling of strategic components in collective parameter design tasks for the four social dilemma strategy dynamics previously introduced. Research questions specific to this work are:

RQ1. How can strategy dynamics be characterized as a phenomenon related to, but distinct from, design optimization in an engineering design problem?
RQ2. How can collective parameter design problems be generated to exhibit specified strategy dynamics?
RQ3. How do strategy dynamics affect strategy selection, collective efficiency, and equality in parameter design tasks?

To answer these questions, we formulate a multi-actor system value modeling framework that maps lower-level design decisions to a measure of preference over upper-level strategy profiles (Section 3). This bi-level model serves as the basis to generate synthetic two-actor parameter design tasks with specified that exhibit steady harmony, coexistence, bistability, or defection dynamics (Section 4). Finally, a human-subject experiment administers pair design tasks to assess the effect of strategy dynamics on collective design performance (Section 5).

3 Bi-level Model of Collective Systems Design

In response to RQ1 about how strategy dynamics relate to traditional design decision-making activities and processes, this section presents a bi-level model of collective decision-making in engineering design as the mathematical foundation of this work. It assumes two types of decisions: lower-level design decisions in a large design space and upper-level strategy decisions in a limited strategy space. Strategy dynamics are attributed to the upper-level decision problem, framed here as a single-shot game, which is influenced by outcomes of lower-level design decisions. Examples in Section 2.2 reinforce the distinction between strategy decisions (e.g. lead or collaborate across disciplines) and design decisions (e.g. select aircraft parameters) present in this model.

This section extends prior research formulating bi-level models for problems with bistability strategy dynamics and risk dominance [45, 46] to other types of strategy dynamics present in a design problem. As illustrated in Fig. 5, the lower-level frames design decisions $d = \langle d_i \rangle$ as an optimization problem within a fixed strategic context while the upper-level frames strategy decisions $s = \langle s_i \rangle$ as a normal-form game. Initially presented as a sequential process from lower- to upper-level, subsequent discussion reveals an iterative nature of the model.

3.1 Lower-level: Design Exploration. The lower-level decision problem models engineering design as an optimization problem, reflecting dominant perspectives in decision-based design literature [13]. The process of engineering design defines and evaluates design solutions from the set of alternatives $d \in \mathcal{D}$. In multi-actor scenarios, the design solution can be decomposed into a vector of elements $d = \langle d_1, \dots, d_n \rangle$ controlled by each of n actors with corresponding design spaces $d_i \in \mathcal{D}_i$. Following axiomatic design theory [47], each design element can be further composed of individual design parameters $d_i = \langle {}^1x_i, {}^2x_i, \dots \rangle$ such that the resulting design space $\mathcal{D}_i$ is a Cartesian product of continuous ($\mathbb{R}$) and discrete ($\mathbb{Z}$) scalar spaces.

Various functions (models) evaluate design solutions by mapping the design space $\mathcal{D}$ to other spaces. Most relevant to decision-based design, a lower-level value function $V_i(d)$ maps a design to a scalar measure of actor i's preference for it (viz. a utility function).

Diverging from most existing design literature, assume valuation takes place within a limiting context as a function of a strategic state in a set of alternatives $s \in \mathcal{S}$. The strategic state implicitly defines a set of assumptions, large in both scope and corresponding commitment [24], that constrain *how* a design delivers value. Strategic states may arise from other actors' decisions (e.g. participation in joint operations; build-up or reduction in arms; pursuit of a new market) or external actions (e.g. environmental conditions; technology maturity; public sentiment). The effect of strategic state on value is captured by a second parameter, superscript s in ${}^sV_i(d)$, and an equivalent function signature ${}^sV_i(d) = {}^sV_i(d_i, d_{-i})$ highlights design decisions controlled by actor i and those controlled by other actors $(-i)$.

The resulting lower-level design process in Eq. (7) resembles an optimization problem where $\delta_i : \mathcal{S} \mapsto \mathcal{D}_i$ finds the context-specific design that maximizes value.

$$\delta_i(s) = \arg\max_{d_i \in \mathcal{D}_i} {}^sV_i(d_i, \hat{\delta}_{-i}) \tag{7}$$

A necessary component of multi-actor design, anticipation of others' design solutions $\hat{\delta}_{-i}$ is based on a transient belief state. Represented here as a fixed point, more detailed design processes assign a probabilistic belief state to maximize expected value.

3.2 Upper-level: Strategy Selection. The upper-level decision problem models engineering design as a strategic game by considering interactive effects among actors driven by strategy dynamics. While the lower-level problem focuses on design decisions, treating the strategy as context, the upper-level problem inverts it to focus on strategy selection, treating design solutions as context. For clarity in presentation, consider a slight notation shift to quantify actor i's payoffs as ${}^dU_i(s) \equiv {}^sV_i(d)$.

The resulting upper-level design process in Eq. (8) resembles a strategic game where $\sigma_i : \mathcal{D} \mapsto \mathcal{S}$ finds the design-specific strategy that maximizes payoff.

$$\sigma_i(d) = \arg\max_{s_i \in \mathcal{S}_i} {}^dU_i(s_i, \hat{\sigma}_{-i}) \tag{8}$$

Similar to the lower-level problem, anticipation of others' strategy selections $\hat{\sigma}_{-i}$ is based on a transient belief state, perhaps with profound uncertainty due to the strategic nature of the information. While notionally expressed as a function maximization, selecting the payoff-maximizing strategy $\sigma_i(d)$ may result to equilibrium analysis or other decision rules to resolve interactive effects.

The above formulation hints at the iterative nature of the bi-level model which is limited by large design spaces (i.e. it is impractical to solve the upper-level problem for each design alternative). Assuming a sequential design process from lower- to upper-level problems suggests designers first optimize the design $\delta_i(s)$ in each strategic context s and, second, select a payoff-maximizing strategy σ_i. However, the reverse process implies designers first select a strategic state $\sigma_i(d)$ based on generalizable strategy dynamics and, second, optimize the design δ_i for it. In practice, both processes likely influence decisions in an iterative scheme.

3.3 Model Assumptions and Limitations. This model has a number of assumptions and limitations that should be discussed. First, it uses utility (value) functions to quantify scalar actor preference for alternatives. While a critical element of decision theory, valid utility functions are difficult to formulate and elicit for prescriptive purposes. In this theoretical application, utility functions represent internal decision-making activities. The model does not exchange utility functions between actors; they are only used (by each actor) to guide internal decision processes and (by an observer) to characterize the strategy dynamics.

Second, this model assumes the lower- and upper-level design activities represent distinct decisions. The lower-level problem explores a large design space with well-characterized interactions between actors to facilitate evaluation and optimization of context-specific value functions ${}^sV_i$. The upper-level problem deals with a smaller strategy space where stronger interaction effects between actors and barriers to strategic information exchange complicate the maximization of the design-specific utility functions ${}^dU_i$.

Finally, although simply expressed as a maximization problem, lower- and upper-level solution processes are, in practice, complex activities. For simplicity of presentation, this paper presents lower-level evaluation functions as deterministic functions, a common but unrealistic practice [48]. Including uncertainty for lower-level design exploration transforms Eq. (7) into an expected value maximization problem but nonetheless is compatible with the general framework. Additionally, both lower-level and upper-level decision processes depend on a belief state about others' actions ($\hat{\delta}_{-i}$ and $\hat{\sigma}_{-i}$) influenced by prior relationships and information accumulated in iterative design processes. Use of normal-form games further suggests a single-shot, simultaneous upper-level strategy selection process. However, in practice, strategy selection is more of a sequential, multi-stage, or even iterative activity that revisits lower-level design decisions. These dynamic effects are not represented in the static bi-level model formulation presented here but could be incorporated in a future extension.

