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Intervention in Collaborative System Design to Increase Efficiency: A Communication Channel for Technical and Social Information Exchange

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Effective communication plays a crucial role in aligning intentions and improving outcomes in collaborative systems. Misunderstandings can hinder collaboration, but a communication channel that enables the exchange of technical and social information may enhance results. The study assesses the effects of such a communication channel on system-level efficiency and accuracy of shared information using data from a human experiment involving a collaborative system design task. 52 undergraduate and graduate student participants represented decision-makers in paired tasks, earning or losing points based on joint decisions. The experiment includes two study groups: a control group and a treatment group with a communication channel for sharing strategic intentions and technical details. Results show the communication channel significantly improves system efficiency and encourages accurate, honest exchanges of intentions. Even when inaccurate communication occur, their partner's reported strategies influence actors' decisions. These findings emphasize the critical role of both social and technical communication in achieving better management and higher efficiencies in collaborative systems.

KEYWORDS
Collaborative Systems, Communication, Decision-Making, Game-Theory, Human Experiments

1 | INTRODUCTION

With drastic technological advancements, collaboration has become a widely used method for engineering processes and products. An example of a collaborative system is Distributed Satellite Systems (DSS), which is a space system including multiple spacecraft sharing different functionalities and roles to achieve a goal [1]. DSS designs suggest the idea of decentralizing ownership, meaning different assets are owned and operated by different organizations as in a collaborative system design [2]. This new architecture requires giving up control over some of the assets and sharing resources so organizations can achieve their goals more cost-effectively [1]. However, the presence of decentralized authorities means the need for strategic decision-making because it involves self-interested actors with different objectives that can create conflicts. Selva et al. suggest a need for research on the strategic management of DSS infrastructure, using technology upgrades to form and manage collaborative systems. This paper aims to suggest a communication tool to enhance efficiencies while forming collaborative systems such as DSS.

Collaboration is a strategic agreement between actors to work together to surpass the capabilities of a single actor [3]. Despite their significance, about half of collaborations fail [4]. In collaborative design systems, outcomes depend on all constituent decisions, making risk inseparable from the process [5;6]. Even if collaboration promises higher gains, lack of understanding, insufficient common knowledge, and the bounded rationality of the actors due to suspicion and distrust towards their partner can discourage collaboration [7;8]. Enhanced communication increases successful collaborative outcomes [8;9;10;11;12].

The paper uses data from a human experiment on a collaborative system design problem to investigate the effects of the communication channel on collaborative outcomes. Participants represent decision-makers of different organizations aiming to increase revenues through paired collaborative tasks. They accumulate benefits by collaborating but face downside risks if collaboration fails. Participants report their collaboration beliefs in each task, and the communication channel provides information on strategic intentions and the minimum required collaboration beliefs to economically benefit from collaboration.

Before making a decision in each task, participants report intentions as a collaboration belief. The communication channel collects intentions and displays information in a communication window. Analysis examines how the communication channel affects collaborative task outcomes, focusing on whether it leads to more frequent successful collaborations and higher system-level efficiency. Additionally, analysis investigates the accuracy of reported intentions and how participants utilize presented information in decision-making process.

Results show the communication channel significantly improves system-level efficiency. Participants share accurate information about their strategic intentions and their decisions significantly shift after learning of partner intentions, particularly when moving from non-collaborative to collaborative decisions. The majority of the participants do not manipulate information via the channel. This study demonstrates that a communication channel enabling technical and social information sharing is vital for improving collaborative efficiency. By fostering honest communication, the channel enhances participant understanding of partner intentions, reducing perceived risks associated with choosing collaborative design options.

2 | BACKGROUND

2.1 | Collaborative Systems

Rechtin defines a system as “a set of different elements so connected or related so as to perform a unique function not performable by the element alone” [3]. Each part in a system has its own value, but the essential value comes from the relationship between the parts and how they all form a system. A system is a collection of different entities composing an outcome that cannot be achieved by an individual entity [3].

Collaborative systems are large systems that assemble two or more complex systems. Collaborative systems possess both operational and managerial interdependence [2]. In collaborative systems, each sub-system can operate independently but actors choose to collaborate when its benefit outweighs the costs. Maier states that the mechanisms and incentives for collaboration must be designed in the system [2].

Research on collaborative engineering design emphasizes human dependent engineering systems with multiple interdependent participants [13]. Collaborative system problems have several self-interested agents who must work together towards a common system-level goal despite different local objectives [14]. Social dilemma arises from conflicts between collective benefits and self-interest [15;16] which adds uncertainty to the system. Decision-making actors can share or retain information for their individual benefit, so strategic decisions must be made to maximize expected gains with limited available information [17].

Game theory provides methods to model strategic dynamics in a collaborative system [18]. Even though the prisoner's dilemma has been widely discussed in the research literature, a Stag Hunt game better models strategic dynamics in a collaborative system [8;18]. Section 3.1 provides detailed information about the Stag Hunt game and how associated theory applies to collaborative systems.

2.2 | Communication and Collaboration

In management science, communication holds an essential place in literature on strategic alliances [9]. In a strategic alliance, communication can shift partner perceptions from competitive to cooperative [8]. Research on strategic alliances acknowledges the significance of interpersonal communication among decision-makers as a pathway to fostering collaboration and alignment [10;19]. Communication can prevent problems arising from bounded rationality and decision biases. Management literature shows that improved communication in strategic alliances also improves economic returns [11] by ensuring better information flow [12].

In strategic alliances, there exists fear related to partner misconduct. Having knowledge about other parties' incentives and orientation toward the strategic alliance can reduce perceived risk. Communication also reduces the chances of surprises and unexpected developments, fostering shared expectations that improve group coordination and unity. Research establishes correlations between communication among partners and enhanced performance in strategic alliances [20]. Consequently, effective communication fosters the cultivation of social capital and trust among partners in strategic alliances [21].

