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When does group chat promote cooperation in shared resource governance?

Abstract

When people use shared resources, overextraction can occur. While deliberation tends to mitigate shared resource exploitation problems, the question remains: under what conditions does group chat improve cooperation in shared resource dilemmas? This study analyzes chat and game data from about 1500 rounds of gameplay involving 143 groups across 4 resource types using Sentiment Analysis and Structural Topic Model. We find that, despite their fundamental differences, the 4 games tend to have similar discussions, including strategizing actions, coordinating on choices, and socialization, but that they differ in which topics explain cooperation within each game. Discussion topics promoting cooperation include coordination in the foraging game (FOR) and long-term goals in the groundwater game (GG). However, discussion topics negatively associated with cooperation include off-topic/socialization in FOR and the irrigation game (IRR) and crop choice affirmation in GG. We suggest that the context in which communication occurs matters and biophysical characteristics, rules of the game, and levels of uncertainty explain some variations of our findings.

Introduction

Individuals can cooperate with one another to successfully manage competing interests under certain conditions in governing commons such as forests, fisheries, irrigations, outer space (Berkes 1985; Ostrom 1990; Ostrom and Gardner 1993; Chhatre and Agrawal 2008; Yap et al. 2023). Factors shaping cooperative behavior in managing commons remain a topic of interest to many scholars in the fields of economics, political science, evolutionary sciences and behavioral sciences (Axelrod 2006). Experiments on cooperation have provided considerable evidence on factors driving cooperation including trust, group size and composition, communication, rules, norms, monitoring and punishment, risk and uncertainty (Ostrom, Walker, Gardner 1992; Cárdenas and Ostrom 2004; Ostrom 2006; Ahn, Ostrom, Walker 2010; Janssen et al. 2010; Rocha et al. 2020).

Experimental studies suggest that group communication – typically in the form of in person or online group chat – makes groups avoid overextraction of shared resources (Ostrom, Walker, Gardner 1992; Ahn, Ostrom, Walker 2010; Balliet 2010; DeCaro, Janssen, Lee 2021; Ahsanuzzaman, Palm-Forster and Suter 2022). While the role of communication has been well-established in mitigating resource exploitation problems, why and how communication improves cooperation is less understood. Often, communication was used as "treatment" in experimental framework, but the detailed analysis of communication themselves has only been done in a handful of works (Pavitt 2011; Lopez and Villamayor-Tomas 2017; Pavitt 2018; Osborne, Sundström, Bodin 2019; DeCaro, Janssen, Lee 2021).

Theories and empirical studies suggest that when interaction is allowed in repeated games, humans can clarify coordination problems in commons management. Effective social interactions lower the cost of detecting and punishing free riders and in turn enhance standard conditional reciprocity (Smith 2010). Indeed, in field experiments, communication allows participants to detect others' actions and make commitment promises (Cárdenas, Ahn, Ostrom 2004). Communication is also integral to having common knowledge among heterogenous participants and updating their own understanding based on social interactions (Thomas et al. 2014). In repeated interactions, communication facilitates homophilic process of social interactions among those who share similar norms and conventions (Smith 2010). This and other evidence suggest that communication tends to reinforce existing reciprocity regimes in human cooperation (Smith 2010; Pavitt 2018). When actions are followed through based on communication, trust is formed, and this logic repeats over multiple rounds, making cooperation stable (Axelrod 2006; Pavitt 2018).

Social-psychological approaches to cooperation start from group consciousness and identity as the foundation for within-group cooperation. Group identity tends to make in-group communication relatively more efficient when resources are shared by multiple groups. This, in turn, generates reciprocity and equity between players. Subsequently, these norms become salient and further enhance trust among players and reinforce group cohesion (DeCaro, Janssen, Lee 2021; Pavitt 2018). While group identity hypotheses have been tested in experimental settings, studies yield mixed results about the effects of group identity mechanism (Kerr and Kaufman-Gilliland 1994; Bouas and Komorita 1996). Studies further show that the framing and manipulation of group identity is critical to cooperation (Dawes and Messick 2000).

Institutionalist perspectives suggest that exogenous factors – rules of the game, and biophysical and material conditions – tend to shape the way in which actors cooperate in shared resource governance (Ostrom 2009; Poteete, Janssen, Ostrom 2010). Contextual factors also affect actors differently and thus change actors' understanding of the game and perceived benefits and costs (Edwards and Steins 1999). In turn, in repeated interactions, those changed understanding and perception would change fundamental incentive structure and thus norms in which groups tend to abide by (Ostrom 1990; Ostrom 2000). Recent experiments suggest that uncertainties of various kinds in shared resource dilemma affect participant behavior significantly, but that the impact and directionality of such uncertainty is not yet clear (Ahn, Baldwin, Girone 2024; Schill and Rocha 2023). These different effects tend to be explained by different types of uncertainties and contexts introduced in experiments.