4 Bi-level Parameter Design Tasks

In response to RQ2 about how design problems can be generated to exhibit specified strategy dynamics, this section formulates a class of symmetric two-actor parameter design problems conforming to the bi-level model of collective systems design described in Section 3. The parameter design tasks represent an abstraction of a design problem based on the following principles:

(1) Tasks exhibit *static* strategy dynamics characterized by parameters S and T in Section 2.1. Although unrealistic, fixing strategy dynamics is essential to this research question.
(2) Tasks exhibit symmetry between two designer roles with identical input decision spaces and output value spaces. Symmetry improves experimental control and sensitivity.
(3) The upper-level strategy space $\mathcal{S}_i \times \mathcal{S}_j$ considers only two alternatives $\mathcal{S}_i = \{\mathtt{0}, \mathtt{1}\}$ canonically labeled defection ($s_i = \mathtt{0}$) and cooperation ($s_i = \mathtt{1}$) in social dilemma games.
(4) The lower-level design space $\mathcal{D}_i \times \mathcal{D}_j$ composes two sub-spaces $\mathcal{X}_i \times \mathcal{X}_j$ (one per diagonal collective strategy) where $\mathcal{D}_i = \mathcal{X}_i \times \mathcal{X}_i$. Sub-spaces have small cardinality $|\mathcal{X}_i| = 9$ to accommodate limited resources in behavioral experimentation.
(5) Lower-level value functions ${}^sV_i$ for each strategy exhibit locally-smooth surfaces with one local-maximizing point on the plane of symmetry and one global-maximizing point off the plane of symmetry. This presents a conflict where the individually-preferred solution is not mutually preferred.

The resulting tasks are representative of engineering design only at an abstract level. Multiple local maxima and conflicting global maxima are common design features; however, others such as smooth value surfaces, finite and small design spaces, symmetry, and context independence are atypical. Therefore, results from these tasks may only be valid at an abstract level and care must be taken before applying conclusions to more specific settings.

Table 1 Parameter design tasks: strategy dynamics, normalized payoffs, fear and greed levels, and value space ranges

Task type	Strategy dynamic	Normalized payoffs				$[{}^sV_{\min},\ {}^sV_{\max}]$	
		S	T	F	G	$s = \mathtt{00}$	$s = \mathtt{11}$
HA	Harmony	1/3	2/3	−1/3	−1/3	[1, 49]	[56, 100]
CX	Coexistence*	1/2	3/2	−1/3	1/3	[1, 33]	[35, 67]
BI	Bistability*	−1/2	1/2	1/3	−1/3	[34, 66]	[68, 100]
DE	Defection	−1	2	1/3	1/3	[34, 50]	[51, 67]

* Risk dominance between strict equilibria is set neutral (i.e. $R = 0$). See Refs. [8, 35, 37].

Each task type and its main characteristics are presented in Table 1 and implementation is discussed in the following sections. The notation introduced in this section builds upon prior work in Ref. [49] and is listed in the Nomenclature section.

4.1 Lower-level Design Spaces. Each actor controls a design vector with two integer parameters $d_i = \langle {}^{\mathtt{00}}x_i, {}^{\mathtt{11}}x_i \rangle$ where ${}^{\mathtt{00}}x_i \in \mathcal{X}_i = \mathbb{Z}_9 = \{0, \dots, 8\}$ targets a context with inferior collective outcome ($s = \langle \mathtt{0}, \mathtt{0} \rangle$, labeled as binary digit $\mathtt{00}$) and ${}^{\mathtt{11}}x_i \in \mathcal{X}_i$ targets a context with superior outcomes ($s = \langle 1, 1 \rangle$, labeled as bit $\mathtt{11}$). In other words, design variable d_i composes two individual design solutions for status quo ($s = \mathtt{00}$) and mutually-beneficial ($s = \mathtt{11}$) settings. The resulting design space has $|\mathcal{D}_i| = |\mathcal{X}_i \times \mathcal{X}_i| = 81$ alternatives per actor and $|\mathcal{D}_i \times \mathcal{D}_j| = 6{,}561$ joint alternatives in total.

A context-specific value function ${}^sV_i(d_i, d_j) \in [{}^sV_{\min}, {}^sV_{\max}]$ maps points in the joint design space to a joint value space by extracting the relevant design parameters for each context in Eq. (9).

$$
{}^sV_i(d_i, d_j) = \begin{cases} {}^{\mathtt{00}}f_i({}^{\mathtt{00}}x_i, {}^{\mathtt{00}}x_j) & \text{if } s = \mathtt{00} \\ {}^{\mathtt{11}}f_i({}^{\mathtt{11}}x_i, {}^{\mathtt{11}}x_j) & \text{if } s = \mathtt{11} \end{cases} \tag{9}
$$

Curated context-specific value functions ${}^sf_i$ are generated using a similar procedure as in Ref. [49] (see the Appendix) to ensure no point simultaneously maximizes both actors' objectives. To enforce symmetry, both actors are assigned the same value function, i.e. ${}^sf_i \sim {}^sf_j$, which yields equal lower-level value for ${}^sx_i = {}^sx_j$.

Strategies are labeled such that ${}^{\mathtt{11}}V_{\min} > {}^{\mathtt{00}}V_{\max}$ as listed in Table 1 to enforce Eq. (2) and constrain $U_i(s) \in [0, 100]$ during upper-level strategy selection. The resulting lower-level problems, shown in Table 2, appear as two $\mathcal{X}_i \times \mathcal{X}_j$ design spaces (labeled $\mathtt{00}$ and $\mathtt{11}$), presented and explored concurrently.

Additional information on the method used to generate the lower-level design spaces used in the parameter design tasks is provided in the Appendix.

4.2 Upper-level Strategy Spaces. The actors' decisions selected during the lower-level design exploration are mapped to a scalar utility space with constants S and T in Eq. (10). Constants for each task type in Table 1 were selected to produce two levels of F and G across the four strategy dynamics in Fig. 2. To preserve constant S and T, actor i's payoff is artificially computed as

$$
{}^dU_i(s) = \begin{cases} {}^sV_i(d) & \text{if } s = \mathtt{00} \text{ or } \mathtt{11} \\ (1 - T) \cdot {}^{\mathtt{00}}V_i(d) + T \cdot {}^{\mathtt{11}}V_i(d) & \text{if } s_i = \mathtt{0} \neq s_j \\ (1 - S) \cdot {}^{\mathtt{00}}V_i(d) + S \cdot {}^{\mathtt{11}}V_i(d) & \text{if } s_i = \mathtt{1} \neq s_j \end{cases} \tag{10}
$$

where d_i are the lower-level designs for each actor. To exert tight control over strategy dynamics, payoffs for conflicting strategies are a function of both ${}^{\mathtt{00}}V_i$ and ${}^{\mathtt{11}}V_i$. In other words, actors observe the direct lower-level valuation under mutual strategies ($\mathtt{00}$ or $\mathtt{11}$)

Table 2 Sample design spaces and utility–utility tradespaces for each type of parameter design task

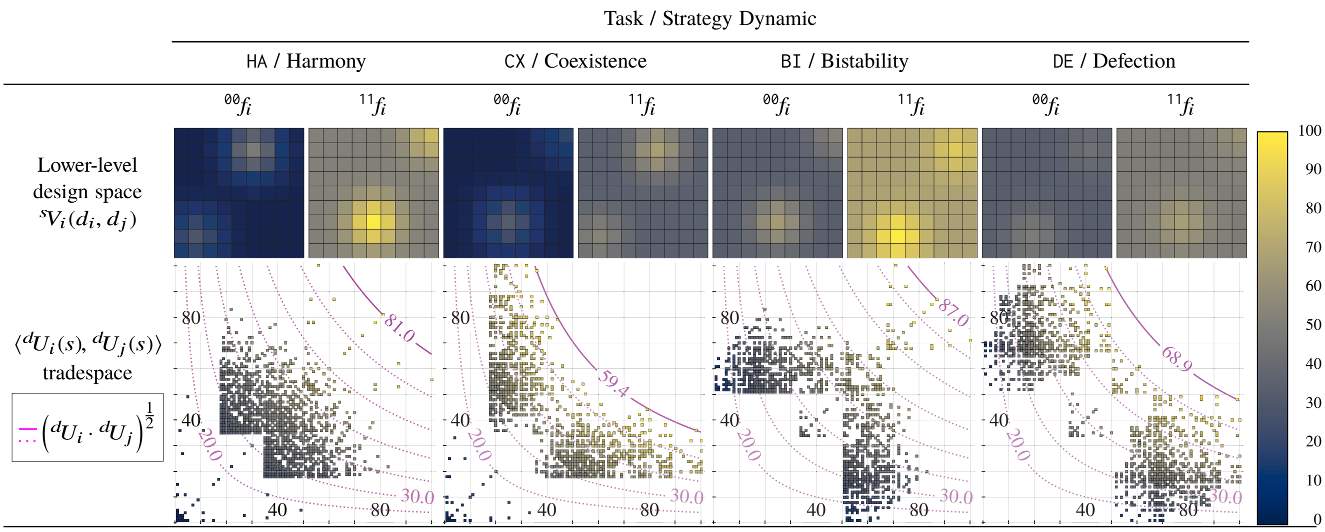


Table 3 Distribution of collective efficiency scores within each task tradespace; p_{90}: top 10th percentile.