Economics literature shows communication does not increase the probability of collaboration in a prisoner's dilemma context [22]. However, strong evidence shows that enhancing communication increases collaborative outcomes in assurance games (such as a Stag Hunt game) having multiple Nash equilibria, which are better representations of strategic alliance context [23]. Agarwal et al. investigate the effects of communication in strategic alliance by conducting a human experiment [8]. Each participant represents a firm deciding the extent to which to engage in cooperative activities within a strategic alliance. Treatment group participants can communicate via a chat box. Experimental results support significant evidence that the ability to communicate approximately doubles the rate of successful collaboration in strategic alliances.

TABLE 1 Stag Hunt Game Example Payoff Matrix

Actor 1 Strategy	Actor 2 Strategy	
	Hare (H)	Stag (S)
Hare (H)	$V_2^{HH} = 2$ $V_1^{HH} = 2$	$V_2^{HS} = 0$ $V_1^{HS} = 4$
Stag (S)	$V_2^{SH} = 4$ $V_1^{SH} = 0$	$V_2^{SS} = 5$ $V_1^{SS} = 5$

2.3 | Research Objective

Literature shows how successful collaborative systems can provide greater benefits for all actors but fragility arises from complexities of actor interactions. Management science literature shows the importance of communication for success of strategic alliances. However, no existing literature addresses how to establish an effective communication channel in collaborative settings. This study investigates the effects and usage of a communication channel by actors in a collaborative system using data from a human experiment. The communication channel enables the exchange of necessary technical and social information. Analysis first investigates whether the communication channel can increase system-level efficiencies in collaborative processes, then focuses on the usage of the communication channel by the actors with the following research questions:

RQ1: How does a communication channel affect task outcome efficiency for pairs in collaborative decision-making tasks?
RQ2: Do actors share accurate information about their strategic decision via the communication channel?
RQ3: Do actors change their strategic decision after learning their partner's intention via the communication channel?
RQ4: Do actors manipulate information via the communication channel for strategic purposes?

3 | METHODOLOGY

3.1 | Background Theory

As engineering systems grow more complex, decentralized ownership and control among collaborating actors pose challenges due to collaborative dynamics. The Stag Hunt game models collaborative dynamics as hunters choosing between hunting a hare for a smaller but more certain individual reward or hunting stag for a potentially larger but more variable collaborative reward [24]. Successful stag hunts depends on mutual effort, while hare hunts are largely independent. This study adopts a Stag Hunt game as a model to study dynamics in collaborative systems [18].

Table 1 illustrates an example Stag Hunt payoff matrix for two actors. Rows represent alternative decisions for actor 1 and columns represent alternative decisions for actor 2. The matrix shows payoff values ($V_1^{S_1 S_2}$, $V_2^{S_1 S_2}$) based on strategic decisions of both actors (S_1, S_2). For simplicity, consider payoffs as utility values. The stag/stag scenario gives the highest payoff (5), a hare/hare scenario gives a modest payoff (2), and an unsuccessful stag hunt results in the lowest payoff (0).

Figure 1 illustrates expected payoffs based on the partner's collaboration probability (p). Rational actors prefer hare hunting for low p and stag hunting for high p. Selten defines normalized deviation loss (u) as the intersection between the two expected value lines [25]. Normalized deviation loss measures the minimum probability of collaboration

FIGURE 1 Stag Hunt Strategy Selection Based on Expected Value of Payoffs and Illustration of Normalized Deviation Loss (the Intersection Point of Expected Value Lines of Stag and Hare Hunting)

TABLE 2 Example Payoff Table from Experimental Tasks

Actor 1		Actor 2 Strategy (S_2)	
Strategy (S_1)	Design (D_1)	Collaboration (C)	Individual (I)
C	A	$V_A^{CC} = 111$	$V_A^{CI} = -90$
C	B	$V_B^{CC} = 92$	$V_B^{CI} = -45$
C	C	$V_C^{CC} = 77$	$V_C^{CI} = -15$
I	Y	$V_Y^{IC} = 50$	$V_Y^{II} = 50$

of one's partner required to pursue the collaborative strategy from an expected value perspective. Stag hunting is rational when $p > u$. Equation (1) calculates u based on the payoff values in Table 1, showing $u = 2/3$, meaning actors require at least 67% confidence that their partner will collaborate to collaborate. Adjustments to payoff values shift this threshold, affecting strategy preferences.

$$u = \frac{V^{HH} - V^{SH}}{(V^{HH} - V^{SH}) + (V^{SS} - V^{HS})} = \frac{2 - 0}{(2 - 0) + (5 - 4)} = \frac{2}{3} \quad (1)$$

Decision theory identifies when collaboration is rational by comparing the normalized deviation loss (u) and probability of collaboration p. However, real-world settings challenge both calculating u and comparing it to an inferred collaboration belief due to factors such as risk aversion, cognitive biases, and information asymmetry. The communication channel provides actors with technical information about u and p to address the difficulty imposed by limited information or time constraints.

The communication channel aims to give actors a clearer technical understanding of the required collaboration rate and, when paired with knowledge of their partner's intent, supports improved risk evaluation. By comparing u with their partner's collaboration intent p, actors are hypothesized to reduce biases, adjust risk perceptions, and develop a more objective and realistic view of collaboration.

This study examines the impact of a communication channel on collaborative decisions [6]. The channel facilitates the exchange of essential technical and social information during design tasks. Using a treatment group with the communication channel and a control group without, the study evaluates the channel's effects on paired and individual outcomes through comparative analysis.