While there is some theoretical diversity to explain cooperative behavior in shared resource dilemmas, recorded group chat from game exercises, particularly chat data, tend to be under-analyzed. As a result, researchers may be overlooking valuable insights that can be gained from rich textual data (Pavitt 2018). Studies show that different types of communication content have varying impacts on game behavior and cooperative outcomes. Specific group strategies are positively associated with group cooperation (Pavitt 2011; Lopez and Villamayor-Tomas 2017). External information tends to have a crowding-out effect on the positive impact of communication on cooperative outcomes (Osborne, Sundström, Bodin 2019). Negative maintenance categories – criticism or disapproval of the group – promote cooperative behaviors (Lopez and Villamayor-Tomas 2017).

While a handful of studies examined the contents of communication and its impact on cooperative outcomes (Pavitt 2011; Pavitt 2018; Osborne, Sundström, Bodin 2019; DeCaro, Janssen, Lee 2021), existing studies tend to analyze data from a single game and thus do not compare similarities and differences among games. We argue that this is a missed opportunity for researchers to build more systematic analyses of experimental game datasets. The goal of this article is to provide a unified dataset and approach to analyze a relatively larger game experimental dataset. To that end, we use computational text analysis tools to analyze communication in multiple behavioral experiments (Grimmer, Roberts, Stewart 2022). We use Sentiment Analysis (SA) to capture emotional temperature and valence in communication and examine whether and to what extent sentiment explains cooperative behavior (Liu 2022; Hutto and Gilbert 2014). Secondly, we use Structural Topic Model (STM) to explore topic content and topic prevalence in chat data and estimate the effect of topic prevalence on levels of cooperation (Roberts et al. 2014). Substantively, we engage in comparative game experimental analyses, and demonstrate that our approach can provide insights that are not readily identifiable in a single game study.

Our findings suggest that in the 4 different shared resource dilemma games, participants tend to engage in similar discussions including strategizing plans, coordinating on choices, and informal socialization. But there are also differences in how each discussion topic we observed is related to levels of cooperation recorded in the groups. Discussion topics promoting cooperation include coordination on where to harvest in FOR and chatting about long-term goals in GG. But discussion topics negatively associated with cooperation include off-topic/socialization in FOR and IRR and crop choice affirmation in GG.[1]

Methods

Dataset

[1] we use abbreviation when we refer to the four games: Foraging Game (FOR), Irrigation Game (IRR), Port of Mars Game (POM), Groundwater Game (GG)

We draw data from previous behavioral experiments examining the management of shared resources namely the Foraging Game (FOR) (DeCaro, Janssen, Lee 2021), the Irrigation Game (IRR) (Janssen et al. 2015), the groundwater game (GG) (Ahn 2023), and the Port of Mars game (POM) (Janssen et al., 2024). While these games have differences in the specific problems they simulate and the design choices, they share two important characteristics. First, all games involve social dilemma situations where players are required to cooperate with each other to avoid the collapse of shared resources. Second, all games allow group chat in multiple rounds of the game, allowing us to analyze how people solve complex problems through synchronous virtual communication. The refined dataset includes individual decision variables and chat data from undergraduate students. Based on these data, we aggregate individual level data into the round-level to extract meaningful information from text analysis.

Table 1 shows the basic attributes of the four datasets: Foraging Game (FOR), Irrigation Game (IRR), Groundwater Game (GG), Port of Mars (POM). We aggregated data at the round-level to capture interactions between participants, which resulted in about 1470 rounds in 143 groups across the four games [For details of the game, see Appendix 1 for game description]. In the Foraging Game (FOR) (DeCaro et al. 2021), four participants share a spatially explicit dynamic resource where they harvest tokens for 4 minutes. When each harvester consumes tokens too quickly, shared resources can be depleted. Participants can chat for five minutes before each harvesting round. In the Irrigation game (IRR) (Janssen et al. 2015), participants should decide how much to invest in infrastructure and how much to invest in water. Upstream participants will have first access to the water, while downstream participants have the last choice to extract water from the shared infrastructure. Before each round, five participants are allowed to chat for 1 minute. In the Groundwater Game (GG) (Ahn 2023), 4-5 participants share a stock of water that has a partial replenishment each round. They play a crop choice game where one crop uses more water and leads to higher returns, and the other crop uses less water and leads to lower returns. Participants are allowed to communicate for about 1 minute between each round of the game, and thus, they can discuss strategies to manage resources sustainably. Finally, in the Port of Mars game (POM) (Janssen et al., 2024) each participant is a resident in a hypothetical habitat on Mars. A participant's mission is to stay alive and achieve victory points. There are Mars events at the start of each round that can positively or negatively impact players. Participants can use 10 time blocks to invest in system health or influence resources. Participants can communicate continuously with others during the game consisting of 8-12 rounds.

