Proceedings of the ASME 2026
International Design Engineering Technical Conferences &
Computers and Information in Engineering Conference
IDETC/CIE 2026
August 23-August 26, 2026, Houston, USA

IDETC/CIE 2026-192094

WHEN INDIVIDUAL EFFICIENCY FAILS TO TRANSLATE: MECHANISM-DEPENDENT MISALIGNMENT IN COMPETITIVE DESIGN

Xiang Li
Walker Department of Mechanical Engineering
University of Texas at Austin
Austin, Texas 78705, USA
Email: lixiang824@utexas.edu

J. Eric Bickel
Walker Department of Mechanical Engineering
University of Texas at Austin
Austin, Texas 78705, USA
Email: ebickel@mail.utexas.edu

Alparslan Emrah Bayrak
Department of Mechanical Engineering and Mechanics
Lehigh University
Bethlehem, Pennsylvania 18015, USA
Email: emb723@lehigh.edu

Zhenghui Sha *
Walker Department of Mechanical Engineering
University of Texas at Austin
Austin, Texas 78705, USA
Email: zsha@austin.utexas.edu

ABSTRACT

In competitive team-based design, it is often assumed that high individual efficiency naturally leads to high collective performance. However, whether this translation holds — and how strongly it holds — may depend on the information-sharing mechanism that governs the interaction among designers. Understanding this relationship is critical for designing appropriate information architectures in competitive design systems, yet whether and how such architectures govern this translation remains largely unexplored. We conduct a controlled experiment using a Team-based Function Optimization Game in which participants make costly sequential sampling decisions under a baseline condition of no information sharing and three different information-sharing mechanisms. We define Individual Outcome Efficiency (IOE) and System Outcome Efficiency (SOE) as outcome-based performance metrics, and examine how SOE relates to both the mean level and within-system inequality of IOE. The results show that the IOE-to-SOE mapping is weak and fragile under the no-sharing baseline, but becomes significantly stronger under information-sharing conditions. Furthermore, within-system inequality of IOE exerts a significant negative effect on SOE once the mean level is controlled for, and this penalty intensifies as information richness increases. These findings demonstrate that stable and robust individual-to-system efficiency translation is mechanism-dependent, and that richer information environments simultaneously strengthen efficiency alignment and amplify the system-level cost of internal efficiency imbalance.

Keywords: Design Competition, Design Behavior, Information-sharing, Mechanism Design

1. INTRODUCTION

A common intuition in collective design and decision-making is that if each individual performs efficiently considering the trade-offs between decision quality and cost of those decisions, the collective outcome should also be efficient. This intuition underlies many organizational and engineering settings in which local actors are encouraged to optimize their own actions under resource constraints, with the expectation that system-level

*Address all correspondence to this author.

performance will improve as a consequence [1, 2]. Moreover, this intuition often shapes how systems, whether design teams, engineering organizations, or competitive platforms, are organized and evaluated. For example, in sequential search processes and cost-aware optimization tasks, such intuition often justifies decentralized decision rules, local incentives, and performance evaluation schemes centered on individual outcomes [3, 4].

However, in many real-world design and decision systems, individual actions do not operate in isolation. They generate externalities through information spillovers, strategic timing effects, and induced adjustments in the behavior of others [5]. As a result, individual efficient behavior can fail to improve or even distort collective performance when the system outcome depends not only on the local success of an actor, but also on how that behavior reshapes the broader interaction structure [1, 6]. Under such conditions, the relationship between individual efficiency and system-level efficiency is no longer reliably translated. Instead, its existence, strength, and robustness become a structural question about mechanism design.

This issue is especially important in competitive design environments. Many design tasks involve costly sequential exploration under incomplete knowledge, where designers must allocate limited resources to search an unknown solution space while simultaneously responding to incentives created by teammates, competitors, or institutional rules [7–9]. In such settings, a designer who uses resources efficiently from an individual standpoint may alter the informational environment, strategic balance, or search dynamics of the broader system. Consequently, **an open question** arises: whether the common intuition remains valid once design activity is embedded in a team-based competitive and information-dependent environment. Our hypothesis is that individual efficiency and system efficiency may become misaligned under those conditions. Understanding when this misalignment emerges, and how it depends on the surrounding information architecture, is therefore a theoretically and practically important problem for design theory and methodology [10].

Motivated by this question, this study investigates whether individual efficiency reliably translates into system outcome efficiency in a competitive team-based design environment, and whether that conversion depends on the underlying information-sharing mechanism. More specifically, we ask: when and why does high individual outcome efficiency fail to produce high system outcome efficiency? Rather than treating individual-to-system alignment as a universal property, we examine whether it is mechanism-dependent and shaped by the institutional structure through which information is revealed and shared.

To answer this question, we developed a controlled experimental platform, called the *Team-based Function Optimization Game* (TFOG), using a sequential black-box optimization task with explicit sampling costs, limited budgets, and team-versus-team competitive interaction. TFOG is a team-based extension of the Function Optimization Game (FOG) originally developed by Sha et al. [11]. Building on a recent team-versus-team extension of FOG with intra-team information sharing [12], TFOG introduces a complete set of four information-sharing mechanisms and formal outcome-based efficiency metrics at the individual and system levels. Participants are formed in teams competing to win the game by repeatedly searching for high-value solutions without knowing the underlying objective function, and their performance unfolds under distinct information-sharing mechanisms, including no sharing, intra-team sharing, opponent-outcome visibility, and richer hybrid information conditions. This setting allows us to isolate how information architecture changes the relationship between local search efficiency and system-level outcome efficiency while holding the core optimization task structurally comparable across games. More details about this game are provided in Section 2.

A central challenge in studying this problem is the measurement of *efficiency*. Since the efficiency of individual search strategies is difficult to observe directly in an experimental search process, for example, the same observed sampling trajectory can be consistent with multiple underlying decision rules, and inferring a unique strategy requires auxiliary modeling assumptions about participants' cognitive processes that are not directly testable, and since participants operate under uncertainty and may use heterogeneous heuristics [13, 14], we adopt an outcome-based efficiency perspective. At the individual level, we construct Individual Outcome Efficiency (IOE) to capture how effectively a participant converts costly exploration into realized solution improvement within one round of the game (i.e., one design space exploration process). At the system level, we construct System Outcome Efficiency (SOE) to evaluate how effectively the full competitive system converts the total exploration cost into achieved outcome quality. This distinction is important: IOE reflects the efficiency of individual search realized, whereas SOE evaluates the performance from the perspective of the system as a whole, incorporating both the quality of the solution and the expenditure of resources under the competitive interaction.

Using these measures, we analyze individual–system alignment from two complementary perspectives. First, we examine whether the mean level of IOE within a system predicts SOE across different information-sharing mechanisms. Second, we examine whether the dispersion of IOE within a system, captured by the Gini coefficient, modulates that relationship. This second perspective is especially important because system-level performance may depend not only on how much individual efficiency exists on average, but also on how evenly that efficiency is distributed across participants within teams. A system composed of highly unequal individual performances may behave differently from one with the same mean efficiency but a more balanced internal structure [15].

Our results show that individual efficiency does not reliably translate into system outcome efficiency under a pure competitive team-based environment. Instead, the conversion depends critically on the information-sharing mechanism. In the no-sharing baseline, the mapping from mean IOE to SOE is weak and fragile. Under richer information conditions, however, this mapping becomes substantially stronger. In addition, while IOE dispersion alone is not a stable predictor of SOE, joint interaction analysis reveals a deeper pattern: mean IOE has a positive association with SOE, whereas inequality in IOE exerts an independent negative effect once the mean is controlled for and further weakens the translation from individual efficiency to system efficiency under information-sharing settings. Together, these results suggest that richer information mechanisms can strengthen individual–system alignment while simultaneously amplifying the penalty of internal efficiency imbalance.

This study makes three main contributions. First, it contributes to design theory by challenging the common assumption that individually efficient behavior naturally aggregates into efficient collective outcomes. Instead, it shows that such alignment is conditional and mechanism-dependent. Second, it introduces a new quantitative framework for evaluating individual–system efficiency relationships in competitive design environments through outcome-based measures of IOE and SOE. Third, it provides experimental evidence that information-sharing mechanisms do more than affect performance levels. They also shape how individual efficiency is transformed into system-level outcomes, including the extent to which inequality within the system becomes consequential.

The remainder of the paper is organized as follows. Section 2 introduces the experimental environment and the information-sharing mechanisms. Section 3 presents the efficiency metrics and statistical models. Section 4 reports the empirical results on level alignment (whether mean individual efficiency within a system predicts system efficiency), dispersion alignment (whether inequality of individual efficiency affects system efficiency), and their joint interaction. Section 5 concludes with implications, limitations, and directions for future research.

2. EXPERIMENTAL ENVIRONMENT

2.1 Experimental Platform Overview

To investigate how individual outcome efficiency translates into system outcome efficiency under competitive design conditions, we developed a controlled experimental platform called the *Team-based Function Optimization Game* (TFOG) using the oTree framework [16]. As shown in Figure 1, the platform implements an online sequential black-box optimization task with explicit exploration costs, limited individual budgets, team-based competition, and different information sharing mechanisms.

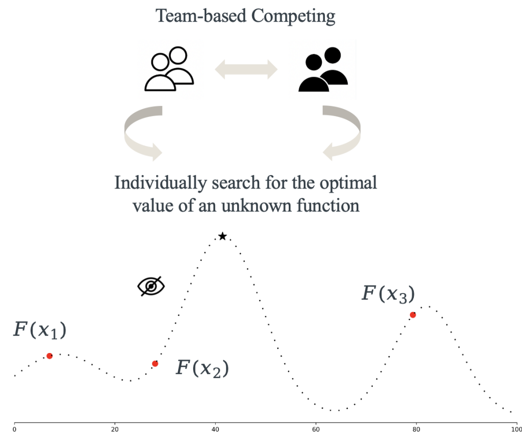

FIGURE 1. TFOG overview used in the experiment: The objective function is hidden to participants. Participants observe the outcomes of sampled points, and must infer promising regions through sequential exploration.