3.2 | Experiment Design

Each session involves four participants working in pairs, representing decision-makers from multiple car manufacturers. Paired actors complete decision-making tasks having Stag Hunt dynamics with three collaborative options and one individual option. In each task, actors choose a design (D) from four options based on payoffs ($V_D^{S_1 S_2}$) contingent on strategic choices. Table 2 illustrates Actor 1's payoff based on Actor 2's choices.

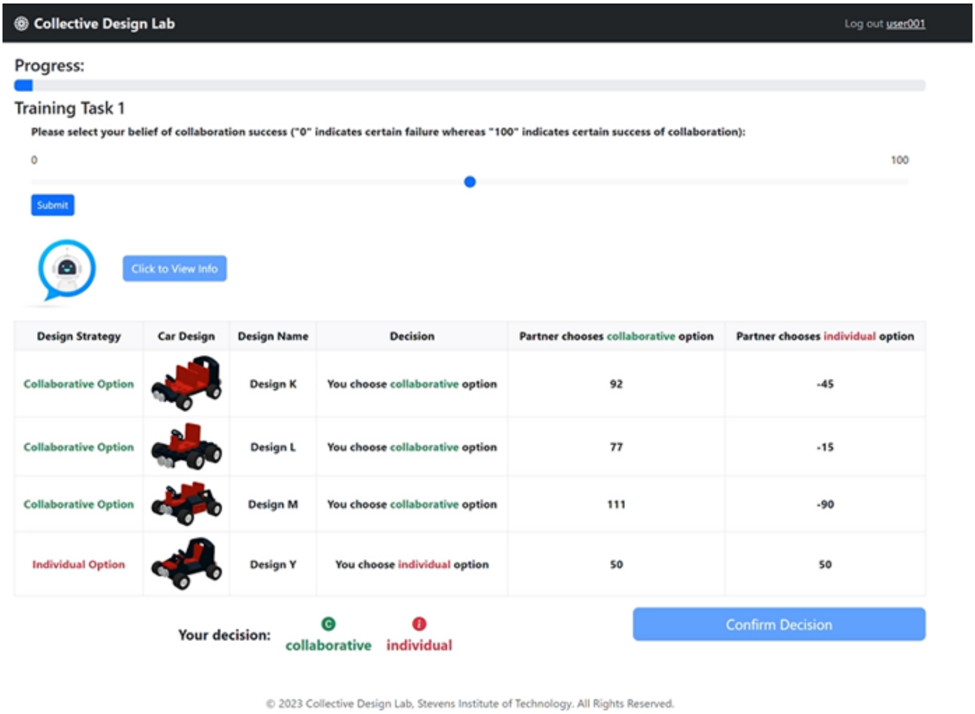


FIGURE 2 Experimental Interface for Training Task 1 for the Treatment Group

Figure 2 shows the first training task interface, with three collaborative options (K, L, M as a randomized order of A, B, C) and one individual option (Y). Alternative collaborative designs offer higher potential revenues if successful but incur larger losses if collaboration fails (e.g., $M : +111/-90$ points, $L : +77/-15$ points). Prior to selecting a design, each task also prompts participants to estimate collaboration success using a slider (0 = certain failure, 100 = certain success).

The experiment design defines two control variables: task difficulty (L) and payoff magnitude (G). Each design alternative in a task has the same difficulty level, and collaborative design options have different payoff magnitude ranges. Differences in payoff magnitude provide greater control over collaborative design implementation, which can shift the risk-dominant equilibrium toward collaboration due to differences in risk perception[6].

Six task difficulty levels ($L \in \{0.55, 0.60, 0.70, 0.75, 0.80, 0.85\}$) define the task normalized deviation loss (u). For instance, an actor requires 55% collaboration probability from their partner for level 1 and 85% for level 6.

Five payoff magnitudes (G) control the upside and downside payoffs for the three collaborative options. Collaborative design options have consecutive payoff magnitudes such that A is the highest, B is in the middle and C is the lowest (e.g., $V_A^{CC} = 100$ and $V_A^{CI} = -9$, $V_B^{CC} = 88$ and $V_B^{CI} = 4$, $V_C^{CC} = 72$ and $V_C^{CI} = 23$ for $L = 1$ and $G = 1$). Through an experimental session, collaborative design A ranges between -400 and 130 points, B ranges between -280 and 115 points, and C ranges between -250 and 105 points. The user interface randomizes the order of options A, B, C, displayed as K, L, M.

The experiment design composes five tasks for each difficulty level. Each task includes three collaborative options with the same difficulty level but different payoff magnitude ranges (e.g., $V_A^{CC} = 100$ and $V_A^{CI} = -9$ for $L = 1$ and

TABLE 3 Example tasks demonstrating payoff values for min/max difficulty levels (L) and payoff magnitudes (G).

Task Difficulty (L)	Payoff Magnitude (G)	Design Option (D)	Upside Payoff	Downside Payoff
1	1	A	100	−9
		B	88	4
		C	72	23
		Y	50	50
6	5	A	130	−400
		B	115	−310
		C	105	−250
		Y	50	50

$G = 1$, $V_A^{CC} = 130$ and $V_A^{CI} = -400$ for $L = 6$ and $G = 5$ while V_Y is constant at 50 for all tasks). Table 3 illustrates payoffs for minimum and maximum difficulty levels and payoff magnitudes. Each pair of participants encounters all possible combinations of difficulty levels and payoff ranges. Pairs face asymmetric tasks, meaning that partners do not face the same payoff values.

The only experimental difference between the two study groups is that the treatment group includes the communication channel and the control group does not. Figure 2 illustrates the experimental interface for the treatment group. According to the experimental design, the **communication channel** has two roles:

1. **Providing technical information**: Experimental tasks exhibit different difficulty levels, and participants may not be able reason about the normalized deviation loss in a one-minute task period; the communication channel illustrates the u-value of the specific task.
2. **Exchanging social information between partners**: The communication channel shows participants the selected collaboration beliefs for each task, enabling communication of intentions.