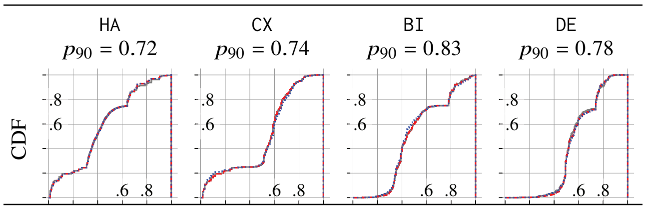
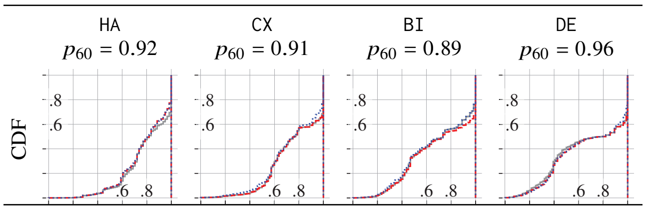


Table 4 Distribution of equality scores within each task tradespace; p_{60}: top 40th percentile.



but cases with conflicting strategies mix the other two outcomes to produce desired strategy dynamics with fixed S and T.

Tables 2 shows the joint utility tradespaces of all possible upper-level strategy outcomes ($4 \times 6{,}561 = 26{,}244$). It includes 6,561 outcomes (each) for upper-level solutions $\langle 0, 1 \rangle$ and $\langle 1, 0 \rangle$ and 81 *unique* outcomes (each) for upper-level solutions `00` and `11` each replicated 81 times to enable descriptive statistics of outcomes via percentile ranks. Tradespace contour lines show the square root of the product ${}^{\delta}U_i(s) \cdot {}^{\delta}U_j(s)$, akin to the generalized Nash product [50] as reference for collective efficiency.

4.3 Collective Design Metrics. Two dimensions assess actors' collective design performance in a task based on the final design δ and strategy σ decisions:

i. Maximization of the product of their payoffs, i.e. converging to a Pareto-efficient solution.
ii. Similarity in their payoffs, comparable to an individual sense of equity and fairness.

The first dimension measures collective efficiency calculated as the ratio of the product of observed payoffs ${}^{\delta}U_i(\sigma)$ and ${}^{\delta}U_j(\sigma)$ to the global maximum within the utility–utility tradespace:

$$\text{Efficiency} = \frac{{}^{\delta}U_i(\sigma) \cdot {}^{\delta}U_j(\sigma)}{\max_{d,s} {}^{d}U_i(s) \cdot {}^{d}U_j(s)} \in [0, 1]. \qquad (11)$$

The second dimension measures equality, calculated in terms of the ratio of the absolute difference between the observed payoffs to the maximum possible disparity between task outcomes:

$$\text{Equality} = 1 - \left| \frac{{}^{\delta}U_i(\sigma) - {}^{\delta}U_j(\sigma)}{\max_{d,s} {}^{d}U_i(s) - {}^{d}U_j(s)} \right| \in [0, 1]. \qquad (12)$$

The aforementioned collective design metrics, as well as the parameter tasks described in this work, are inherently symmetric with respect to the design actors' identities and roles.

Table 3 and 4 show plots collective efficiency and equality cumulative distribution functions (CDFs) for outcomes of three generated design problems (red, blue, and gray lines) in each task tradespace. Although each metric is similarly distributed across task types and generated instances, assessment of the effect of a strategy dynamic on collective performance uses the percentile rank (PR) within their tradespace to allow a more direct comparison of outcomes.

Finally, it is worth mentioning that Eq. (11) is not intended to represent a measure of "social efficiency" even though it mimics Nash's solution to bargaining games [51]. Similarly, minimizing Eq. (12) does not translate into higher social welfare because equal payoffs could be equally poor. Nevertheless, both metrics provide a good starting point to assess collective design performance.

5 Design Experiment Methodology

In support of RQ3 to assess the effect of strategy dynamics (Section 2) on outcomes of collective design tasks, we conducted a human-subject experiment using the bi-level parameter design tasks defined in Section 4. Observations measure the effect of four fixed strategy dynamics with two dimensions (fear and greed) on collective efficiency, equality, and individual strategy selection.

5.1 Experimental Design. The experiment follows a hybrid within- and between-subjects design with replication at task and design pair units. A design session is structured as a round-robin, all-play-all tournament for each of the four task types. Four participants per session provide three possible design team pairings.

Assigning each pair to complete one task per strategy dynamic requires 12 parameter design tasks per session. Across 10 sessions, this experimental design generates $10 \times 12 \times 2 = 240$ pair design task observations, 60 of each strategy dynamic.

Table A.1 lists the rounds in each session (including training rounds T1–T4), the task type (HA, CX, BI, or DE), context-specific maxima for ${}^{00}f_i({}^{00}x_i, {}^{00}x_j)$ and ${}^{11}f_i({}^{11}x_i, {}^{11}x_j)$ in Eq. (9), and pairing of designers with indices 1–4. The algorithm generating lower-level value spaces (see Section 4.1 and the Appendix) is further constrained to require different local maxima between consecutive tasks to limit anchoring effects.

5.2 Designer Interface. Human actors participate in a parameter design task using a graphical user interface (GUI) illustrated in Figs. 6(*a*)–(*b*). Although embodying the bi-level parameter design task, the GUI does not label strategies or strategy dynamics. It consists of three panels, left, right, and center of the display:

- The left and right panels give actors control over lower-level design decisions within strategic contexts $s = \mathtt{00} \rightarrow ⓪$ and $s = \mathtt{11} \rightarrow ①$. Each actor controls the horizontal axis of a design space and their partner controls the vertical axis.
- The center panel shows the task number (round), a timer to complete lower-level design exploration, and a timer to complete a final upper-level strategy selection.

Clicking on a panel sets actor i's corresponding strategy s_i. For example, designer 1 in Fig. 6(*a*) clicks on panel 00 to set $s_1 = 0$.

The interior of each of the 00 and 11 panels contains a colored square grid plot of ${}^{s}f_i$ (partially visible), a color bar, and one horizontal slider:

- Actor i modifies d_i using the horizontal sliders below each grid to set design parameters (left: ${}^{00}x_i$, right: ${}^{11}x_i$). The other actor's decision d_j appears, in real time, along the vertical axis of the corresponding panel (left: ${}^{00}x_j$, right: ${}^{11}x_j$).
- To disguise the sameness between ${}^{s}f_i({}^{s}x_i, {}^{s}x_j)$ and ${}^{s}f_j({}^{s}x_j, {}^{s}x_i)$, the ${}^{s}x_j$ axes are reversed and the design alternatives are labelled with the first $|\mathcal{X}_i| = 9$ letters from the English alphabet (e.g. ${}^{s}x_i = 0 := \mathsf{A}$ and ${}^{s}x_j = 0 := \mathsf{I}$).
- The design grid focal point expanded in Fig. 7 reveals payoffs for the selected design in the current context ${}^{d}U_i(s_i, s_i)$ (upper-left triangle), the selected design in an alternate context ${}^{d}U_i(s_i, 1 - s_i)$ (lower-right triangle), and payoffs for the 4-neighborhood around $\langle {}^{s}x_i, {}^{s}x_j \rangle$. The numerical values correspond to payoffs in the normal form bimatrix in Fig. 8; however, it is not presented as such in the design task.
- Grid plot payoff colors use the perceptually-uniform *cividis* colormap optimized for color vision deficiency [52]. The colorbar ranges from 0 (dark blue) to 100 (yellow).