In each round of the game, participants face an unknown maximization problem and must decide how to allocate costly sampling actions in order to discover high-value solutions. To make the task accessible to participants from different backgrounds, including both engineering and non-engineering students, the optimization task is presented through a coffee-brewing narrative. Participants are told that they must choose a brewing temperature for a mixed batch of coffee beans, where the final flavor quality depends on a complex and unknown relationship between temperature and performance. This contextual framing serves a dual purpose. First, it improves interpretability by grounding the abstract optimization task in a familiar, everyday activity while preserving the underlying black-box optimization structure. Second, it helps mitigate potential confounding effects arising from participants' prior domain knowledge. By situating the problem in a context that does not privilege any specialized expertise, the experimental results are less likely to be biased toward participants with specific technical backgrounds, allowing the main effects of interest—the information-sharing mechanisms—to be more cleanly identified.

The experimental environment is designed to capture several core features of competitive design decision-making: goal-oriented, with unknown objective landscape, with costly information acquisition, design space exploration under budget constraints, involving intra- and inter-team dynamics, and strategic interdependence across participants [17]. Within this setting, individually efficient behavior may or may not improve system-level outcomes, which makes the platform suitable for studying individual-system efficiency alignment.

2.2 Optimization Task and Function Space

In every round, when choosing the brewing temperature for coffee beans, participants solve a one-dimensional maximization problem over a bounded design space,

$$x \in [0, 100]. \tag{1}$$

Under the experimental narrative, x represents a brewing temperature in degrees Celsius, and the corresponding function value $F(x)$ represents the evaluated flavor score of the brewed coffee. The objective function is fixed within a round but changes across rounds. This design serves to ensure that each round presents a fresh search problem for a different type of coffee bean, preventing participants from carrying over learned knowledge of the function landscape from previous rounds. As a result, each round can be treated as a statistically independent observation of search behavior under the assigned information-sharing mechanism.

In each round of the game, the objective function is drawn from the same family of smooth multi-peak Gaussian mixtures:

$$F(x) = \sum_{i=1}^{3} a_i e^{-b_i(x-c_i)^2} \tag{2}$$

This functional form was selected because it provides a structured but nontrivial optimization landscape with multiple local optima and a unique global maximum. As a result, participants must search without analytical guidance and cannot rely on simple heuristics to find a single obvious peak. Such multi-modal landscapes are common in engineering design and response surface optimization problems, where nonlinear relationships between design variables and performance outcomes often generate multiple candidate optima rather than a single convex solution [18, 19]. Although the functional form is kept constant between rounds, the parameter values vary, so each round presents a distinct response surface.

Again, both the function form and the theoretical global optimum F^{opt} are unseen from participants but only known to the experimenter. Participants can only learn about the landscape by actively sampling points in the design space and observing their realized values. No analytical expression, gradient information, or structural hint is provided. This preserves the black-box nature of the task and ensures that performance improvements arise from the number of costly searches and search strategies rather than prior structural knowledge.

2.3 Sampling Budget and Cost Structure

One game with a particular set-up can have multiple rounds, and each round proceeds with a sequential sampling process. At the beginning of the search, every participant receives 200 tokens as the initial funds. Each sampling action costs 10 tokens and reveals the function value at the selected x value. Each round is subject to a 2-minute time limit. Unused tokens do not carry over across rounds. In principle, participants may differ in their willingness to sample due to heterogeneous strategic interpretations, payoff perceptions, and risk attitudes. However, to ensure that every two-versus-two design competition (referred to as a "system") yields a well-defined competitive outcome, the platform requires each participant to perform at least one sampling action per round. Without this rule, an extreme case could arise in which all four participants in a system choose zero samples, leaving the round with no realized outputs and making the winner determination impossible. The least-one-sample requirement therefore serves as an operational safeguard rather than a behavioral assumption. Under this structure, each participant can make between 1 and 20 samples per round.

TABLE 1. Experimental Settings Summary

Parameter	Content	Description
Design variable	$x \in [0, 100]$	Brewing temperature
Objective function	Gaussian mixture	Multi-peak response surface
Initial tokens	200	Budget per participant
Sampling cost	10 tokens	Cost per sample
Minimum samples	1	Minimum sampling requirement
Maximum samples	20	Budget constraint
Time limit	2 minutes	Per participant per round
Team structure	2 vs. 2	Four-person competitive system
Rounds per game	5	Each round changes function
Number of games	4	Different mechanisms

Let $C_{i,j}^{used}$ denote the total number of tokens spent by participant i in round j, and let $C_j^{max} = 200$ denote the per-round expenditure limit. The token budget imposes a binding trade-off between exploration and cost conservation. More sampling increases the chance of discovering higher-performing solutions [11], but it simultaneously reduces final payoff through accumulated expenditure.

This cost structure is central to the logic of the experiment. The objective is not simply to find the optimal solution without cost awareness, but to do so *efficiently* under resource and time constraints. Because both the quality of the results achieved and the sampling cost are directly observable, the platform supports an outcome-based notion of efficiency that jointly reflects performance and resource expenditure. In general, Table 1 summarizes the key experimental settings of TFOG.

2.4 Team Competition Structure

In each round, participants are randomly assigned to multiple battles of two-versus-two. Within each four-person system, two participants form one team and compete against the opposing pair. Teams and competitions are re-formed at the beginning of every round, and token budgets are reset. This random re-pairing is designed to isolate the effect of the information-sharing mechanism from potential confounds introduced by persistent team dynamics. If team composition remained fixed across rounds, repeated interaction could give rise to familiarity effects, implicit coordination conventions, or interpersonal trust that would confound the treatment effect of the information mechanism itself. By re-shuffling teams each round and resetting budgets, the design ensures that rounds are strategically independent to the greatest extent possible, so that observed differences in efficiency alignment can be attributed to the information architecture rather than to accumulated relational history among specific participants.

This competitive structure creates strategic interdependence at two levels. First, each participant's sampling decisions affect not only individual standing but also team performance. That is, the best individual performance represents the best performance of their team. Second, depending on the information-sharing mechanism, the actions of one participant may alter what other participants can observe and infer during the round. As a result, search behavior that appears individually efficient need not align with improved performance at the level of the four-person system.

More importantly, this competitive structure also creates a coexistence of cooperation and competition within each team. On the one hand, teammates share a collective incentive to outperform the opposing pair, since the winning team captures a portion of the non-winning team's remaining funds. On the other hand, the two members of the winning team receive asymmetric payoff shares based on their relative individual performance, which introduces a within-team competitive pressure to be the stronger contributor. This dual incentive structure means that a participant must simultaneously consider how to help the team win and how to distinguish oneself within the team. The specific payoff rules that implement this nested incentive design are detailed in Section 2.6. This feature is central to the main research question in this study.

2.5 Information-Sharing Mechanisms

To study how institutional structure affects efficiency alignment, we vary the information-sharing mechanism across four games while keeping the underlying optimization task comparable. The key treatment variation lies in what sampling information is visible to participants during the search process.

Game 1: No sharing. Participants observe only their own sampling history. The interface displays their own sampled points in a coordinate system chart, and a real-time updated summary table of their best three and worst three sampled values. No teammate or opponent information is visible.

Game 2: Teammate sharing. In addition to their own information, participants can observe their teammate's sampled points and the corresponding function values in real time. The summary display is therefore expanded to include both members of the team. This mechanism creates within-team informational transparency without revealing competitors' information.

Game 3: Opponent-outcome sharing. Participants continue to observe only their own sampled points on the search chart, but they also receive real-time information about the top three sampled results (i.e., the function values, $F(x)$) achieved by themselves and their opponents. But, they do not see the opponents' sampled design points (i.e., the x values). So, only outcome information is revealed. This asymmetric disclosure is motivated by the structure of real-world competitive design environments, where competing teams can typically observe the performance outcomes of a rival's product—such as benchmark results, market reception, or published specifications—but cannot observe the underlying design decisions, development process, or technical solutions that produced those outcomes. In our experimental abstraction, function values represent observable design outcomes, while sampled x values represent the design choices themselves. Game 3 thus models a competitive setting in which outcome visibility coexists with process opacity.

Game 4: Combined sharing. This mechanism combines the previous two conditions. Participants can observe both teammate search information and opponent outcome information. Thus, Game 4 provides the richest information environment among the four mechanisms. As an example, Figure 2 shows the user interface of Game 4. This interface is displayed for illustrative purposes because it contains all major information elements introduced in the four games. The interfaces of Games 1–3 follow the same general layout but provide a reduced set of information consistent with their respective mechanisms.

Each game consists of five rounds for a total of twenty rounds in the four mechanisms. Since the optimization task remains structurally comparable while the visibility of information varies, the four-game design allows us to isolate how the information architecture changes search behavior, cost allocation, and translation from individual efficiency to system-level efficiency.

2.6 Outcome Determination and Payoff Rules

At the end of each round, only each participant's best sampled value is retained for competitive evaluation. The winning team is the team containing the participant with the highest flavor score (i.e., the function value) in that round, where the best performer within the winning-team is defined as the member whose highest value in that round is greater.