Figure 3 illustrates the interface for the treatment group with the communication channel window. The black vertical plotted line shows u-value of the task, the purple dashed line shows the collaboration intention p the partner supplied, and the dotted blue line shows the collaboration intention the actor supplied.

3.3 | Experimental Protocol and Data

The Institutional Review Board at Stevens Institute of Technology approved the experimental protocol (#2020-015). All sessions were conducted in person at the Stevens campus, involving a demographics survey, pre- and post-surveys, and instructions, totaling around 60 minutes per session.

Each session includes four participants paired randomly at the start of the session, completing 30 decision-making tasks where participants individually earned or lost points based on joint decisions. Participants were instructed that collaborative designs had a 5% risk of technical failure beyond human decisions, simulating real-world risks in collaborative efforts, although this factor was not implemented in recorded payoffs. Six distraction tasks with prisoner's dilemma dynamics were also included to vary the strategic context during an experiment.

Pairs sat face to face and were able to communicate verbally without viewing each other's screens. They could hear other pairs' conversations but faced different randomized tasks. Participants could share or withhold honest or misleading information. The experimenter observed the session and advanced tasks after all decisions were made.

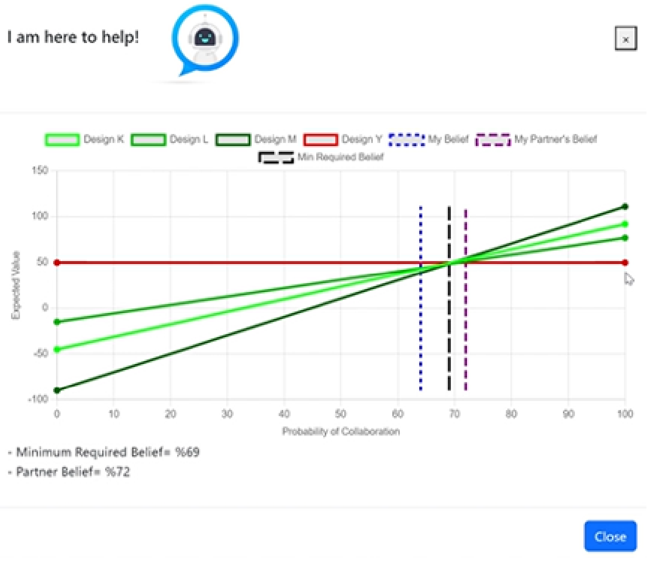


FIGURE 3 Experimental Interface for the Communication Channel

Table 4 presents participant demographics. Social closeness with pairs was self-rated on a 1 (first time meeting) to 5 (relative, partner, very close friend) scale. The study yielded 780 task observations (360 control, 420 treatment).

4 | ANALYSIS AND RESULTS

The analysis first aims to understand the effects of the communication channel on the paired outcomes of collaborative tasks. Next, it investigates how the communication channel affects actors decisions. The next section presents results and analysis for all research questions. Table 5 summarizes all variables and their definitions used in the analysis and results.

4.1 | Effects of the Communication Channel on Paired Outcomes

RQ1: How does a communication channel affect efficiency of task outcomes for pairs in collaborative decision-making tasks?

The first research question examines the impact of the communication channel on paired outcomes, focusing on system-level efficiencies. The analysis compares collective decision outcomes from 780 experimental tasks, with 420 in the treatment group and 360 in the control group. On the paired level, the experimental tasks have three possible categorical outcomes:

1- **Successful Collaboration (O_S)**: Both actors select a collaborative strategy and receive the upside payoff.
2- **Mutual Individual (O_I)**: Both actors select an individual strategy and receive the individual payoff.
3- **Coordination Failure (O_F)**: Actors choose different strategies such that the collaboration fails; one actor receives the individual payoff and the other receives the downside payoff.

TABLE 4 Demographic Factor Statistics of Participants

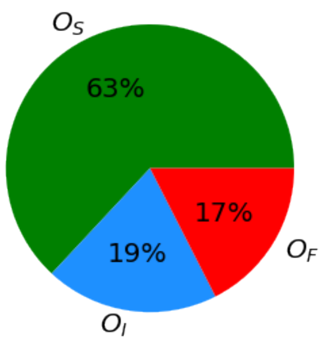
Demographic Factor	Statistic	Control Group	Treatment Group	All
Gender	Female	7	8	15
	Male	17	20	37
Age	min	21	20	20
	max	38	33	38
	mean	27.0	25.3	26.1
Education Level	min	4	3	3
	max	11	12	12
	mean	6.3	6.0	6.2
Experience Level	min	1	1	1
	max	11	12	12
	mean	5.5	5.6	5.6
English Proficiency	min	3	2	2
	max	5	5	5
	mean	4.3	4.1	4.2
Social Closeness	min	1	1	1
	max	4	5	5
	mean	1.8	2.2	2.0