The lower-level design process within strategic context s proceeds with designer i modifying parameter ${}^{s}x_i$ left-and-right and designer j modifying parameter ${}^{s}x_j$ up-and-down. Designer i observes and uses nominal payoff ${}^{d}U_i(s)$ to direct the search process while designer j likewise observes and uses payoff ${}^{d}U_j(s)$. Both pursue maximum individual values; however, lack of vertical control and competing objectives require satisficing solutions.

Although clearly an artificial design problem, the resulting interface seeks to combine both perspectives of lower-level design exploration as an optimization problem and upper-level strategy selection as an interactive game. The visual representation of two static design spaces with real-time exchange of design parameters helps to elicit optimizing behaviors to maximize individual objectives. Meanwhile, the display of alternative payoffs under misaligned strategies and no equivalent sharing of strategy decisions facilitates strategic behavior common in social dilemma problems.

5.3 Experimental Protocol. The experiment protocol was approved by Stevens Institute of Technology's Institutional Review Board. Framed as a game-based engineering design experiment, each session gathers four participants for about 50 min as follows:

+ 5 min: Informed consent and demographics survey
+ 5 min: Multi-dimensional locus of control questionnaire [53]
+ 10 min: Introduction and training (4 rounds)
+ 30 min: Main design experiment (12 rounds).

The introduction explains the task formulation and instructs participants to to maximize their individual aggregated scores (i.e. sum of final ${}^{\delta}U_i(\sigma)$ payoffs across 12 rounds) with increasing financial incentives (gift cards worth \$8, \$10, \$12, and \$15) tied to successive ranks. Training explains how to use the designer GUI including user interface controls, meaning of numerical displays with respect to payoffs (scores), and the timer function. Training consists of four parameter design tasks, one per strategy dynamic, that differ from the main 12 tasks in S, T, and scaling of local maxima (Table A.1). Subjects are prompted to ask questions about the use of the GUI or task representation during training which can be paused to permit sufficient explanation.

Paired subjects sit face-to-face and are allowed to talk but cannot see or share each other's screen. Each round allots two minutes to find a collective solution for a bi-level parameter task as follows:

+ 1 min 45 s: Lower-level design exploration / design time
+ 15 s: Upper-level strategy selection / strategy time.

Each task is initialized at ${}^{s}x_i = {}^{s}x_j = 4$ (non-local maximum) on left and right panels for $s = \mathtt{00}$ and $s = \mathtt{11}$. During design time, subjects iterate between lower-level design exploration and upper-level strategy selection with visibility of their partners' actions. In this stage, subjects navigate to desirable regions of the design space to maximize value and improve their payoff structure, aware of strategic trade-off and uncertainty of their partners' final strategy.

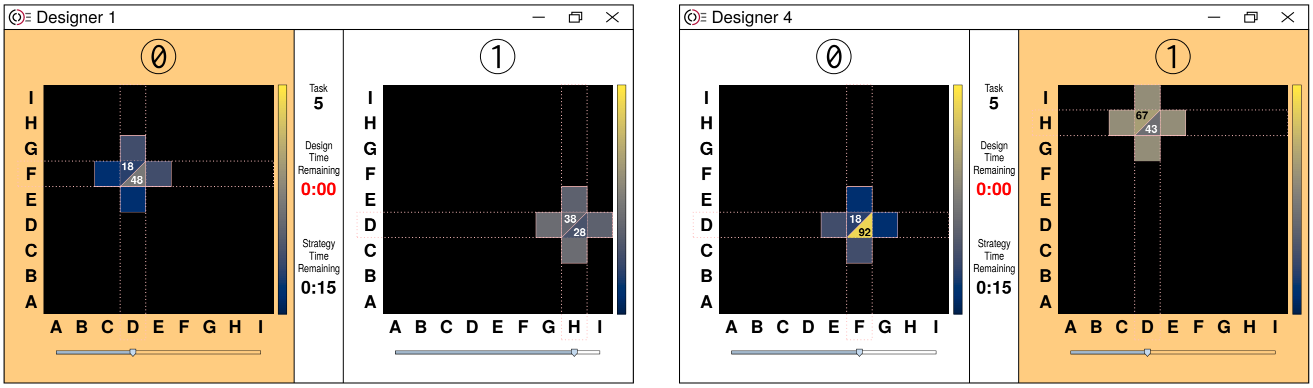
When the design time runs out, input sliders are locked at the final design decision δ and subjects have 15 seconds extra (strategy time) to select final upper-level strategies σ by clicking anywhere on the 00 or 11 panels, viz. playing the normal-form game resulting from lower-level design exploration (Figs. 8(*a*)–(*b*)).

While the interface exchanges real-time design selections during the lower-level design exploration activity, no updates are displayed during the upper-level strategy selection activity to preserve strategic information. When the task ends, the GUI turns black and participants proceed to switch partners for the next task. Participants cannot see final payoffs after each parameter design task to limit positive or negative reputation effects. Aggregated scores for the main 12 tasks are announced only at the end of the session.

5.4 Participant Demographics. A total of 40 subjects were recruited in 10 study sessions. All participants previously completed or were in their last year of science, technology, engineering, or mathematics (STEM) undergraduate studies. Participants reported age, gender, years of education, professional experience, English proficiency level, and familiarity with each other:

- The subjects ranged between 21–38 years of age with a median of 26.5 and a mode of 23 (8 occurrences).
- 14 subjects identified as female and 26 as male.
- Post-secondary STEM education ranged between 4–13 years with a median of 7.0 and a mode of 5 (12 occurrences).
- Professional experience ranged between 0–10 years with a median of 2.0 years and a mode of 1 year (12 occurrences).
- Regarding English proficiency, 18 reported TOEFL scores above 95 (IELTS > 7.0), 9 between 85–94 (IELTS 6.5-7.0), 4 below 84 (IELTS ≤ 6.0). Others are fluent/native speakers.

Finally, participants generally had limited prior interaction with each other. At least one participant did not know any other participant in 8 of 10 sessions. Most participants knew at least one other person and only nine participants across 5 of 10 sessions reported knowing at least two others.



(*a*) (*b*)

Fig. 6 Snapshot of parameter design task CX.3 between designers $i = 1$ and $j = 4$ (round No. 5, pair 2, in Table A.1): *(a)* designer 1: $d_1 = \langle {}^{00}x_1, {}^{11}x_1 \rangle = \langle 3, 7 \rangle$; *(b)* designer 4: $d_4 = \langle {}^{00}x_4, {}^{11}x_4 \rangle = \langle 3, 5 \rangle$. Current selected collective strategy is $s = \langle 0, 1 \rangle$.

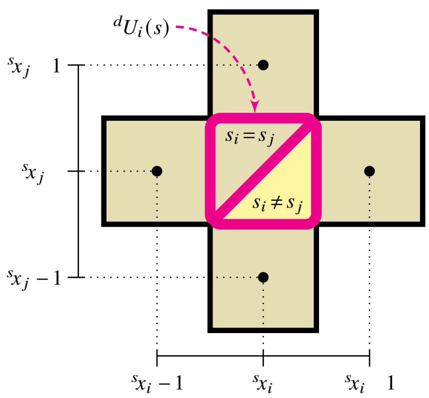


Fig. 7 Visible value subspace for strategic context $s \in \{00, 11\}$ in the designer GUI. Values of ${}^{d}U_i(s)$ for $s_i = s_j$ and $s_i \neq s_j$ calculated using Eq. (10).