The payoff structure in this experiment implements a two-tier incentive design. At the team level, the winning team captures a portion of the non-winning team's remaining funds, creating a direct competitive incentive to achieve a higher best score than the opposing team. At the individual level, the two members of the winning team receive asymmetric shares of this prize pool, creating an additional within-team incentive for each participant to strive to be the stronger performer on their side. This nested structure ensures that participants receive meaningful incentives at both the collective and individual levels throughout the round,

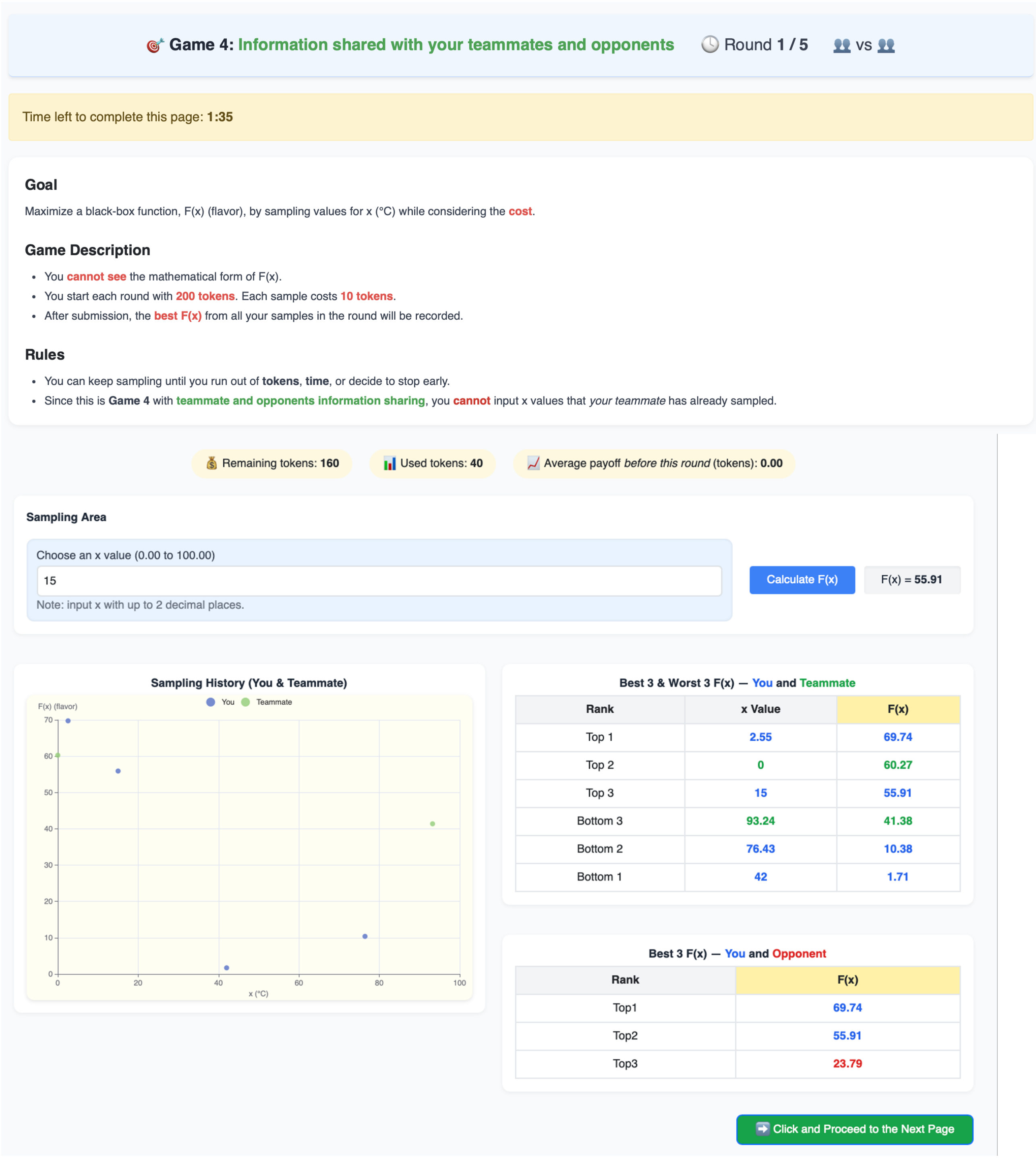

FIGURE 2. User interface for Game 4, the most information-rich condition in the experiment. The upper portion of the interface presents the current game and round, a countdown timer, and an instruction panel briefly summarizing the task objective, token budget, per-sample cost, and condition-specific sampling rules. The middle interaction area displays the participant's remaining and used tokens, the mean payoff before the current round, and the input field and calculation button for evaluating a selected x-value. The lower-left panel shows the sampling history of the participant and teammate, while the lower-right panels provide ranked summaries of the participant–teammate pair's best and worst sampled outcomes as well as the opposing side's best outcomes. Consistent color coding is used across the chart and tables to distinguish self, teammate, and opponent information.

rather than reducing effort once a team outcome appears determined.

Formally, let n denote the number of samples taken by a participant in one round and let $c = 10$ denote the fixed cost per sample. For the two members of the non-winning team, payoffs are given by

$$P_1 = P_2 = 0.5 \times (200 - n \cdot c) \tag{3}$$

The 50% retention factor imposes a meaningful competitive penalty on the non-winning team while ensuring that losing does not result in a zero payoff. This is important because if the non-winning team received nothing, participants who perceive themselves as falling behind during the game would face a diminished incentive to continue sampling thoughtfully, potentially leading to disengagement or erratic search behavior. By guaranteeing a positive residual payoff even in the event of a loss, the design preserves within-game participation incentives for all participants throughout the search process.

For the winning team, payoffs are

$$P_3 = (200 - n \cdot c) + 0.7 \times (P_1 + P_2) \tag{4}$$
$$P_4 = (200 - n \cdot c) + 0.3 \times (P_1 + P_2) \tag{5}$$

where P_3 is assumed to be the best performer in the winning team and P_4 is the other member. The asymmetric 70-30 share split is designed to introduce a non-trivial prize spread within the winning team. Consistent with tournament theory [20], a sufficiently large reward differential incentivizes individual effort even when team membership is already secured. The $7/3$ ratio provides a prize spread of approximately 2.3 : 1, large enough to maintain individual optimization incentives without approaching the extreme case of winner-takes-all, which can induce excessive risk-taking or discourage sampling efforts among those with lower confidence in their relative performance [21].

In the event of a tie in the best sampled value, the tie is broken by the time at which the tied score was first achieved. This rule serves two complementary purposes. First, it ensures that every round produces a determinate competitive outcome, eliminating the possibility of unresolved draws that would otherwise complicate payoff allocation and undermine the clarity of competitive incentives. Second, and more substantively, it introduces a temporal dimension into the competitive evaluation: among participants who discover equally good solutions, the one who does so earlier is rewarded. This creates an implicit incentive for cost-efficient early discovery rather than prolonged search, which is consistent with the broader design goal of rewarding efficient resource utilization. When two participants reach solutions of equal quality, the one who does so in less time should be ranked higher than the one who requires more time. The time-based tiebreaker thus reinforces the cost-awareness logic embedded throughout the payoff structure, rather than treating all equal-quality outcomes as interchangeable regardless of the resources expended to achieve them.

Thus, one's final payoff depends jointly on solution quality, sampling expenditure, teammate performance, and competitive outcome. This payoff structure embeds cost-aware optimization directly into participant incentives at multiple levels. Since participants do not know the theoretical optimum during decision-making, they must balance exploration and expenditure under incomplete information. The institutional design therefore links search behavior, competition, and payoff consequences in a way that is behaviorally meaningful for the study of efficiency alignment. To provide real economic incentives, each participant's average token payoff across the 20 rounds (4 games) was converted into a monetary bonus at the end of the experiment at a rate of 20 tokens = $1. In addition, each participant received a fixed $25 participation payment independent of game performance.

2.7 Recorded Variables and Observability

For each participant i in round j, the experiment records the initial sampled value $F_{i,j}^{init}$, the best sampled value $F_{i,j}^{*}$, total individual sampling cost $C_{i,j}^{used}$, and the complete time-stamped sampling trajectory. Team assignment and opponent identity are also recorded.

These recorded data provide the observables needed to construct outcome-based performance measures at both the individual and system levels. In particular, they allow us to evaluate how effectively participants and the four-person design system convert costly exploration into final solution quality. The next section builds on these observables to formally define Individual Outcome Efficiency (IOE) and System Outcome Efficiency (SOE).

3. EFFICIENCY METRICS AND EMPIRICAL STRATEGY

This section introduces the proposed outcome-based efficiency framework and the empirical models developed to examine individual–system alignment. Our goal is not to infer strategy-level efficiency from the search process but to evaluate how effectively costly design exploration translates into design performance at different levels of analysis. This outcome-based perspective is appropriate for our setting because both solution quality and sampling cost are directly observable, whereas the cognitive and strategic processes underlying participant decisions are implicit. We construct both metrics from a shared structural template and then describe how system-level efficiency is related to both the average level (i.e., the main effect) and the internal distribution of individual efficiency across the four information-sharing mechanisms.

Both IOE and SOE are constructed from the same meta-structure inspired by the traditional output–input efficiency concept [9, 22]:

$$\text{Efficiency} = \text{Performance Achieved} \times \text{Resource Conservation} \tag{6}$$

This multiplicative form reflects a deliberate design choice: an agent or system that achieves high outcome quality but at excessive cost, or conserves resources while achieving little, should not be considered efficient in either dimension alone. Multiplying the two components avoids introducing arbitrary additive weights and yields a dimensionless, bounded indicator that jointly reflects both dimensions. Beneath this unified exterior, we incorporate different cores for each metric based on the distinct perspectives of the individual participant and the four-person competitive system, as detailed in the following subsections.