TABLE 5 Abbreviation Table for Results and Analysis

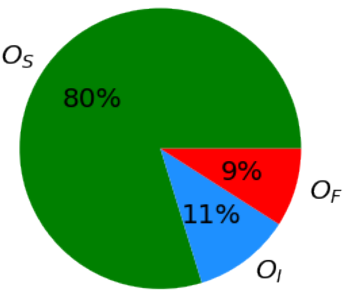
Variable	Source	Range	Definition
T	Controlled Variable	$[0, 1]$	Group: Treatment (1) or control (0)
o	Controlled Variable	$[1, 36]$	Task order (sequence in experimental session)
L_i	Controlled Variable	$[1, 6]$	Task difficulty level for actor i
G_i	Controlled Variable	$[1, 5]$	Task payoff magnitude level for actor i
s_i	Input Variable	$[1, 5]$	Reported social closeness for actor i
P_i	Output Variable	$[0, 100]$	Collaboration belief reported via slider for actor i
S_i	Output Variable	$[\mathcal{I}, \mathcal{C}]$	Strategy of actor i: Collaborative ($\mathcal{C}$) or individual ($\mathcal{I}$)
V_i	Output Variable	$[-400, 130]$	Task score obtained by actor i
u_i	Eq. (1)	$[0.55, 0.85]$	Task normalized deviation loss for actor i
r_{ij}	$0.5\log(\frac{u_i}{1-u_i}) + 0.5\log(\frac{u_j}{1-u_j})$	$[0.3, 1.6]$	Task risk dominance for actor i and j
O_{ij}	$\begin{cases} O_S & \text{if } S_i = S_j = \mathcal{C} \\ O_\mathcal{I} & \text{if } S_i = S_j = \mathcal{I} \\ O_F & \text{if } S_i \neq S_j \end{cases}$	$[O_S, O_\mathcal{I}, O_F]$	Outcome of actors i and j: Successful collaboration (O_S), mutual independence ($O_\mathcal{I}$), or coordination failure (O_F)
E_{ij}	Eq. (2)	[0, 1]	Task outcome efficiency for actors i and j
Q_i	$P_i - u_i$	$[-85, 45]$	Modified collaboration belief for actor i
Q_{ij}	$P_j - u_i$	$[-85, 45]$	Modified partner's collaboration belief perceived by actor i
N_i	$\mathcal{C}$ if $Q_i > 0$ else $\mathcal{I}$	$[\mathcal{I}, \mathcal{C}]$	Implied strategic intent for actor i
N_{ij}	$\mathcal{C}$ if $Q_{ij} > 0$ else $\mathcal{I}$	$[\mathcal{I}, \mathcal{C}]$	Partner's implied strategic intent perceived by actor i

TABLE 6 Experimental Data for RQ1 Comparing Outcomes of Treatment and Control Groups

Actor i Strategy (S_i)	Actor j Strategy (S_j)	Paired Task Outcome (O_{ij})	Treatment Group Occurrence (%)	Control Group Occurrence (%)
C	C	O_S	335/420 (79.8%)	227/360 (63.1%)
I	I	O_I	47/420 (11.2%)	70/360 (19.0%)
C	I	O_F	38/420 (9.0%)	63/360 (17.5%)



(a) Control Group



(b) Treatment Group

FIGURE 4 Pie Charts Comparing Outcome Percentage Difference between Experimental Groups

Table 6 and Figure 4 present experimental data for RQ1 comparing the control and treatment group results.

Analysis of RQ1 first performs a nonparametric Mann-Whitney U test between ordinal outcomes ($O_S = 2$, $O_I = 1$, $O_F = 0$) of the treatment and control groups with the null hypothesis that there is no difference in median rank. Test results show a statistically significant difference in outcomes between the treatment and control groups ($U = 88380.5$ and $p = 2.31 \cdot 10^{-7}$).

Further analysis investigates the relationship between the communication channel and paired task outcomes by calculating a system level efficiency (E_{ij}) using normalized scores earned by actor i by adding minimum possible V to all obtained scores to make $V_i \geq 0$. Based on collective design metrics from Valencia-Romero and Grogan [16], the system level efficiency compares the earned collective score to the maximum possible collective score. Equation 2 shows the calculation by dividing the product of earned scores for actors i and j by the product of maximum possible scores. Efficiency ranges from 0 to 1 for each task.

$$E_{ij} = \frac{V_i \cdot V_j}{(\max_{D_i, S_j} V_i) \cdot (\max_{D_j, S_i} V_j)} \tag{2}$$

Analysis investigates if there is a significant difference between the efficiency of the treatment group and the control group using a two population t-test conducted. Results show a significant difference in efficiency between the two experimental groups ($t(778) = 4.84$, $p = 1.59 \cdot 10^{-6}$).

After showing significant differences between the efficiency outcomes of the two experimental groups, the analysis investigates the magnitude and direction of communication channel effects on task efficiency outcomes using a

TABLE 7 Regression Results Investigating Effects of Input Variables on Paired Outcome Efficiency

Variable	Coefficient	Std. Error	t Statistic	p Value
intercept	2.5207	0.086	29.161	$1.13 \cdot 10^{-126}$
T	0.1216	0.027	4.553	$6.14 \cdot 10^{-6}$
$\bar{s}$	0.0571	0.011	5.372	$1.03 \cdot 10^{-7}$
L_i	−0.0607	0.019	−3.125	0.002
L_j	−0.0736	0.019	−3.807	$1.52 \cdot 10^{-4}$
$L_i : L_j$	0.0100	0.005	1.998	0.046
$\log(o)$	0.0315	0.017	1.894	0.059

regression test. The regression model includes T and the other observed variables in the experiment including: absolute difference of the reported social closeness ($\bar{s} = |s_i - s_j|$), task difficulty level (L_i) and partner's task difficulty level (L_j), interaction effects between L_i and L_j ($L_i : L_j$), and log transformation of task order (o) to capture learning effects. Preliminary multicollinearity analysis shows low (below 0.1) correlation among all input variables. Analysis performs an Ordinary Least Square regression model with the mathematical model in Eq. (3). An exponential transformation on efficiency normalizes a natural skew towards 1. Results show statistically significant relationships between T and exponentially transformed E_{ij}, illustrated in Table 7.

$$\exp(E_{ij}) = B_0 + B_1 T + B_2 \bar{s} + B_3 L_i + B_4 L_j + B_5 (L_i \cdot L_j) + B_6 \log(o) \tag{3}$$

4.2 | Usage Accuracy of the Communication Channel

RQ2: Do actors share accurate information about their strategic decision via the communication channel?