Designer 4

${}^{d}U_1(s)$	${}^{00}x_4 = 3$	${}^{11}x_4 = 5$
${}^{00}x_1 = 3$	18	48
${}^{11}x_1 = 7$	28	38

(*a*)

Designer 1

${}^{d}U_4(s)$	${}^{00}x_1 = 3$	${}^{11}x_1 = 7$
${}^{00}x_4 = 3$	18	92
${}^{11}x_4 = 5$	43	67

(*b*)

Fig. 8 Payoff matrices for snapshot of parameter design task in Fig. 6 exhibiting coexistence dynamics: *(a)* designer 1's payoff matrix; *(b)* designer 4's payoff matrix

6 Results and Analysis

The outcomes of the design experiment, i.e. the final decisions selected by each actor and the resulting payoffs realized for each task, were aggregated by task type. Cumulative link model (CLM) regression analyzes the effect of the strategy dynamics, in terms of fear and greed factors, on collective design outcomes.

6.1 Experimental Results. Table 5 summarizes final joint strategies (σ) for 60 design pairs and individual strategies (σ_i) for 120 designers across each task type. In brief:

- Harmony dynamics show frequent selection of the payoff-dominant collective strategy individually (104/120 choose $\sigma_i = 1$) and in pairs (49/60 choose $\sigma_i = \sigma_j = 1$), aligning with normative strategies in Fig. 2(*a*).
- Coexistence dynamics show mixed strategy selection individually (55/120 choose $\sigma_i = 0$, 65/120 choose $\sigma_i = 1$) and anti-coordination strategies as a pair (37/60 choose $\sigma_i \neq \sigma_j$), aligning with normative strategies in Fig. 2(*b*).
- Bistability dynamics show frequent selection of the payoff-dominant collective strategy individually (101/120 choose $\sigma_i = 1$) and in pairs (47/60 choose $\sigma_i = \sigma_j = 1$), in contrast to the normative strategy in Fig. 2(*c*) that makes no distinction between the two strategies.
- Defection dynamics show mixed strategy selection individually (66/120 choose $\sigma_i = 0$, 54/120 choose $\sigma_i = 1$) and in pairs (21/60 choose $\sigma_i = \sigma_j = 0$), in partial alignment with normative strategies of collective inefficiency in Fig. 2(*d*).

In addition to strategy selection, collective design performance also depends on value-driven outcomes of the lower-level design exploration phase. Figure 9 shows a box plot of percentile rank (PR) collective efficiency and equality observed during upper-level strategy selection, contrasting outcomes of the most collectively-efficient strategy $s = \arg\max_s {}^{\delta}U_i(s) \cdot {}^{\delta}U_j(s)$ and the final selected strategy σ. For collective efficiency:

- Lower-level design activities are generally productive across all tasks, generating collectively-efficient upper-level alternatives with a median percentile rank above 97%.
- The median percentile rank of collective efficiency for final strategy selections scored above 97% for harmony and bistability dynamics, slightly declined to 87% for coexistence dynamics, and greatly declined to 60% for defection dynamics.

For equality:

- The median percentile rank of equality for the most collectively-efficient upper-level alternative was 100% for harmony and bistability dynamics compared to 65% for coexistence, and 69% for defection, suggesting design search was more equitable under harmony and bistability dynamics.
- The final percentile rank of equality remained at 100% for harmony and bistability dynamics but further dropped to 37% and 55% for coexistence and defection dynamics, respectively, indicating the final strategy selection amplified inequality in those settings.

The aforementioned results suggest that strategy-induced greed, a differentiating factor of coexistence and defection dynamics compared to harmony and bistability dynamics, has a stronger impact on collective action than fear which differentiates harmony from bistability and coexitence from defection. The following section performs statistical analysis to further investigate this insight.

Table 5 Observed upper-level strategy selection in collective parameter design tasks for each strategy dynamic

	Strategy dynamic			
Joint σ	Harmony	Coexistence	Bistability	Defection
$\sigma_i = \sigma_j = 0$	8.$\bar{3}$3%	15.00%	10.00%	35.00%
$\sigma_i \neq \sigma_j$	10.00%	61.$\bar{6}$7%	11.$\bar{6}$7%	40.00%
$\sigma_i = \sigma_j = 1$	81.$\bar{6}$7%	23.$\bar{3}$3%	78.$\bar{3}$3%	25.00%

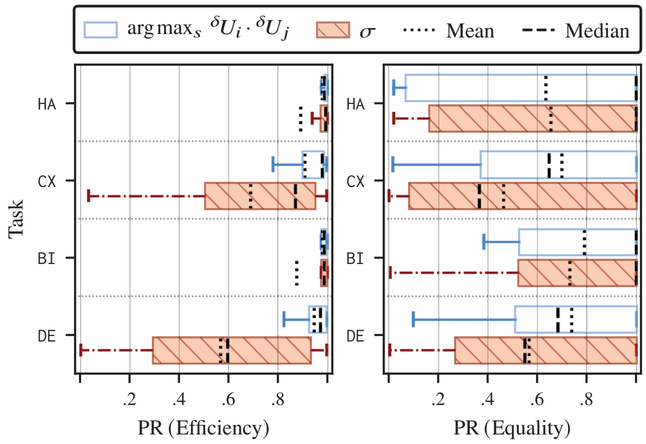


Fig. 9 Observed percentile ranks of collective efficiency and equality outcome metrics compared to those possible under strategy $\arg\max_s {}^{\delta}U_i \cdot {}^{\delta}U_j$, the most-collectively efficient solution available after completing lower-level design exploration

6.2 Effect of Strategy Dynamics. Initial analysis suggests qualitative differences among the four strategy dynamics. Additional statistical analysis evaluates the effect of fear (F) and greed (G) factors on collective design with respect to dependent variables PR(Efficiency) and PR(Equality). They are, by definition, ordinal variables, requiring non-parametric statistical methods. CLM regression is appropriate to evaluate interaction and random effects.

The proposed model

$$\text{logit}(\Pr(Y_k \leq l)) = \theta_l - \beta_k(F) - \beta_k(G) - \beta_k(F{:}G) \quad (13)$$

computes the cumulative probability of the k-th score falling in the l-th category or below, where k indexes the 240 observations (Y_k), l indexes response categories, and θ_l is the threshold for the l-th logit [54]. For the sake of simplicity, we assume such thresholds are equally-spaced by $\Delta\theta$. Finally, $\hat{\beta}_k$ coefficients estimate effects of F, G, and the interaction $F{:}G$.

In fitting Eq. (13), we tested the appropriateness of including a normally-distributed blocking variable in the CLM regression analysis to account for repeated measures for subjects. Results from an analysis of deviance test on the differences between candidate models with and without the aforementioned random effect are presented in Table 6. At a statistical significance level of $\alpha = 5\%$, there is insufficient evidence to conclude that blocking by participants has an impact on the goodness-of-fit of the candidate models for collective efficiency and equality. We continue our analysis on the effect of structural fear and greed on collective performance assuming independence between repeated measures on participants.

Table 7 lists goodness-of-fit statistics for two fixed-effects candidate logistic regression models per dependent variable including the baseline "null model" $\text{logit}(\Pr(Y_k \leq l)) = 1$ for verification. Model selection considers three methods: Akaike Information Criterion (AIC) score, Bayesian Information Criterion (BIC) score, and analysis of deviance to assess differences between candidate models. The AIC scores favor the interaction effects model for analysis of collective efficiency (albeit with relatively small differences between candidate models). The BIC method recommends

Table 6 Analysis of deviance test* on random effects of participants in the design experiment

	No interaction		With interaction	
Dimension	LR ~ χ^2	p-value	LR ~ χ^2	p-value
Efficiency	3.5183	0.0607	3.1842	0.0744
Equality	3.3112	0.0688	3.2023	0.0735

∗ The models with and without random effects are not significantly different at $\alpha = 5\%$.