3.1 Individual Outcome Efficiency (IOE)

We define Individual Outcome Efficiency (IOE) as an outcome-based measure of how effectively a participant converts costly exploration into improvement achieved within a round. The metric is constructed from experimentally observable quantities and is designed to jointly reflect three properties: final solution quality, improvement achieved during the round, and cost awareness. Formally, IOE is defined as

$$\text{IOE} = \max\left(0, \frac{F^{*} - \overline{F^{init}}}{F^{opt} - \overline{F^{init}}}\right) \cdot \left(\frac{C^{min}}{C^{used}}\right) \in [0,1] \tag{7}$$

where

- $\overline{F^{init}}$: the average initial sampled value across all N participants in this round,
- F^{opt}: the theoretical global optimum in this round,
- F^{*}: the best value sampled by the participant in this round,
- C^{used}: the total sampling cost spent by the participant in this round,
- C^{min}: the minimum required sampling cost per participant (10 tokens, corresponding to one required sample).

The metric consists of two multiplicative components. The first component, $(F^{*} - \overline{F^{init}})/(F^{opt} - \overline{F^{init}})$, captures in-round learning progress and final solution quality by measuring the proportion of attainable improvement that the participant actually realized [23]. The second component, C^{min}/C^{used}, captures cost efficiency by comparing the minimum possible expenditure to the participant's actual expenditure.

Several design choices in this formulation merit explanation. First, we use the cross-participant average of initial sampled values, $\overline{F^{init}}$, rather than each participant's own initial value, F^{i}_{init}, as the baseline reference. The rationale is that any single participant's initial sample is highly influenced by randomness. Averaging across participants creates a unified and more stable benchmark. In addition, this averaged baseline partially absorbs variation in function complexity across rounds: functions that are harder to optimize tend to produce lower average initial values, and the baseline adjusts accordingly.

Second, the truncation operator $\max(0,\cdot)$ ensures that IOE reflects only non-negative improvement efficiency [24]. If a participant's best sampled value falls below the round-level initial average, the participant has failed to generate any improvement relative to the shared baseline, and the metric assigns an efficiency of zero. This avoids the interpretive difficulty of negative efficiency values in an improvement-based framework.

The boundary cases of IOE are instructive. In the theoretical best case, a participant samples the global optimum on the first (and only required) attempt, yielding $\text{IOE} = 1$. In the worst case, the participant fails to exceed the initial average in the entire round, yielding $\text{IOE} = 0$. From a resource allocation perspective, achieving a high-quality solution with minimal cost represents efficient resource utilization regardless of whether the outcome reflects deliberate strategy or stochastic luck [25–28]. IOE therefore measures the outcome efficiency of converting search cost into solution improvement, rather than the underlying cognitive or strategic efficiency of the search process.

3.2 System Outcome Efficiency (SOE)

We define System Outcome Efficiency (SOE) from the perspective of the four-person design competition system. In our experimental design, each two-versus-two battle constitutes the smallest unit that fully integrates all relevant structural elements: within-team collaboration, cross-team competition, payoff allocation, and individual sampling decisions. Accordingly, we treat each four-participant battle as a system.

A natural question is why we define efficiency at the system level rather than at the team level. The system-level perspective corresponds to the viewpoint of the competition organizer, who bears the aggregate cost of the entire competitive process and evaluates the quality of the best solution that emerges from it. As an analogy, consider a company that sponsors parallel design teams to compete internally over alternative product concepts—a practice observed in firms such as Apple [29, 30], where multiple teams have simultaneously developed competing prototypes before a final design is selected. From the company's perspective, the relevant efficiency question is not how well one team performed in isolation, but how effectively the entire competitive structure converted total resources into a winning design. A team-level metric would capture only one side of the competition and miss the cost borne by the opposing team, whose exploration effort also contributes to the competitive pressure that shapes the outcome. The system-level formulation incorporates the full cost–outcome trade-off generated by the competition as a whole.

Following the same meta-structure used for IOE, we construct SOE to capture how effectively a system transforms total exploration cost into final solution quality under competitive interaction. Formally, SOE is defined as:

$$\mathrm{SOE} = \left(\frac{F^{*}_{sys}}{F^{opt}}\right) \cdot \left(\frac{C^{min}_{sys}}{C^{used}_{sys}}\right) \in [0,1] \tag{8}$$

where

- F^{*}_{sys} : the best function value sampled by any of the four participants in the system during this round,
- F^{opt} : the theoretical global optimum in this round,
- C^{min}_{sys} : the minimum required sampling cost for four-participant system in this round (40 tokens, corresponding to one required sample per participant),
- C^{used}_{sys} : the total sampling cost actually spent by all four participants in the system during this round.

The first component, F^{*}_{sys}/F^{opt}, captures the quality of the best solution discovered within the system relative to the theoretical optimum. The second component, $C^{min}_{sys}/C^{used}_{sys}$, captures the cost efficiency of the system by comparing the minimum possible aggregate expenditure to the actual total expenditure. As with IOE, the multiplicative structure avoids artificial weighting and produces a bounded, dimensionless efficiency measure.

An important structural premise underlying this formulation is that, under the payoff rules described in Section 2.6, each two-versus-two battle can be viewed as a zero-sum game at the system level. The only cost that is irreducibly consumed by the system is the sampling cost. From the system organizer's perspective, the relevant evaluation is purely outcome-based: the question is how much irreducible cost the system collectively expended to obtain how good a solution. Details of individual search strategies, within-team coordination patterns, and cross-team interaction dynamics are treated as endogenous to the system; their effects are reflected in this outcome-based metric.

3.3 Statistical Evaluation Methods

With IOE and SOE defined, we now describe the empirical method used to examine whether and how individual efficiency translates into system efficiency across different information-sharing mechanisms. Our analysis addresses three complementary questions:

Level alignment. How does the mean level of individual efficiency within a system relate to system-level efficiency under different mechanisms?

Dispersion alignment. How does inequality of individual efficiency affect system-level efficiency across mechanisms?

Joint interaction of level and dispersion. How does the combination of mean efficiency and efficiency inequality jointly determine the individual-to-system translation?

3.3.1 Level Alignment Models

We employ three regression models to examine the relationship between mean IOE and SOE.

Model 1: Basic OLS. For each Game i ($i = 1,2,3,4$), we estimate:

$$\mathrm{SOE} = \beta_0 + \beta_1 \cdot \overline{\mathrm{IOE}} + \varepsilon \tag{9}$$

with HC3 robust standard errors.[1] This model tests whether the mean individual efficiency within a system is a significant predictor of system efficiency under each mechanism separately.

Model 2: OLS with round-specific fixed effects. To account for potential variation in search difficulty due to different objective functions across rounds, we augment the basic model with round-specific fixed effects:

$$\mathrm{SOE} = \beta_0 + \beta_1 \cdot \overline{\mathrm{IOE}} + \sum_{r=2}^{5} \delta_r \cdot \mathrm{Round}_r + \varepsilon \tag{10}$$

This model controls for the possibility that certain objective functions are inherently easier or harder to optimize, which could confound the estimated IOE–SOE relationship. HC3 robust standard errors are used throughout.

Model 3: Pooled interaction regression with Game $\times$ Round fixed effects. To explicitly compare the strength of the IOE–SOE mapping across mechanisms, we pool all four games and estimate a single regression with Game $\times$ Round fixed effects. These fixed effects comprise a full set of indicator variables for each of the 20 unique game-round combinations (4 games $\times$ 5 rounds) captured by $\alpha_{G\times R}$ in the following equation, thereby absorbing both mechanism-level and function-specific variation:

$$\mathrm{SOE} = \alpha_{G\times R} + \beta_1 \cdot \mathrm{IOE} + \theta_2 \cdot (\mathrm{IOE} \times G_2) \tag{11}$$

$$+\theta_3 \cdot (\mathrm{IOE} \times G_3) + \theta_4 \cdot (\mathrm{IOE} \times G_4) + \varepsilon \tag{12}$$

The interaction terms θ_k capture the incremental change in the IOE–SOE slope relative to the Game 1 baseline. HC3 robust standard errors are applied, and the number of observations increases from 30 per game to 120 in the pooled sample.

[1] HC3 is a heteroskedasticity-consistent standard error estimator that applies a stronger correction for high-leverage observations than HC1 or HC0. It is recommended for small-sample settings because it reduces the risk of over-rejection under heteroskedasticity [31].

3.3.2 Dispersion Alignment Models

To capture the degree of inequality in individual efficiency within a system, we use the Gini coefficient:

$$Gini = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n^2\bar{x}} \tag{13}$$

The Gini coefficient is chosen over variance-based dispersion measures for two reasons. First, our interest is not merely in overall variability but in the degree of inequality in how efficiently team members convert resources into outcomes. The Gini coefficient directly quantifies distributional inequality, whereas variance reflects aggregate spread without distinguishing between symmetric and asymmetric dispersion patterns. Second, both IOE/SOE and the Gini coefficient are bounded between 0 and 1, which makes the mean level and within-team inequality of IOE directly comparable in scale and facilitates joint interpretation.

We apply the same two-model structure used for level alignment. The basic OLS model is:

$$\text{SOE} = \beta_0 + \beta_1 \cdot Gini_{IOE} + \varepsilon \tag{14}$$

and the round-specific fixed effects model is:

$$\text{SOE} = \beta_0 + \beta_1 \cdot Gini_{IOE} + \sum_{r=2}^{5} \delta_r \cdot \text{Round}_r + \varepsilon \tag{15}$$

Both models use HC3 robust standard errors and are estimated separately for each game.