Remaining analysis only considers data from the treatment group to investigate usage of communication channel. Observed data consists of 420 experimental tasks with strategic decisions and strategic intentions reported via the collaboration belief slider for each actor, resulting in 840 observations.

The second research question investigates whether actors use the collaboration belief slider to accurately communicate strategic intentions. Recall that actors report collaboration belief (P_i) on a scale from 0 (certain belief of collaboration failure) to 100 (certain belief of collaboration success) prior to making a final decision. Each actor faces a different normalized deviation loss (u_i) linked to the task difficulty level L_i. An actor reporting a collaboration belief of $P_i > u_i \iff Q_i = P_i - u_i > 0$ indicates they intend to collaborate ($Q_i > 0 \iff N_i = C$). Conversely, reporting $P_i < u_i \iff Q_i < 0$ indicates they intend to choose individual option ($Q_i < 0 \iff N_i = \mathcal{I}$). This research questions focuses on the relationship between an actor's modified collaboration belief (Q_i) and strategic decision (S_i). Shared information is considered accurate if the strategic intention and strategic decision match (i.e., $N_i = S_i$).

Observations summarized in Table 8 show actors share accurate information in 83% (703/840) of tasks. Statistical analysis employs point biserial correlation to evaluate the relationship between the modified collaboration belief Q_i and strategic decision S_i. Results show a statistically significant moderate correlation with correlation coefficient 0.555 and p-value $3.52 \cdot 10^{-69}$.

A logistic regression test is selected for further analysis of the effects of continuous input Q_i on binary output S_i. The logistic regression model is $S_i = B_0 + B_1 Q_i$ and results in Table 9 show that Q_i has a statistically significantly effect on the S_i. Figure 5 illustrates the relationship between Q_i and S_i as a scatter plot with overlaid logistic regression

TABLE 8 Experimental Data for Accuracy of Collaboration Belief Slider

Information Accuracy	Actor i		Occurrence (%)
	Intention (N_i)	Strategy (S_i)	
Accurate	C	C	625/840 (74.4%)
	I	I	78/840 (9.3%)
Inaccurate	C	I	54/840 (6.4%)
	I	C	83/840 (9.9%)

TABLE 9 Logistic Regression Results Investigating Effects of Q_i on S_i

Variable	Coefficient	Std. Error	z Statistic	p Value
intercept	1.3787	0.117	11.818	$3.151 \cdot 10^{-32}$
Q_i	0.0551	0.005	11.795	$34.132 \cdot 10^{-32}$

curve.

4.3 | Inaccuracy of Reported Beliefs and Final Decisions

RQ3: Do actors change their strategic decision after learning their partner's intention via the communication channel?

The third research question investigates if inaccuracy between reported strategic intentions and final decisions can be attributed to the partner's strategic intention (P_j) available through the communication channel as the purple vertical line in Fig. 3. If partner's strategic intention is sufficiently large (i.e., $P_j > u_i \iff Q_{ij} = P_j - u_i > 0$), the actor perceives a positive collaboration belief from their partner ($Q_{ij} > 0 \iff N_{ij} = C$). Otherwise, if $P_j < u_i \iff Q_{ij} < 0$, the actor perceive collaboration risky ($Q_{ij} < 0 \iff N_{ij} = I$). This research question focuses on the relationship between the perceived partner's collaboration belief (Q_{ij}) and final decisions of the actor (S_i), hypothesizing that an actor may change their decision from the initial intention if N_{ij} does not match N_i.

Analysis only considers observations with inaccurate strategic intention reports (i.e., $N_i \neq S_i$). Table 10 shows that for actors who reported collaborative intensions ($N_i = C$) but selected the individual strategy ($S_i = I$), their partner reported individual intentions $N_{ij} = I$ in 64.8% of samples. For actors who reported individual intensions ($N_i = I$) but selected a collaborative strategy ($S_i = C$), their partner reported collaborative intentions ($N_{ij} = C$) in 96.4% of samples.

The logistic regression test is again selected to investigate effects of the continuous input Q_{ij}, on the binary output S_i within the set of tasks labeled as inaccurate. Logistic regression model ($S_i = B_0 + B_1 Q_{ij}$) results in Table 11 show that Q_{ij} has a statistically significant effect on actor decisions.

TABLE 10 Experimental Data for Partner Responses for Inaccurate Actions

Information Accuracy	Actor i		Actor j	Occurrence (%)
	Intent (N_i)	Strategy (S_i)	Intent (N_{ij})	
Inaccurate	C	I	I	35/54 (64.8%)
			C	19/54 (35.2%)
	I	C	C	80/83 (96.4%)
			I	3/83 (3.6%)

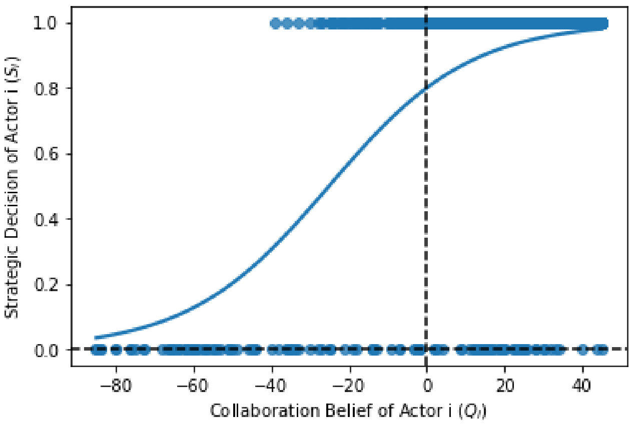


FIGURE 5 Scatter Plot of Modified Collaboration Belief (Q_i) and Strategic Decision (S_i) with Logistic Regression Curve

TABLE 11 Logistic Regression Results Investigating Effects of Q_{ij} on S_i for Cases with $S_i \neq N_i$

Variable	Coefficient	Std. Error	z Statistic	p Value
intercept	−0.0071	0.241	−0.030	0.976
Q_{ij}	0.0545	0.011	5.069	$4 \cdot 10^{-7}$

4.4 | Manipulative Behavior on the Communication Channel

RQ4: Do actors manipulate information via the communication channel for strategic purposes?