Table 7 Information criteria estimates† and likelihood ratio test comparison between fixed-effect CLMs used to assess the effect of fear and greed on collective efficiency and equality

	Statistic	Null model	No interaction	With interaction
Efficiency	LL	−1146.3665	−1105.3090	−1104.1171
	AIC	2296.7331	2218.6181	2218.2341
	BIC	2303.6943	2232.5406	2235.6373
	LR ~ χ^2	0.0000	82.1150	84.4989
	p-value	- -	< 0.0001*	< 0.0001*
	Deviance	- -	- -	0.1226
Equality	LL	−778.2249	−770.1624	−770.0206
	AIC	1560.4499	1548.3248	1550.0411
	BIC	1567.4112	1562.2474	1567.4443
	LR ~ χ^2	0.0000	16.1250	16.4086
	p-value	- -	0.0003*	0.0009*
	Deviance	- -	- -	0.5943

† Select the model that minimizes the loss of information (lower AIC and BIC scores).
∗ The alternative models are significantly different from the null model at $\alpha = 5\%$.

Table 8 CLM regression† estimates of collective efficiency and equality versus fear and greed (no interaction effects)

	Statistic	$\hat{\theta}_1$	$\Delta\hat{\theta}$	$\hat{\beta}_k(F)$	$\hat{\beta}_k(G)$
Efficiency	Estimate	−4.0901	0.0483	−0.3740	−1.5533
	SE	0.2636	0.0028	0.1610	0.1833
	p-value	- -	- -	0.0201*	< 0.0001*
	PO (nominal)	- -	- -	0.1306	0.2490
	PO (scale)	- -	- -	0.3811	0.3369
Equality	Estimate	−2.7582	0.0369	0.2461	−0.6291
	SE	0.2095	0.0027	0.1691	0.1720
	p-value	- -	- -	0.1457	0.0003*
	PO (nominal)	- -	- -	0.0443*	0.0643
	PO (scale)	- -	- -	0.0610	0.0559

∗ Statistically-significant results at $\alpha = 5\%$. Insufficient evidence to accept PO at $\alpha = 5\%$.

a no-interaction model for both estimations. Finally, analysis of deviance between candidate models for both collective efficiency and equality results in lack of evidence to suggest difference at $\alpha = 5\%$. We select the no-interaction model for both collective efficiency and equality based on the latter two criteria.

Table 8 shows coefficient maximum likelihood estimates, standard errors (SE), and p-values from the fixed-effect CLMs with no interaction effects. Results on the proportional odds assumption (PO) test validity of the CLM regression. The hypothesis in these tests is that the goodness-of-fit of the model will not improve by relaxing the proportional odds assumption [54]. At $\alpha = 5\%$, the PO nominal and scale tests for fear and greed cannot be rejected for collective efficiency, thus confirming CLM regression is appropriate. However, the PO test for nominal effects is rejected for the fear estimate in the equality model, indicating this variable is not a good ordinal predictor of equality outcomes.

CLM regression results indicate both fear and greed have significant negative effects on collective efficiency with greed showing a stronger impact than fear. Additionally, greed has a significant negative effect on equality; however, this result needs further inspection as the proportional odds assumption was violated for fear.

6.3 Discussion. Results show collective efficiency during lower-level design exploration is not significantly influenced by differences in strategy dynamics. This supports viewing the lower-level decisions as design optimization unimpeded by strategic information barriers associated with unfavorable dynamics. Nevertheless, a design alternative that ranks high in collective efficiency using Eq. (11) does not guarantee a fair distribution of payoffs, particularly in tasks that exhibit coexistence and defection dynamics. The low equality scores, as measured using Eq. (12), resulting from lower-level design exploration in such tasks point at how the absence of upper-level incentives for cooperation affects overall system performance under high levels of structural greed.

At the upper-level, strategy selection follows the normative Nash equilibrium criteria for dynamics with low levels of structural fear, namely harmony and coexistence. Although the underlying dynamics for both the coexistence and bistability parameter design tasks anticipate a similar frequencies for $\sigma_i = 0$ and $\sigma_i = 1$, most subjects pursue the payoff-dominant equilibrium for bistability dynamics. This result could be attributed to increased trust between participants in the face-to-face experimental setting. Similarly, the normative predictions of non-cooperative behavior were not accurate for the majority of tasks with defection dynamics, with a considerable amount of final individual strategies selecting the socially-efficient alternative.

While experimental results concerning collective behavior in symmetric and asymmetric games with harmony dynamics are scarce in the literature, the empirical evidence gathered in this study is comparable to previous findings in the field of behavioral economics for coexistence, bistability, and defection dynamics. For coexistence games, while results in this work show a selection frequency of the Nash equilibria $\sigma_i \neq \sigma_j$ around 62%, work by Cabrales et al. [55] reports rates around 51–74% after adding up frequencies for both $\sigma = \langle 0, 1 \rangle$ and $\sigma = \langle 1, 0 \rangle$. In the case of bistability dynamics, Schmidt et al. [35] reports a selection frequency of the mutually-beneficial Nash equilibrium ($\sigma_i = 1$) between 40–60% versus 84% in this work. It is worth noting, however, than two of four normal-form games in Schmidt et al.'s work exhibit risk dominance conditions that favor selection of the inefficient equilibrium ($\sigma_i = 0$), i.e. $R > 0$, while in the other two games, as well as in this work, risk dominance is neutral, i.e. $R = 0$. Finally, for defection dynamics, Ahn et al. [56] report cooperation rates up to 35% in symmetric and 43% in asymmetric games versus 25% in this work, while a review paper by Rand & Nowak [57] shows first-round cooperation rates between 10–90% in repeated Prisoner's Dilemma games. More careful assessment of the differences in experimental results between works must account for not only actual levels of structural fear and greed but also factors such as type of game (e.g. simultaneous, sequential), players' backgrounds and history of play, and asymmetry between normalized individual payoffs, among others.

Results comparing bistability and defection dynamics suggest the structural fear factor may be sensitive to how subjects interact. While participants did not generally have prior working experience with each other, they all attend the same university and can communicate with each other face-to-face during the task. Rich verbal and non-verbal communication may mitigate concerns about possible defection. Similar mitigating actions may be beneficial as interventions in broader design problems identified to have a substantial structural fear component.

Further analysis identifies strategy-induced greed as the factor with stronger negative influence on both collective performance and equality in the parameter design tasks. Results from CLM regression for collective efficiency show that the coefficient estimate for structural greed is larger in magnitude than fear. Although the latter has a significant effect on collective efficiency, we do not have enough evidence to suggest that strategy-induced fear has a significant effect on equality. These results are consistent with previous findings by Ahn et al. [32] that suggest only structural greed, not fear, has a significant effect on cooperative behavior.

Results also show that low-greed harmony and bistability strategy dynamics are desirable to improve efficiency and fairness in collective systems design processes. Eliciting these dynamics in multi-actor design problems may be possible by changes in incentives or management action. For example, a technological race modeled as a Prisoner's Dilemma can turn into a *Deadlock* (a game with harmony dynamics) by including the potential for scientific breakthroughs resulting from strategic competition [58]. From this perspective, the collectively-inefficient course of action to "stay on the race" can turn into a Pareto-efficient strategy. Similarly, adjustments to resource allocation and substitutability of engineers in a multidisciplinary design project can bring about multiple strict equilibria that lead to mutually-beneficial outcomes [5].

Finally, analysis provided in this section primarily compares experimental results to single-shot games as a simple strategic setting with two main shortcomings. First, while the experiment did not enforce negotiated agreements (in alignment with non-cooperative game theory), participants were allowed to communicate before final strategy selection. Connecting results to research on strategic information exchange [59] would help understand strategic implications of the design exploration period. Second, despite experimental controls to hide strategy selection outcomes, the design tasks carry partial information about actors based on facial expressions, cultural background, etc. Applications of Bayesian games with incomplete information [60] would help understand how factors such as trust and reputation shape strategy selection.