3.3.3 Joint Interaction Model

Finally, to test whether the distribution of efficiency within a system modulates the translation from individual efficiency to system efficiency, we estimate a centered interaction model with main effects:

$$SOE = \beta_0 + \beta_1 \widetilde{Mean\ IOE} + \beta_2 \widetilde{Gini_{IOE}} \tag{16}$$

$$+\beta_3(\widetilde{Mean\ IOE} \times \widetilde{Gini_{IOE}}) + \delta_{round} + \varepsilon \tag{17}$$

where $\widetilde{Mean\ IOE}$ and $\widetilde{Gini_{IOE}}$ denote the grand-mean-centered versions of the respective variables. Centering serves two purposes [32]: it reduces multicollinearity between the main effects and the interaction term, and it ensures that the main effect coefficients are interpretable at the sample mean of the other variable rather than at zero. Round-specific fixed effects are included as a robustness control. This model is positioned as a supplementary mechanism test to examine whether within-system efficiency inequality exerts an independent effect on SOE and whether it moderates the mean IOE–SOE relationship differently across information-sharing mechanisms.

4. EXPERIMENTAL PROTOCOL AND RESULTS

This section describes the data collection process and reports the empirical results for the three research questions outlined in Section 3.3: level alignment between mean IOE and SOE, dispersion alignment between Gini IOE and SOE, and the joint interaction of level and dispersion.

4.1 Data Collection

We conducted two experimental sessions on February 18 and February 20, 2026. The first session included 8 participants and the second included 16, for a total of 24 participants from two four-year research universities. Each session lasted approximately 90 minutes. Because the experimental structure consists of independent two-versus-two battles, splitting the 24-participant pool across two sessions does not introduce confounding. For any given round within a game, the function faced by all participants in the first session was identical to that faced by all participants in the second session. This design ensures that data from both sessions can be combined for analysis.

Also, to ensure that participants fully understood the task prior to data collection, we implemented a multi-layer instruction procedure. Participants were provided with a short introduction video before the experiment, followed by an in-session overview using slides. In addition, brief instructional reminders were also embedded in the user interface of each game (see Figure 2).

In each session, participants first completed a trial game to familiarize themselves with the platform interface and task mechanics. They then played all four games sequentially, with each game consisting of five rounds. At the beginning of each round, participants were randomly re-assigned into two-versus-two systems and a new objective function was drawn. This re-grouping and function refresh procedure was designed to make rounds within each game as statistically independent as possible.

Combining the two sessions, each game yields 30 system-level observations (Session 1: 2 systems per round $\times$ 5 rounds from session 1; Session 2: 4 systems per round $\times$ 5 rounds from session 2). The pooled sample across all four games contains 120 system-level observations.

4.2 Level Alignment: Mean IOE and SOE

We begin by examining whether the mean level of individual efficiency within a system predicts system-level efficiency, and whether this relationship varies across information-sharing mechanisms.

4.2.1 Basic OLS Results

Table 2 reports the results of the basic OLS regression of SOE on mean IOE for each game separately.

In Game 1 (no information sharing), the estimated slope is positive but statistically insignificant ($\beta_1 = 0.299, p = 0.254$),

TABLE 2. Basic OLS results for the mean IOE–SOE relationship

Game	β_1	p-value	R^2
1	0.299	0.254	0.347
2	0.612	< 0.001	0.761
3	0.521	0.021	0.657
4	0.487	< 0.001	0.752

TABLE 3. Fixed-effects OLS results for the mean IOE–SOE relationship

Game	β_1	p-value	R^2	ΔR^2	Round FE (joint F-test)
1	0.206	0.178	0.770	0.423	$p = 0.0053$
2	0.618	< 0.001	0.780	0.019	$p = 0.3023$
3	0.538	0.025	0.710	0.053	$p = 0.7609$
4	0.489	< 0.001	0.777	0.025	$p = 0.6168$

indicating that mean IOE does not reliably predict SOE under the baseline mechanism. In contrast, Games 2 through 4 all exhibit significant and positive slopes ($p < 0.05$), with estimated coefficients ranging from 0.487 to 0.612, suggesting that under information-sharing mechanisms, higher mean individual efficiency within a system is associated with higher system efficiency. Whether these slopes differ significantly from the Game 1 baseline is formally tested in the pooled interaction model reported in Section 4.2.3.

4.2.2 OLS with Round-specific Fixed Effects Table 3 reports the results from OLS regressions augmented with round-specific fixed effects. The Round FE column reports the $p-$value from a joint F-test of the four round indicator variables, testing whether cross-round variation in objective function complexity explains additional variance in SOE beyond mean IOE. Equivalently, the null hypothesis is that the round fixed effects are jointly zero, meaning that there is no additional round-specific baseline variation in SOE after controlling for mean IOE.

After controlling for function complexity, the mapping from mean IOE to SOE in Game 1 remains insignificant ($p = 0.178$), while Games 2 through 4 retain their statistical significance. This result confirms that the misalignment observed in Game 1 is not an artifact of cross-round variation in function complexity.

An additional observation concerns the role of round-specific fixed effects. Because the objective function changes across rounds, some rounds may present easier or harder optimization landscapes. Round-specific fixed effects control for this variation by allowing each round to have its own baseline SOE level. In Games 2 through 4, these round-specific effects are not statistically significant, which means that once we know the mean IOE of a system, the specific function used in that round adds little additional information to predict SOE. In other words, mean IOE is already a sufficient summary of what drives system efficiency under information-sharing conditions. In Game 1, by contrast, round-specific fixed effects are significant ($p = 0.0053$). This indicates that when the IOE–SOE mapping is itself weak—as it is under the no-sharing condition—system efficiency is driven more by which function happened to be drawn in that round than by how efficiently participants searched. Therefore, under no-information-sharing condition, the mapping from mean IOE to SOE fails to internalize systematic across-round variation. By contrast, the information-sharing mechanism acts precisely as a stabilizer for such variation.

TABLE 4. Pooled interaction regression results for the mean IOE–SOE relationship

Variable	Coefficient	p-value
Mean IOE (Game 1 baseline slope)	0.206	0.165
$\overline{\text{IOE}}\times$ Game 2	0.412	0.036
$\overline{\text{IOE}}\times$ Game 3	0.332	0.217
$\overline{\text{IOE}}\times$ Game 4	0.283	0.087

TABLE 5. Estimated mean IOE–SOE slopes by game from the pooled interaction model

Game	Implied slope	p-value
1	0.206	0.165
2	0.618	< 0.001
3	0.538	0.016
4	0.489	< 0.001

4.2.3 Pooled Interaction Regression To explicitly test whether the strength of the IOE–SOE mapping differs across mechanisms, Table 4 reports the results of the pooled interaction regression with 'Game $\times$ Round' fixed effects. Game 1 serves as the reference category, so β_1 represents the baseline slope and the interaction terms θ_k capture the incremental change in slope for each subsequent game.

The baseline slope in Game 1 is not statistically significant ($p = 0.165$), indicating that under no-information-sharing, even after controlling for 'Game $\times$ Round' fixed effects, the linear predictive power of IOE for SOE remains weak.

The interaction term for Game 2 is significant ($p = 0.036$), indicating that the introduction of teammate information sharing produces a statistically detectable enhancement in the IOE–SOE mapping relative to the no-sharing baseline.

The interaction terms for Games 3 and 4 are positive but do not reach conventional significance levels (e.g., 0.01 or 0.05) individually ($p = 0.217$ and $p = 0.087$, respectively).

Table 5 reports the implied slope for each game, computed by summing the baseline slope and the corresponding interaction term. The implied slopes confirm the pattern observed in the game-by-game regressions: Game 1 is not significant, whereas Games 2 through 4 are all significant at $p < 0.05$ or better.

TABLE 6. Comparison of model specifications for the mean IOE–SOE relationship

Game	Basic OLS	+ Round FE	Pooled Interaction
1	ns	ns	ns
2	***	***	↑***
3	*	*	*
4	***	***	***

Notes: ns = not significant. * $p < 0.05$, *** $p < 0.001$. ↑ indicates that the IOE–SOE slope is significantly larger than the Game 1 baseline in the pooled interaction model.

4.2.4 Summary for Level Alignment

Table 6 integrates the three modeling approaches. Across all specifications, the IOE–SOE mapping is insignificant in Game 1 but consistently significant in Games 2–4, with the pooled interaction model further confirming that Game 2's slope is significantly steeper than Game 1's baseline ($\theta_2 = 0.412$, $p = 0.036$). The level-alignment results are revisited in the integrated discussion in Section 5.1.

An interesting question is why the IOE–SOE relationship in Game 3 remains comparable to those in Games 2 and 4, despite the absence of teammate information sharing. We interpret this as follows. Opponent-outcome visibility may provide external performance benchmarks that influence sampling aggressiveness, stopping decisions, and perceived competitive pressure, thereby creating system-level coupling even without direct within-team communication. Learning effects across rounds may also contribute, although the random re-pairing and per-round function refresh procedures are designed to limit them. A rigorous test through sampling-trajectory analysis is left for future work.

A related concern is whether the observed differences across Games 1–4 might partly reflect learning effects, given that participants played the four games in a fixed sequential order. We note, however, that a pure learning explanation would predict a monotonic improvement in SOE level from Game 1 to Game 4. By contrast, our core finding concerns a structural difference in the IOE–SOE mapping strength between Game 1 and Games 2–4, which a uniform learning trend cannot easily account for. A more direct test through an explicit trial-order control is left for future work.

4.3 Dispersion Alignment: Gini IOE and SOE

We next examine whether the inequality of individual efficiency in the four-participant battle, measured by the Gini coefficient of IOE, independently predicts system efficiency.

4.3.1 Basic OLS Results

Table 7 reports the basic OLS regression of SOE on Gini IOE for each game. None of the four games produces a statistically significant slope at the $p < 0.05$ level, although Game 3 approaches marginal significance ($p = 0.079$). The R^2 values are uniformly low ($0.026 - 0.081$), indicating that Gini IOE alone explains very little of the variation in SOE. These results indicate that within-system inequality of individual efficiency does not, by itself, serve as a reliable predictor of system efficiency.