Introducing a communication channel in collaborative processes poses a risk of manipulation, as actors might deceive their partners for strategic gains. The basic Stag Hunt game does not incentivize this type of manipulative behavior; however, because points are accumulated individually in the experiment, participants have some incentive to harm their partner to improve their own relative position. That said, manipulation has significant limits in this setting because actors can generally out-perform the competing pair through successful collaboration.

This research question focuses on scenarios where actors report collaborative intentions ($N_i = C$) but ultimately select the individual option ($S_i = \mathcal{I}$), indicating potential deceit. Such cases account for only 6.4% of tasks (54/840). Moreover, in 65% of these samples, the partner's perceived intent (N_{ij}) is also individual, potentially influencing decisions. Cases where $N_i = N_{ij} = C$, but the actor chose individually ($S_i = \mathcal{I}$), occur in less than 3% of tasks (19/840).

Despite limited evidence of manipulation, specific actors may exhibit manipulative tendencies. Using the data subset with mutual collaborative intensions ($N_i = N_{ij} = C$, 560 samples), an ANOVA test compares collaborative decisions ($0 : S_i = \mathcal{I}, 1 : S_i = C$) among all 50 actors. Results show a significant difference in mean collaboration rate for at least one actor ($F(50, 762) = 4.304$, $p = 4.62 \cdot 10^{-19}$). Post-hoc one-tailed t-tests identify five actors having statistically significant differences ($p < 0.05$) from a null hypothesis of "always collaborate" ($S_i = C$) expected for this setting. Table 12 presents these findings.

TABLE 12 t-Test Results: Actors with Mean Collaboration for Cases with $N_i = C$ and $N_{ij} = C$

Actor ID	Mean Collaboration Rate	t Statistic	d.f.	p Value
13	0.800	-1.871	14	0.041
41	0.823	-1.852	16	0.041
43	0.758	-2.985	28	0.003
44	0.758	-2.985	28	0.003
48	0.500	-3.873	15	$7 \cdot 10^{-4}$

5 | DISCUSSION

5.1 | Synthesis of Analysis Results

5.1.1 | Results of Research Questions

RQ1: *How does a communication channel affect efficiency of task outcomes for pairs in collaborative decision-making tasks?* Results show a significant difference between the outcomes of the treatment and control groups. The communication channel significantly increases successful collaboration rates, reduces coordination failures, and improves system-level efficiencies, enabling pairs to achieve better shared outcomes.

RQ2: *Do actors share accurate information about their strategic decision via the communication channel?* Analysis results reveal a statistically significant relationship between actors' reported strategic intentions and strategic decisions, suggesting that actors share accurate information about their strategic intentions using the collaboration belief slider. Results show the rate of collaborative strategy selection follows the collaboration belief value reported by the actors.

RQ3: *Do actors change their strategic decision after learning their partner's intention via the communication channel?* Results show actors adjust decisions based on their partner's reported intentions. Notably, observations show actors switch from an individual to a collaborative strategy after learning their partner intends to collaborate in more than 96% of cases.

RQ4: *Do actors manipulate information via the communication channel for strategic purposes?* While a key concern in designing a communication channel is the risk of manipulation, results reveal that most actors honestly communicate their intentions, prioritizing the common good. Only a few participants demonstrated manipulative behavior. Future studies should focus on detecting and mitigating such behaviors to maintain the channel's intended purpose.

5.1.2 | Discussion of Results

Even though actors can maximize scores by choosing collaborative design options, collaboration is high-risk because each actor is self-interested. There is a lack of transparency in collaborative design tasks, and actors do not have any social or technical information about the other actor's options or beliefs. Miscommunication, reduced transparency, and lack of information exchange increase uncertainty, making collaboration a risky option. Actors require higher perceived trust and control levels to perceive collaboration as a palatable risk.

The preceding analysis investigates *how* the communication channel helps the actors to achieve more efficient system-level outcomes. Results suggest the communication channel plays three key roles affecting the strategic decisions of actors:

1- Act as a communication tool between actors: During the experiment, even though actors are allowed to share verbal information, they have different communication preferences. Some actors prefer to share information willingly, whereas others prefer to retain information or feel uncomfortable sharing information verbally. Accordingly, some pairs do not communicate effectively or have miscommunication issues, meaning they cannot obtain essential information related to collaborative risks and rewards. The communication channel allows actors to share relevant information about the task without verbal communication, thereby increasing the communication rate. Experimenter observations find many actors are more comfortable and honest when sharing their beliefs about collaboration via the communication channel rather than verbally. Statistical results show actors are willing to share accurate information about their intentions via the communication channel.

2- Improve collaborative system transparency: The communication channel makes the collaborative process more transparent by providing social information about the partner's intent to collaborate. Natural variability produces risk-taking and risk-averse actors, where risk-averse actors perceive collaboration as more risky due to the structure of their utility functions. Experimenter observations find that the communication channel can demonstrate to risk-averse actors that collaboration is not as risky as they perceive it to be because their partner has a high probability of collaborating (perceived trust). This significant result indicates that the communication channel can lead to higher rates of collaborative decisions and successful collaborations by enabling a more transparent social picture.