7 Conclusion

This paper describes and demonstrates strategy dynamics as the fundamental interactive relationship between multiple, independent design actors. A bi-level model of collective design uses concepts from game theory to propose distinct lower- and upper-level processes based on design optimization and strategy selection. Constructed parameter design tasks exhibit fixed harmony, coexistence, bistability, and defection dynamics. Finally, a designer experiment collects observations of design behavior across a set of design tasks. Results contrast observations with results of single-shot game theory, showing that the greed factor associated with defection and coexistence dynamics has a stronger negative effect than the fear factor associated with bistability dynamics.

Contributions from this paper provide new constructs to support the study of strategy dynamics in engineering design problems. While highly simplified in the parameter design tasks employed in this paper, future research must distill the strategy dynamics present in a larger class of design problems, including classifying regions of a lower-level design space that exhibit similar strategy dynamics. Increased knowledge of strategy dynamics in the design of engineering systems will enable new methods and processes to mitigate potentially unfavorable effects of an underlying dynamic or even induce strategic trade-offs that favor cooperative behaviors through the application of mechanism design. This type of research will ultimately cross the domains of engineering systems design, behavioral economics, and cognitive psychology, requiring a significant theoretical foundation on which to build future studies and motivating new design efforts to develop incentives or other coordination mechanisms to align objectives of design actors.

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Nomenclature

00 = bit representing strategic context $s = \langle 0, 0 \rangle$
11 = bit representing strategic context $s = \langle 1, 1 \rangle$
$\mathcal{D} = \mathcal{D}_1 \times \cdots \times \mathcal{D}_n$, set of all n-actor design decisions
$d = \langle d_1, \ldots, d_n \rangle$, a multi-actor design decision
$d_i = \langle {}^{00}x_i, {}^{11}x_i \rangle$, actor i's design decision vector
F = structural/strategy-induced fear

$f_i(x)$ = raw value function
$\mathcal{G}$ = a normal-form game
G = structural/strategy-induced greed
i = a design actor
j = a design actor different from i
$\mathcal{N} = \{1, \dots, n\}$ is the set of design actors
R = Risk dominance measure (bipolar games) [37]
$s = \langle s_1, \dots, s_n \rangle$, strategic context (strategy vector)
$\mathcal{S} = \mathcal{S}_1 \times \cdots \times \mathcal{S}_n$, set of all pure-strategy profile vectors
S = sucker's payoff
T = temptation payoff
U_i = utility (payoff) function for actor i
${}^dU_i(s)$ = design-specific utility function for actor i
u_i = normalized payoff for actor i
V_i = transformed value function for design actor i
${}^sV_i(d)$ = context-specific value function for actor i
${}^sV_{\max}$ = maximum individual value in strategic context s
${}^sV_{\min}$ = minimum individual value in strategic context s
$\mathcal{X}_i$ = set of design alternatives
$x = \langle x_1, \dots, x_n \rangle$, a vector of design alternatives
${}^sx_i$ = a context-specific design alternative for actor i
Y_k = k-th observation/datum in the experiment

Greeks

α = Statistical significance level
β = Fixed effect ordinal regression parameter
$\delta = \langle \delta_1, \dots, \delta_n \rangle$ is a selected n-actor design decision
θ_l = Structured threshold (intercept) for the l-th logit
$\sigma = \langle \sigma_1, \dots, \sigma_n \rangle$ is a selected n-actor strategy vector
χ^2 = Chi-squared distribution value

Acronyms

AIC = Akaike information criterion
BIC = Bayesian information criterion
CDF = Cumulative distribution function
GUI = Graphical user interface
LL = Log-likelihood
LR = likelihood-ratio test statistic
PO = Proportional odds assumption test results (as p-values)
PR = percentile rank function
SE = Standard error

Appendix A: Value Space Generation

Lower-level design valuation uses a normalized multimodal function ${}^sf_i$ defined for design parameters ${}^sx = \langle {}^sx_i, {}^sx_j \rangle$ (indices i and j are interchangeable) in strategic context s, ranging between limits ${}^sV_{\min}$ and ${}^sV_{\max}$ and rounded to the nearest integer ($\approx$):

$$ {}^sf_i({}^sx) \approx {}^sV_{\min} + \left({}^sV_{\max} - {}^sV_{\min}\right) \left[f_{\text{asym}}({}^sx) + f_{\text{sym}}({}^sx) \right], \tag{A.1} $$

composing asymmetric (f_{asym}) and symmetric (f_{sym}) functions

$$ f_{\text{asym}}(x_i, x_j) = \mathrm{e}^{-a\left[\left(x_i - x_i^\star\right)^2 + \left(x_j - x_j^\star\right)^2\right]}, \tag{A.2} $$

$$ f_{\text{sym}}(x_i, x_j) = c \cdot \mathrm{e}^{-b\left[\left(x_i - x_{\text{sym}}^\star\right)^2 + \left(x_j - x_{\text{sym}}^\star\right)^2\right]}, \tag{A.3} $$

with $0 < a, b, c < 1$ (this work uses $a = b = 0.31$ and $c = 0.60$). Here, symmetry refers to the set of design parameters with $x_i = x_j$.

Equations (A.2) and (A.3) are based on a similar multimodal test optimization function in Ref. [61] (the original equation includes stochastic components not considered here). Each value space is generated through heuristic sampling of critical points $x_i^\star$, $x_j^\star$, and ${}^sx_{\text{sym}}^\star$ until the following consistency constraints are met:

$$ x_i^\star \neq x_j^\star, \tag{A.4} $$

$$ x_{\text{sym}}^\star = \arg\max_{x_i} \; {}^sf_i(x_i, x_j) \quad \text{s.t.} \quad x_i = x_j, \quad x_i \notin \left\{x_i^\star, x_j^\star\right\}, \tag{A.5} $$

$$ f_{\text{sym}}^\star > \max_{x_i} \; \frac{1}{2}\left[f_i(x_i, x_j) + f_j(x_j, x_i)\right] \quad \text{s.t.} \quad x_i = x_j, \quad x_i \neq x_{\text{sym}}^\star. \tag{A.6} $$

Two additional constraints specific to this work were added to increase topology similarities between generated value spaces:

$$ \left| \langle x_i^\star, x_j^\star \rangle - \langle x_{\text{sym}}^\star, x_{\text{sym}}^\star \rangle \right| = \langle 4, 2 \rangle, \tag{A.7} $$

$$ x_{\text{sym}}^\star \notin [3, 5] \tag{A.8} $$

Each of these consistency constraints is described below:

- Eq. (A.4): forces asymmetry between individual global maximizers $x_i^\star$ and $x_j^\star$
- Eq. (A.5): finds a symmetric (local) maximizer $x_{\text{sym}}^\star$ that differs from either $x_i^\star$ and $x_j^\star$
- Eq. (A.6): forces the symmetric maximizer $x_{\text{sym}}^\star$ to yield the highest aggregated value
- Eq. (A.7): forces a fixed separation between the symmetric and individual global maximizers
- Eq. (A.8): guarantees that the symmetric maximizer $x_{\text{sym}}^\star$ does not fall on $x = \langle 4, 4 \rangle$ (the initial point) or its 8-neighborhood to stimulate design exploration.

Table A.1 lists the symmetric and global maxima and maximizers of the value spaces generated for each of the parameter design tasks in the design experiment.