TABLE 7. Basic OLS results for the Gini IOE–SOE relationship

Game	β_1 (Gini IOE)	p-value	R^2
1	0.050	0.192	0.056
2	0.065	0.332	0.026
3	0.064	0.079	0.079
4	0.107	0.225	0.081

TABLE 8. Fixed-effects OLS results for the Gini IOE–SOE relationship

Game	β_1 (Gini IOE)	p-value	R^2	ΔR^2	Round FE (joint F-test)
1	0.050	0.152	0.695	0.639	< 0.001
2	0.044	0.572	0.190	0.164	0.595
3	0.068	0.077	0.166	0.087	0.514
4	0.056	0.551	0.286	0.205	0.450

TABLE 9. Summary comparison of models for the Gini IOE–SOE relationship

Game	Basic OLS	+ Round FE
1	$p = 0.192$	$p = 0.152$
2	$p = 0.332$	$p = 0.572$
3	$p = 0.079$	$p = 0.077$
4	$p = 0.225$	$p = 0.551$

4.3.2 OLS with Round-specific Fixed Effects

Table 8 reports the round-specific fixed effects specifications. After controlling for round-level function complexity, the Gini IOE coefficient remains insignificant in all games except Game 3, where it is marginally significant ($p = 0.077$). This is fully consistent with the basic OLS results. Notably, in Game 1, the R^2 increases substantially (from 0.056 to 0.695) after adding round-specific fixed effects, suggesting that much of the variation in SOE under the no-sharing condition is attributable to function complexity rather than to efficiency dispersion. However, because Game 1 was the first formal game participants played, part of these round-specific effects may also reflect residual learning effects. Although a one-round trial game was provided beforehand, it may not have fully eliminated deeper strategic adaptation in the early formal rounds.

4.3.3 Summary for Dispersion Alignment

Table 9 summarizes the dispersion-alignment results. Gini IOE alone is not a robust predictor of SOE under any of the four mechanisms.

TABLE 10. Centered interaction regression results: Mean IOE, Gini IOE, and their interaction

Game	Mean IOE	Gini IOE	Interaction	R^2
1	0.657 (0.015*)	−0.103 (0.032*)	−0.968 (0.476)	0.838
2	0.846 ($< 0.001^{***}$)	−0.183 ($< 0.001^{***}$)	−1.418 ($0.059^{\dagger}$)	0.945
3	0.957 ($< 0.001^{***}$)	−0.129 ($< 0.001^{***}$)	−1.476 ($0.089^{\dagger}$)	0.971
4	0.830 ($< 0.001^{***}$)	−0.216 ($< 0.001^{***}$)	−1.263 ($< 0.001^{***}$)	0.974

$^{*}p < 0.05$, $^{\dagger}p < 0.10$, $^{***}p < 0.001$

The implications of this null result, particularly when contrasted with the joint-interaction results that follow, are discussed in Section 5.1.

4.4 Joint Interaction of Level and Dispersion

The preceding analysis examined mean IOE and Gini IOE as separate predictors of SOE. However, the motivation for studying dispersion is not only that inequality might independently determine system outcomes, but also that it may modulate the translation from individual mean-level efficiency to system efficiency. We therefore estimate the centered interaction model described in Section 3.3.3.

4.4.1 Interpretation of Main Effects

Table 10 reports the results for all four games. The centered mean IOE coefficient (β_1) is now significantly positive across all four games ($p < 0.05$ to $p < 0.001$), with estimates ranging from 0.657 to 0.957. This indicates that, in centered interaction regression, the average level of individual efficiency is the primary driver of system efficiency across all mechanisms.

The centered Gini IOE coefficient (β_2) is significantly negative across all four games ($p < 0.05$ to $p < 0.001$), with estimates ranging from -0.103 to -0.216. $\beta_2 < 0$ means that among systems with the same mean IOE, a larger Gini (meaning more unequal distribution) leads to worse SOE.

This result stands in sharp contrast to the standalone Gini regressions reported in Section 4.3, where Gini IOE was not a significant predictor. The contrast reveals a key structural insight: the negative effect of efficiency inequality on system performance is masked when mean IOE is not controlled for, because systems with high inequality tend to have varying mean levels that confound the marginal effect of dispersion. Once the mean is held constant, however, the independent drag of the inequality on system efficiency becomes statistically apparent.

4.4.2 Interpretation of the Interaction Term

The interaction coefficient (β_3) captures whether efficiency inequality moderates the translation from mean IOE to SOE. Across all four games, β_3 is negative, indicating that higher inequality weakens the positive association between mean IOE and SOE. However, the statistical significance of this interaction varies by mechanism in a theoretically informative way.

In Game 1 (no information sharing), the interaction term is not significant ($p = 0.476$). This suggests that under the baseline mechanism, where participants operate in informational isolation, the moderating role of inequality is absent. Each participant's efficiency contributes to the system essentially in isolation, so the distribution of efficiency across system members has limited structural consequence beyond its mean.

In Games 2 and 3 (teammate sharing and opponent-outcome sharing, respectively), the interaction terms are marginally significant ($p = 0.059$ and $p = 0.089$), with substantial negative coefficients (-1.418 and -1.476). These results suggest that as information becomes available, efficiency inequality begins to exert a moderating effect. In other words, within each game, when the mean efficiency of a system is already high, the additional penalty for high inequality is greater.

In Game 4 (combined sharing), the interaction term is strongly significant ($p < 0.001$, $\beta_3 = -1.263$). Under the richest information environment, the moderating effect of inequality is fully activated.

Across all information-sharing conditions, the negative interaction can be understood intuitively: when mean IOE is high, the system is operating near its performance frontier, and the marginal damage caused by low-efficiency members becomes more consequential. Conversely, when mean IOE is low, all members are performing poorly, and the incremental harm of inequality is diluted. This pattern indicates that information-sharing mechanisms not only strengthen the IOE–SOE mapping but also amplify the system-level penalty of internal efficiency imbalance, and this amplification is strongest under the richest information condition.

4.4.3 Role of Round-specific Fixed Effects

Table 11 shows the round-specific effects result in centered interaction regression. In Games 1 through 4, all round-specific fixed effects are insignificant now, which stands in contrast to the earlier model (without mean IOE) where Game 1 exhibited highly significant round effects ($p < 0.001$). This indicates that the combination of mean IOE and Gini IOE absorbs the difficulty-related variation that was previously captured by round dummies.

4.4.4 Model Fit

The addition of the interaction term produces a substantial improvement in explanatory power. According to Table 10, the R^2 values range from 0.838 (Game 1) to 0.974 (Game 4), representing a qualitative leap compared to the Gini-only models ($0.026-0.081$ in basic OLS) and even the mean-only models with round-specific fixed effects (0.710–0.780). This indicates that the joint model of mean IOE and Gini IOE, combined with their interaction, achieves very strong explanatory power for system-level efficiency, particularly

TABLE 11. Centered interaction regression result: Round FE Joint F-test Results

Game	$F(4, 22)$	p-value
1	1.455	0.250
2	0.467	0.759
3	0.795	0.541
4	0.702	0.599

under information-sharing mechanisms.

4.4.5 Summary for Joint Interaction

The joint analysis yields three principal findings. First, after controlling for within-system inequality, mean IOE ($\beta_1 > 0$) is a significant positive predictor of SOE across all four mechanisms, including Game 1, although the Game 1 coefficient (0.657) remains notably smaller than those of Games 2–4 (0.830–0.957). Second, Gini IOE ($\beta_2 < 0$) exerts a significant negative effect on SOE across all four games, but only after the mean level is accounted for—an effect masked in the bivariate analysis of Section 4.3 due to confounding between mean and dispersion. Third, the negative interaction between mean IOE and Gini IOE ($\beta_3 < 0$) emerges only under information-sharing conditions—marginally significant in Games 2 and 3 and strongly significant in Game 4—while absent in Game 1. The theoretical interpretation of these patterns—particularly the refinement of the Section 4.2 result and the activation of inequality's moderating role under information sharing—is developed in detail in Section 5.1 and Section 5.2.

5. DISCUSSION AND CONCLUSION

5.1 Summary of Findings

This study investigated how individual efficiency translates into system-level efficiency in a competitive team-based design environment, and how that translation is influenced by the information-sharing mechanism governing interaction. Using a controlled Team-based Function Optimization Game experiment with four distinct information architectures, we constructed outcome-based efficiency metrics at both the individual level (IOE) and the system level (SOE), and examined their relationship through a multi-layered statistical framework.

Three principal findings emerge. First, when each participant's individual efficiency is used alone to predict system efficiency, the prediction works well under information-sharing conditions (Games 2–4) but is weak and unreliable under the no-sharing baseline (Game 1). Once inequality is accounted for in the joint model, the prediction becomes significant even in Game 1, but remains notably weaker than in Games 2–4. This indicates that the translation from individual efficiency to system efficiency is not absent without information sharing, but is fragile — fragile enough to be undetectable unless other factors are controlled for. Information-sharing mechanisms substantially strengthen and stabilize this translation.

Second, when we compare systems that have the same average level of individual efficiency, those with a more unequal distribution of efficiency across members tend to achieve worse system-level outcomes. This penalty of inequality is hidden when we look at inequality alone without accounting for the average efficiency level, because in the raw data, high-inequality systems and low-inequality systems also tend to differ in their average efficiency, which masks the independent harm of inequality.