3- Provide a clearer technical picture: The communication channel provides decision-theoretic information of normalized deviation loss for each task. This technical information gives actors a minimum probability of collaboration required to pursue a collaborative strategy based on task-specific payoff values. Actors have only one minute to evaluate decisions, a limited amount of time to make detailed economic calculations. The communication channel information provides greater control over the process with technical analysis supporting the evaluation and decision-making processes.

Results also reveal a significant relationship between social closeness, task difficulty level, partner's task difficulty level, and order of the tasks with task outcome efficiency for pairs. Social closeness measures how well the actors within a pair know each other. Initial hypotheses anticipated it would influence outcomes, as stronger relationships typically enhance communication effectiveness. Indeed, results show that social closeness positively influences collaborative task efficiency. Prior to the experiment, initial hypotheses anticipated that task difficulty levels would affect collaboration rates and task outcomes. Results shows the task difficulty level of both actors negatively influence task efficiency. Results also show significant interaction effects between task difficulty levels, meaning that the effects of one actor's difficulty level change based on the other's difficulty level. Lastly, analysis shows that task order positively affects task outcome efficiencies, which is attributed to learning effects.

5.2 | Limitations

This study has several limitations. First, the experiment's simplified bi-level design and four design options do not fully capture the complexity of real-world collaborative tasks, which often involve more decision options and multiple actors, increasing social complexity. However, the design tasks highlight the essential dynamics present in a Stag Hunt game while providing a degree of control over design alternatives.

Second, social closeness between pairs was an uncontrolled input variable measured through a pre-experiment questionnaire. As this measurement was not validated, its reliability remains uncertain. Experimental control over social closeness may provide stronger conclusions on its effect in treatment and control conditions.

Third, despite evidence from Avsar and Grogan that risk attitudes influence utility functions and require personalized calculations [26], the communication channel's technical information on normalized deviation loss was not tailored to individual risk attitudes, an observed uncontrolled variable. Incorporating individual risk attitudes would shift the values of modified collaboration belief and implied strategic intent, influencing statistical analyses.

Lastly, resource constraints limited the study to thirteen sessions, producing a dataset focused on two-person interactions over a short period within a specific design context. Financial rewards incentivize participants but may not fully reflect broader, domain-specific scenarios. These limitations suggest results may vary across populations and collaborative design tasks.

5.3 | Implications for Systems Engineering and Future Directions

Even though collaboration enables actors to achieve goals that are beyond their individual capabilities [27], significant number of collaborations fail [4], due to misunderstandings, conflicts, social dilemma, and distrust among actors [7;8]. Communication is vital to form effective collaborations [8;9;10;11;12]. The results of this paper show that collaborative systems such as Distributed Satellite Systems can benefit from the introduced intervention, the communication channel. The communication channel would be helpful in the strategic management of the DSS by enabling exchange of vital technical and social information. Drawing from the findings of this paper, a collaborative system management tool should encompass the following attributes:

1. **Efficiency Assessment**: Verifying that collaboration provides high efficiencies for all actors and system-level outcomes.
2. **Technical Guidance**: Providing navigational support in the technical search, ensuring the eventual product optimization to satisfy the needs of all stakeholders while aligning with system-level objectives.
3. **Role and Task Allocation**: Facilitating the strategic distribution of roles and responsibilities among system actors to yield desired outcomes.
4. **Information and Communication Enabler**: Ensuring that all actors possess the requisite technical and social information and fostering effective communication channels.
5. **Mediation in Management**: Overseeing the decentralization of ownership and operations through adept mediation, safeguarding the equitable treatment of all parties involved.

In practical implementations, establishing rules, policies, and agreements is essential to prevent individual actors from exploiting the communication channel/management tool for personal gains. Additionally, preserving confidentiality is crucial to uphold the rights of all actors. In the evolving landscape, future system management tools should be able to detect fraudulent activities, safeguarding the collective welfare of all system actors. The adaptability of management tools to address diverse real-world challenges holds the promise of heightened efficiency in system design endeavors.

6 | CONCLUSION

In collaborative systems, make decisions based on both technical information and an evaluation of partner intentions toward collaboration. Even when partners may exchange verbal information, constraints prevent successful communication. This paper investigates a communication channel to exchange necessary technical and social information during collaborative design activities. It provides actors with social collaboration beliefs of their partners and technical analysis for the minimum required collaboration belief to pursue collaboration. Results show the communication channel significantly increases collaboration rates and task outcome efficiencies.

Further analysis supports has three major roles of the communication channel. 1- **Act as a communication tool between actors**, results show that actors share accurate information about their strategic intentions using the communication channel. Experimenter observations find designers are more comfortable and honest when communicating their beliefs technically rather than verbally. 2- **Improve collaborative system transparency**, analysis shows actors change their decision after learning about their partner's strategic intentions. Through improved transparency, the communication channel can shift from individual to collaborative decisions by exposing high intentions towards collaboration. 3- **Provide a clearer technical picture**, the communication channel supplies actors with technical normalized deviation loss analysis, helping to structure collaborative decisions. Furthermore, results show that manipulation of the communication channel for strategic purposes was observed to be limited to a few participants.

In conclusion, this study contributes to the literature by showing that interventions in the management processes of collaborative systems can increase collaboration rates and system-level efficiencies. Understanding how the intervention works and improving the communication channel can help to achieve a management system to enhance complex collaborative systems. Future studies should focus on building experiments with enhanced management tools with a wider-scoped input and output information range, increasing actor numbers within a system, having a wider and broader range of design decisions, measuring risk attitudes of participants prior to the experiment to personalize technical analyses. Incremental improvements to a communication channel supported by future experiments will propose and evaluate management systems for complex collaborative systems.

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Conflict of Interest Statement

The authors report no conflicts of interest.

Data Availability Statement

Data are available from the authors upon request.

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