Appendix B: Example of Calculation of Payoffs for a Parameter Design Task

This end-to-end example shows how to calculate payoffs ${}^dU_i(s)$ and ${}^dU_j(s)$ in a parameter design task, viz. CX.3 (round No. 5) in Table A.1, given design decision $d = \langle d_i, d_j \rangle$ visible in Fig. 6:

$$ d_i = \langle {}^{\mathtt{00}}x_i \,,\, {}^{\mathtt{11}}x_i \rangle = \langle 3, 7 \rangle, $$
$$ d_j = \langle {}^{\mathtt{00}}x_j \,,\, {}^{\mathtt{11}}x_j \rangle = \langle 3, 5 \rangle. $$

Step 0: Generate Lower-level Value Spaces. From Table 1, for parameter design tasks exhibiting coexistence dynamics:

$$ S = 1/2; \qquad T = 3/2; $$
$$ {}^{\mathtt{00}}V_{\min} = 1; \quad {}^{\mathtt{00}}V_{\max} = 33; \quad {}^{\mathtt{11}}V_{\min} = 35; \quad {}^{\mathtt{11}}V_{\max} = 67. $$

From Table A.1, and in accordance with consistency constraints Eqs. (A.4–A.8), we require:

$$ {}^{\mathtt{00}}x_i^\star = 4; \qquad {}^{\mathtt{00}}x_j^\star = 2; \qquad {}^{\mathtt{00}}x_{\text{sym}}^\star = 8; $$
$$ {}^{\mathtt{11}}x_i^\star = 5; \qquad {}^{\mathtt{11}}x_j^\star = 7; \qquad {}^{\mathtt{11}}x_{\text{sym}}^\star = 1; $$

After substituting into Eqs. (A.1–A.3), we obtain the value model for task CX.3:

$$ {}^{\mathtt{00}}f_i({}^{\mathtt{00}}x) \approx 1 + 32.0 \cdot \mathrm{e}^{-0.31\left[\left(x_i - 4\right)^2 + \left(x_j - 2\right)^2\right]} + 19.2 \cdot \mathrm{e}^{-0.31\left[\left(x_i - 8\right)^2 + \left(x_j - 8\right)^2\right]} \tag{B.1} $$

$$ {}^{\mathtt{11}}f_i({}^{\mathtt{11}}x) \approx 35 + 32.0 \cdot \mathrm{e}^{-0.31\left[\left(x_i - 5\right)^2 + \left(x_j - 7\right)^2\right]} + 19.2 \cdot \mathrm{e}^{-0.31\left[\left(x_i - 1\right)^2 + \left(x_j - 1\right)^2\right]} \tag{B.2} $$

Figures B.1(*a*) and B.1(*b*) show grid plots of the value functions Eqs. (B.1) and (B.2), respectively.

Table A.1 Experimental design round sequence: parameter design tasks, critical points, and pairing of participants 1 to 4

Round			Local Maxima for $^{00}f_i$					Local Maxima for $^{11}f_i$					Des. Pair 1		Des. Pair 2	
No.	Dynamic	Task ID	$^{00}x_i^\star$	$^{00}x_j^\star$	$^{00}f_i^\star$	$^{00}x_{\text{sym}}^\star$	$^{00}f_{\text{sym}}^\star$	$^{11}x_i^\star$	$^{11}x_j^\star$	$^{11}f_i^\star$	$^{11}x_{\text{sym}}^\star$	$^{11}f_{\text{sym}}^\star$	i	j	i	j
T1	Harmony	`HA.0`	4	2	100	8	60	5	7	100	1	60	4	1	2	3
T2	Coexistence	`CX.0`	3	1	67	7	54	2	0	100	6	60	4	1	2	3
T3	Bistability	`BI.0`	2	0	100	6	60	5	7	67	1	54	4	2	1	3
T4	Defection	`DE.0`	3	1	67	7	54	4	2	67	8	54	1	2	3	4
1	Coexistence	`CX.1`†	2	0	67	6	54	5	7	33	1	20	1	3	4	2
2	Harmony	`HA.2`	3	1	49	7	30	4	2	100	8	81	1	4	3	2
3	Bistability	`BI.1`†	4	2	100	8	87	3	1	66	7	53	3	4	1	2
4	Defection	`DE.1`†	5	7	67	1	61	2	0	50	6	44	2	4	1	3
5	Coexistence	`CX.3`	4	2	33	8	20	5	7	67	1	54	2	3	1	4
6	Harmony	`HA.1`†	3	1	100	7	81	2	0	49	6	30	2	1	3	4
7	Defection	`DE.2`	5	7	50	1	44	2	0	67	6	61	4	1	3	2
8	Bistability	`BI.3`	4	2	66	8	53	3	1	100	7	87	4	2	3	1
9	Defection	`DE.3`	3	1	50	7	44	4	2	67	8	61	4	3	2	1
10	Bistability	`BI.2`†	2	0	100	6	53	5	7	66	1	87	4	1	2	3
11	Harmony	`HA.3`	5	7	49	1	30	4	2	100	8	81	3	1	2	4
12	Coexistence	`CX.2`†	2	0	67	6	54	3	1	33	7	20	2	1	3	4

† The visual ordering of lower-level design value spaces `00` and `11` are reversed on the GUI to mitigate visual anchoring effects but the task is otherwise unchanged.

Step 1: Get Lower-level Values. Using Eq. (9), for $s = 00$:

$$^{00}V_i(d_i, d_j) = {}^{00}f_i({}^{00}x_i, {}^{00}x_j) = {}^{00}f_i(3,3) = 18;$$
$$^{00}V_j(d_j, d_i) = {}^{00}f_j({}^{00}x_j, {}^{00}x_i) = {}^{00}f_j(3,3) = 18.$$

For $s = 11$:

$$^{11}V_i(d_i, d_j) = {}^{11}f_i({}^{11}x_i, {}^{11}x_j) = {}^{11}f_i(7,5) = 38;$$
$$^{11}V_j(d_j, d_i) = {}^{11}f_j({}^{11}x_j, {}^{11}x_i) = {}^{11}f_j(5,7) = 67.$$

Step 2: Obtain Payoff Structure. Using Eq. (10), for actor i:

$$^{d}U_i(s) = \begin{cases} 18 & \text{if } s = 00 \\ (1 - 3/2)(18) + (3/2)(38) & \text{if } s_i = 0 \neq s_j \\ (1 - 1/2)(18) + (1/2)(38) & \text{if } s_i = 1 \neq s_j \\ 38 & \text{if } s = 11 \end{cases}$$

For actor j:

$$^{d}U_j(s) = \begin{cases} 18 & \text{if } s = 00 \\ (1 - 3/2)(18) + (3/2)(67) & \text{if } s_j = 0 \neq s_i \\ (1 - 1/2)(18) + (1/2)(67) & \text{if } s_j = 1 \neq s_i \\ 67 & \text{if } s = 11 \end{cases}$$

The above payoff structures are shown as a normal-form game in Fig. 6 with $i = 1$ and $j = 4$ (note inverted axes where labeled to disguise symmetry). Note that a design actor's payoff matrix is affected instantaneously by changes in their counterpart lower-level decisions. For instance, if actor j moves $^{00}x_j$ from 3 to 4, $^{00}V_i$ drops from 18 to 8 while $^{00}V_j$ rises from 18 to 24. This also affects payoffs $^{d}U_i(s_i, s_j)$ and $^{d}U_j(s_j, s_i)$ for $s_i \neq s_j$, but it does not affect payoffs $^{d}U_i(1,1)$ or $^{d}U_j(1,1)$ which only depend on both $^{11}x_i$ and $^{11}x_j$.

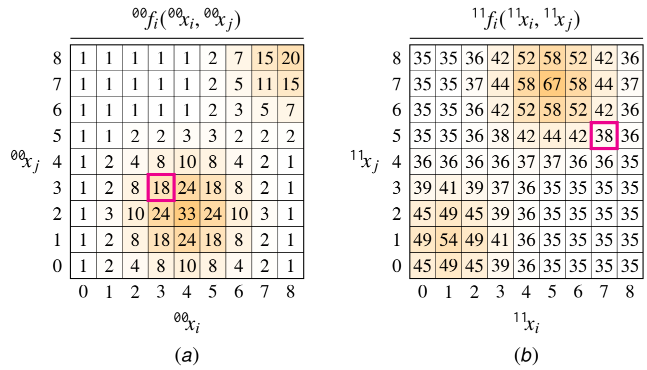

Fig. B.1 Generated lower-level value spaces for parameter design task `CX.3` (round No. 5) in Table A.1: strategic contexts (*a*) $s = 00$ and (*b*) $s = 11$

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