Third, the combination of high average efficiency and high inequality is particularly damaging to system performance, but only when information is shared. In plain terms, inequality hurts more when the system is otherwise performing well, because the system has more to lose from its weakest members. This amplification effect is absent under the no-sharing condition, marginally present under partial sharing, and strongest under the richest information environment. In other words, richer information mechanisms are not unconditionally beneficial — **they raise the ceiling of what well-balanced systems can achieve, but also increase the cost of internal imbalance.**

Taken together, these results suggest that the individual-to-system efficiency translation is not a stable structural property of competitive design systems, but a mechanism-dependent relationship whose strength, robustness, and sensitivity to internal inequality are all shaped by the information architecture in which agents operate.

5.2 Theoretical Implications

5.2.1 Against the Aggregation Assumption

A foundational premise in many design and decision frameworks is that system performance can be understood, at least approximately, as an aggregate of individual performances [33,34]. This assumption underpins decentralized design philosophies, local incentive structures, and performance evaluation systems that reward individuals in the expectation that system-level gains will follow. Our results challenge this premise within the nested cooperative–competitive setting examined here, and suggest that its validity in other system architectures—such as purely cooperative or purely competitive environments—warrants further empirical investigation.

In Game 1, where participants operate in informational isolation, the linkage between individual efficiency and system efficiency is weak and fragile, and this relationship becomes detectable only after other structural factors are controlled for. This is not merely a case of noise or measurement error. It reflects a structural condition in which the absence of informational architecture makes the individual-to-system translation weak, unstable, and easily obscured. The aggregation assumption, far from being a universally reliable default, becomes fragile precisely when individuals lack the informational infrastructure to coordinate—or even to inadvertently benefit from—each other's search progress.

The implication is that efficiency alignment is not determined solely by the properties of agents but also by the mechanisms that structure their interaction. Two systems with identical distributions of individual efficiency can produce markedly different system-level outcomes depending on the information architecture that connects them. This reframes the question of system performance away from "how good are the individuals?" toward "how effectively does the mechanism translate individual quality into collective outcomes?"

5.2.2 Information as a Structural Coupling Device

The progressive strengthening of the IOE–SOE mapping from Game 1 through Games 2–4 reveals a deeper role for information-sharing mechanisms than is typically acknowledged in the design literature. Information sharing does not simply reduce uncertainty or improve individual decisions. More fundamentally, it shapes the structural coupling between individual and system performance. Under the no-sharing condition, the four participants within a system behave largely as informationally isolated atoms whose performances combine through purely mechanical aggregation—the system outcome is determined by the best individual draw, with little opportunity for one participant's search progress to influence another's trajectory. Under sharing conditions, information creates interdependence: one participant's discovery can redirect a teammate's search, and awareness of opponent outcomes can alter the timing and aggressiveness of exploration. These informational pathways transform the system from a loose collection of independent agents into a coupled dynamical structure in which individual efficiency gains can propagate, compound, and be leveraged at the system level.

This interpretation connects to the broader theoretical distinction between mechanistic and emergent properties of complex systems. The IOE–SOE mapping under no sharing is largely mechanistic: it is driven primarily by the statistical aggregation of individual outcomes, with only limited pathways through which participants' searches can influence one another. Under information sharing, the mapping acquires emergent characteristics: the system-level outcome reflects not only the quality of individual inputs but also the interaction structure through which those inputs are processed. Information architecture, in this view, is the mechanism that governs whether a system behaves more like a mere collection of individuals or as a genuinely interconnected system.

5.2.3 Inequality as a Latent Vulnerability

Perhaps the most theoretically striking pattern is the qualitative shift in the role of Gini IOE across our modeling sequence (Sections 4.3 and 4.4): inequality appears inert when examined in isolation, but exerts a consistent negative effect on system efficiency once the mean level is controlled for, with a moderating effect that emerges and intensifies as information sharing becomes richer.

This finding carries a precise theoretical interpretation. Inequality in individual efficiency is not inert; it is a latent vulnerability whose consequences are activated by information-sharing mechanisms. In the absence of shared information, inequality is invisible to the system because participants cannot observe, react to, or be harmed by the inefficiency of others. Under information sharing, however, low-efficiency participants are no longer isolated—they consume shared attentional resources, generate misleading signals for teammates, or fail to capitalize on informational opportunities that the mechanism provides. The richer the information environment, the more channels exist through which inefficiency can propagate and impose costs on the system as a whole.

The negative interaction between mean IOE and Gini IOE deepens this interpretation. When a system's average efficiency is high, it operates near its performance frontier, and the marginal damage of low-performing members is amplified: the system has more to lose, and the informational infrastructure that enables alignment also transmits the disruptive effects of internal imbalance. Conversely, when average individual efficiency is low, inequality matters less because no member is generating substantial value that could be undermined by others' inefficiency. Information-sharing mechanisms thus exhibit a dual character: they strengthen the positive translation from individual efficiency to system efficiency while simultaneously amplifying the system-level penalty of internal efficiency inequality. This duality means that richer information environments are not unconditionally beneficial—they raise both the ceiling of what aligned systems can achieve and the cost of what misaligned systems must bear.

5.3 Practical Implications

These findings have direct implications for the design of organizational and competitive systems where information-sharing policies are subject to institutional choice.

First, the results caution against evaluating information-sharing mechanisms solely by their effect on average performance. A mechanism that improves mean efficiency but simultaneously amplifies the cost of internal inequality may produce worse outcomes in systems where individual efficiency is unevenly distributed. System designers should therefore assess mechanisms not only by their level effects but also by their distributional sensitivity—the degree to which system performance depends on the internal balance of individual contributions.

Second, the finding that inequality is a latent vulnerability activated by information sharing suggests that organizational investments in information infrastructure should be accompanied by attention to the homogeneity of individual capability. Providing richer information to a team with large capability gaps may be counterproductive if the weaker members cannot effectively utilize the shared information, thereby imposing externalities on stronger members through misallocated coordination effort or degraded signal quality.

Third, the weakness and fragility of the IOE–SOE mapping in Game 1 carries its own practical lesson. In environments where information sharing is absent or minimal—whether by design, regulatory constraint, or technological limitation—individual efficiency improvements may yield weaker and less robust system-level returns. Under such conditions, the most effective intervention may not be to improve individual performance but to restructure the information architecture itself, thereby strengthening the structural pathways through which individual gains can translate into collective outcomes.

To illustrate these implications concretely, consider the practice of internal design competitions observed at firms such as Apple, where multiple teams simultaneously develop competing prototypes before a final design is selected. Our results suggest that enabling both within-team information transparency and cross-team performance visibility — analogous to the combined sharing condition (Game 4) in our experiment — is not unconditionally beneficial. If the competing teams are roughly equal in capability, richer information sharing can strengthen the translation from individual effort to the quality of the final selected design. However, if the individual contributors across the competing teams differ substantially in capability, the same information sharing may amplify the cost of this imbalance — weaker teams may misallocate effort in response to shared signals, while stronger teams may face degraded signal quality. Under such conditions, the organization should consider not only the richness of the information environment but also the balance of individual capability within the system, as richer information may fail to deliver its full benefit — or even backfire — when internal efficiency inequality is high. This should not be interpreted as evidence that high-performing contributors ought to be sorted into the same system. Rather, the broader implication is that the design of information mechanisms should be aligned with the underlying capability distribution, because richer information environments make the cost of internal imbalance more consequential.

5.4 Limitations

Several limitations of this study should be acknowledged. First, the sample size of 24 participants, while sufficient for the multi-level statistical analysis conducted here, limits the generalizability of the findings. Each game produces 30 system-level observations, which constrains the complexity of models that can be estimated with adequate statistical power. Replication with larger participant pools would strengthen confidence in the reported effect sizes and significance patterns.

Second, the optimization task used in this study, while carefully designed to be accessible across participant backgrounds, proved to be relatively easy for the current family of test functions. A substantial proportion of participants were able to identify the global optimum or near-optimal solutions within the budget. As a consequence, the value-improvement component of IOE frequently approaches its upper bound, reducing the metric's discriminative power and causing IOE to be predominantly driven by the cost component. This ceiling effect [35] limits the range of individual efficiency variation observable in the data and may attenuate the strength of the estimated IOE–SOE relationships. Future studies should employ objective functions with higher-dimensional design spaces, more complex landscapes, or tighter budget constraints to ensure greater separation in individual performance.

Third, the ceiling effect also points to an important dimension of individual performance that the current IOE metric does not capture: convergence speed. When multiple participants ultimately reach the same solution quality, the efficiency of the path, how quickly a participant converges to a near-optimal solution, becomes the more discriminating dimension of performance. Convergence-based efficiency metrics, measuring the cost incurred to first reach a near-optimal threshold, would provide a complementary perspective that is particularly valuable in settings where the optimization task is not sufficiently difficult to generate variation in final solution quality. We leave the formal construction of such metrics and the analysis of their system-level mapping relationships to future work.

Fourth, team composition in this study is randomly assigned and changes across rounds, which isolates the effect of information mechanisms from persistent team dynamics. However, real organizational settings involve persistent teams, learning across interactions, and endogenous sorting. The extent to which the mechanism-dependent alignment patterns identified here transfer to settings with stable team composition remains an open question.

Fifth, the current experiment uses a fixed team size of two members in a two-versus-two competitive structure. While this minimal team size provides clean experimental control and simplifies the identification of individual contributions, it limits the range of intra-team dynamics that can emerge. In larger teams, additional phenomena may arise, such as higher coordination costs, role differentiation, and more complex patterns of information utilization, that could alter both the level and distributional effects documented here. For example, the Gini coefficient of IOE may behave differently in a system with ten participants than in the four-participant system studied here, because as team size increases, both the potential scope for internal inequality and its interaction with information sharing expand, potentially in a non-linear manner. Extending the experimental framework to larger team sizes would test whether the mechanism-dependent alignment patterns identified here scale beyond minimal teams.

5.5 Future Directions Beyond addressing the limitations noted above, several directions for future research are motivated by this study's findings. First, the current analysis treats information-sharing mechanisms as exogenous treatments. In many real-world design environments, however, the degree of information sharing is endogenous: agents choose how much to reveal, when to observe, and what to communicate. Extending this framework to settings with strategic information disclosure would connect the efficiency alignment question to the mechanism design and strategic communication literature.

Second, the convergence-based efficiency perspective discussed in Section 5.4 opens a natural avenue for future investigation. While the current study focuses on the efficiency of the final outcome, the specific dynamics of the search process like how quickly and at what cost individual participants and systems converge toward high-quality regions, may reveal additional structure in the individual-to-system mapping that outcome-based metrics alone cannot capture. This is especially relevant for design environments where time pressure or sequential deadlines impose constraints beyond total budget. Process-level analysis of sampling trajectories under different information-sharing mechanisms could also help disentangle the behavioral pathways through which mechanisms shape system outcomes—for instance, by examining how opponent-outcome visibility (Game 3) influences sampling aggressiveness, stopping decisions, and perceived competitive pressure even in the absence of within-team communication.

Third, while the present study indicates that information-sharing mechanisms amplify the system-level penalty of internal efficiency inequality, it does not directly prescribe which information architecture is optimal for a given capability distribution. Developing such *capability–mechanism matching* guidelines would require a factorial experimental design that systematically manipulates both the heterogeneity of individual capability and the information-sharing mechanism. We view this as an important direction for future work, with direct implications for the design of internal design competitions and similar competitive innovation environments.

Finally, the theoretical framework developed here, mechanism-dependent alignment between individual and system efficiency, is not specific to optimization tasks. It applies in principle to any competitive or cooperative system or sequential decision-making process with costly information acquisition, where local performance is mediated by institutional structure before manifesting at the system level. Extending the empirical investigation to other design contexts, such as collaborative product development, distributed engineering teams, or open innovation competitions, would test the generality of the alignment patterns documented in this study and potentially reveal domain-specific moderating factors.

ACKNOWLEDGMENTS AND DISCLAIMERS

The authors gratefully acknowledge the financial support from the National Science Foundation (NSF) through the grants CMMI-2321463 and CMMI-2419423. This work was also partially supported by the Air Force Office of Scientific Research (AFOSR) under the grant FA9550-24-1-0265. The authors thank Nikoo Javadpour of Lehigh University for her assistance in organizing and conducting the experimental sessions and for helping recruit participants at Lehigh University. The authors also thank all 24 participants for their time and engagement in the experiments.

The authors used ChatGPT (OpenAI, Instant 5.3 and Thinking 5.4) and Claude (Anthropic, Opus 4.6 and Sonnet 4.6), accessed via web browser, in February and March 2026 for language editing, paragraph revision and readability improvement across multiple sections, including the Abstract, Introduction, Discussion and Conclusion sections. The authors also used Video Agent 2.0 (HeyGen, Creator Plan), accessed via web browser, in February 2026 to create the introduction video described in Section 4.1. The authors reviewed all edits and take full responsibility for the integrity and final wording of the manuscript.

REFERENCES

[1] Puranam, P., Alexy, O., and Reitzig, M., 2014. "What's "new" about new forms of organizing?". *Academy of Management Review,* ***39***(2), pp. 162–180.

[2] Sommer, S. C., and Loch, C. H., 2004. "Selectionism and learning in projects with complexity and unforeseeable uncertainty". *Management Science,* ***50***(10), pp. 1334–1347.

[3] Aggarwal, I., and Woolley, A. W., 2019. "Team creativity, cognition, and cognitive style diversity". *Management Science,* ***65***(4), pp. 1586–1599.

[4] Von Hippel, E., and von Krogh, G., 2016. "Crossroads—identifying viable "need–solution pairs": Problem solving without problem formulation". *Organization Science,* ***27***(1), pp. 207–221.

[5] Boudreau, K. J., Lacetera, N., and Lakhani, K. R., 2011. "Incentives and problem uncertainty in innovation contests: An empirical analysis". *Management Science,* ***57***(5), pp. 843–863.

[6] Knudsen, T., and Srikanth, K., 2014. "Coordinated exploration: Organizing joint search by multiple specialists to overcome mutual confusion and joint myopia". *Administrative Science Quarterly,* ***59***(3), pp. 409–441.

[7] Afuah, A., and Tucci, C. L., 2012. "Crowdsourcing as a solution to distant search". *Academy of Management Review,* ***37***(3), pp. 355–375.

[8] Chen, S., Bayrak, A. E., and Sha, Z., 2025. "A cost-aware multi-agent system for black-box design space exploration". *Journal of Mechanical Design,* ***147***(1), p. 011703.

[9] Levinthal, D. A., and March, J. G., 1993. "The myopia of learning". *Strategic Management Journal,* ***14***(S2), pp. 95–112.

[10] Puranam, P., 2018. *The Microstructure of Organizations*. Oxford University Press, Oxford.

[11] Sha, Z., Kannan, K. N., and Panchal, J. H., 2015. "Behavioral experimentation and game theory in engineering systems design". *Journal of Mechanical Design,* ***137***(5), p. 051405.

[12] Javadpour, N., Mutlu, K., Sha, Z., and Bayrak, A. E., 2025. "Impact of information sharing between members in design teams under competition in unknown design space exploration". In Proceedings of the ASME 2025 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE2025), Vol. 89237, American Society of Mechanical Engineers, p. V03BT03A029.

[13] Felin, T., Koenderink, J., and Krueger, J. I., 2017. "Rationality, perception, and the all-seeing eye". *Psychonomic Bulletin & Review,* ***24***(4), pp. 1040–1059.

[14] Nickerson, J. A., and Zenger, T. R., 2004. "A knowledge-based theory of the firm—the problem-solving perspective". *Organization Science,* ***15***(6), pp. 617–632.

[15] Bunderson, J. S., Van der Vegt, G. S., Cantimur, Y., and Rink, F., 2016. "Different views of hierarchy and why they matter: Hierarchy as inequality or as cascading influence". *Academy of Management Journal,* ***59***(4), pp. 1265–1289.

[16] Chen, D. L., Schonger, M., and Wickens, C., 2016. "otree—an open-source platform for laboratory, online, and field experiments". *Journal of Behavioral and Experimental Finance,* ***9***, pp. 88–97.

[17] Chen, S., Bayrak, A. E., and Sha, Z., 2024. "Distributed multi-agent bayesian optimization for unknown design space exploration". In Proceedings of the ASME 2024 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE2024), Vol. 88377, American Society of Mechanical Engineers, p. V03BT03A040.

[18] Myers, R. H., Montgomery, D. C., and Anderson-Cook, C. M., 2016. *Response Surface Methodology: Process and Product Optimization Using Designed Experiments*, 4 ed. John Wiley & Sons, Hoboken, NJ.

[19] Rao, S. S., 2009. *Engineering Optimization: Theory and Practice*, 4 ed. John Wiley & Sons, Hoboken, NJ.

[20] Lazear, E. P., and Rosen, S., 1981. "Rank-order tournaments as optimum labor contracts". *Journal of Political Economy,* ***89***(5), pp. 841–864.

[21] Gilpatric, S. M., 2009. "Risk taking in contests and the role of carrots and sticks". *Economic Inquiry,* ***47***(2), pp. 266–277.

[22] Farrell, M. J., 1957. "The measurement of productive efficiency". *Journal of the Royal Statistical Society: Series A (General),* ***120***(3), pp. 253–281.

[23] Gächter, S., Orzen, H., Renner, E., and Starmer, C., 2009. "Are experimental economists prone to framing effects? a natural field experiment". *Journal of Economic Behavior & Organization,* ***70***(3), pp. 443–446.

[24] Cook, W. D., and Seiford, L. M., 2009. "Data envelopment analysis (dea)—thirty years on". *European Journal of Operational Research,* ***192***(1), pp. 1–17.

[25] Denrell, J., and Liu, C., 2012. "Top performers are not the most impressive when extreme performance indicates unreliability". *Proceedings of the National Academy of Sciences,* ***109***(24), pp. 9331–9336.

[26] Knudsen, T., and Levinthal, D. A., 2007. "Two faces of search: Alternative generation and alternative evaluation". *Organization Science,* ***18***(1), pp. 39–54.

[27] Denrell, J., and Fang, C., 2010. "Predicting the next big thing: Success as a signal of poor judgment". *Management Science,* ***56***(10), pp. 1653–1667.

[28] Pisano, G. P., 2015. "You need an innovation strategy". *Harvard Business Review,* ***93***(6), pp. 44–54.

[29] Lashinsky, A., 2012. *Inside Apple: How America's Most Admired—and Secretive Company Really Works*. John Murray, London.

[30] Kocienda, K., 2018. *Creative Selection: Inside Apple's Design Process During the Golden Age of Steve Jobs*. St. Martin's Press, New York.

[31] Long, J. S., and Ervin, L. H., 2000. "Using heteroscedasticity consistent standard errors in the linear regression model". *The American Statistician,* ***54***(3), pp. 217–224.

[32] Aiken, L. S., and West, S. G., 1991. *Multiple Regression: Testing and Interpreting Interactions*. Sage Publications, Newbury Park, CA.

[33] Steiner, I. D., 1972. *Group Process and Productivity*. Academic Press, New York.

[34] Baldwin, C. Y., and Clark, K. B., 2000. *Design Rules: The Power of Modularity*. MIT Press, Cambridge, MA.

[35] Terwee, C. B., Bot, S. D. M., de Boer, M. R., van der Windt, D. A. W. M., Knol, D. L., Dekker, J., Bouter, L. M., and de Vet, H. C. W., 2007. "Quality criteria were proposed for measurement properties of health status questionnaires". *Journal of Clinical Epidemiology,* ***60***(1), pp. 34–42.