Table 1: Basic attributes of the four data sets

	Foraging	Irrigation	Groundwater	Port of Mars
Communication rounds	123	879	249	219
Chats	4470	13675	1419	4095
Words	27003	66437	7743	26595
Groups	41	44	25	33

Dependent Variable: Cooperation

The aim of our analysis is to explain how the content of text chat impacts cooperation in different collective action experiments. Since the games are different, the notion of cooperation is not identical among the games. We explain in this section how we measure the dependent variable "cooperation" for each game, in order to have comparative metrics.

Broadly speaking, cooperation is "two or more actors work together with the intent to solve certain issues or problems for mutual benefit (Bodin, García, Robins 2020 472)." It is the prioritization of public interests over private interests (Rocha et al. 2020). Although many shared resource dilemma games have general trade-off structures between private gains and common benefits, each game tends to have unique features depending on game payoffs, nature of shared resources, external events affecting social interactions, and structural/positional differences. Since the four games differ in the actions participants can take in balancing private and public interests, we define an indicator that is comparable among the games to capture cooperative behavior at the group level. In FOR, cooperative behavior at the group level refers to the total number of tokens collected in a round. Theoretical social optimum is 1233 tokens (DeCaro, Janssen, Lee 2021). We divide the number of tokens by 1233 to derive a cooperation indicator value between 0 and 1. In IRR, cooperative behavior at the group level refers to the total earnings a group can derive in a round. The social optimum depends on the initial infrastructure level and is thus not the same for each round. We divide the earnings by the social optimum earnings to derive a cooperation indicator between 0 and 1. In GG, cooperative behavior at the group level refers to selecting the water efficient crop, limiting the decline of the groundwater levels. The cooperation indicator is 0 if all participants select the crop with the highest water use, and 1 if all players select the crop with the lowest water use. In POM, cooperation is measured as the relative reinvestment of the loss of system health. System health can decline due to wear and tear, events, and actions of players. Lower system health increases the likelihood of resource collapse and thus reinvestment is key. The cooperation indicator is 0 if there has been no investment, and 1 if the group reinvests sufficiently to avoid a decline of the system health. [See Appendix 1.2 for descriptive statistics].

Regression Model

This study uses data from four behavioral experiments to identify correlations between (1) sentiment and cooperation; and (2) topics and cooperative behavior that help sustain shared resource management. The resulting dataset includes 4 different games, with 143 groups, and 1470 rounds of games. The unit of observation is a round in the experiment by a group. Since rounds are nested within groups and groups are nested within game types, we use hierarchical linear ~~models~~ regression to model the relationship between sentiment and cooperation (Laird and Ware 1982; Snijders and Bosker 2011; StataCorp 2023). Our primary model is developed as below:

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$$Y_{i,j,z} = (B_0 + U_{0,j,z}) + (B_1 X_{1,i,j,z}) + \left(\sum_{k=1}^{K} \beta_{2k} X_{2k,i,j}\right) + \varepsilon_{i,j,z} \quad (1)$$

We first run a single-level linear regression models with covariate adjustment (Model 1 and 2 in Table 2). Then, we specify models by adding more parameters and levels. In equation (1), $Y_{i,j,z}$ is the level of group investment towards shared resources in round *i,* group *j,* and game *z*. $B_1 X_1$ is the effect of sentiment score. $B_{2k} X_{2k}$ is the vector of covariates that are hypothesized to affect cooperative behavior including demographic and group characteristics. We run models with the same kinds of covariates to maintain consistency of models by each game. B_0 is the overall mean across different groups. U_0 is the group-level random variance unexplained by the main effect. $e_{i,j,z}$ is the individual-level random effect.

$$B_1 = B_1 + U_1 \quad (2)$$
$$Y_{i,j,z} = (B_0 + U_{0,j,z}) + (B_1 + U_1)X_{1,i,j,z} + (\sum_{k=1}^{K} \beta_{2k} X_{2k,i,j}) + \varepsilon_{i,j,z} \quad (3)$$

Based on equation (1), we insert equation (2) into equation (1) to allow for different slopes for different groups. U1*X1 is the cluster-specific random slopes that reflect the heterogeneous effects of sentiment on cooperation in each game. Other regression parameters in equation (3) are the same with equation (1). For full sample analysis, we run random intercept models in Table 2 to fit models. For split sample analysis, in some games, we allow for random slope models to account for the different effects of sentiment on cooperation depending on other important covariates [see Appendix 2.1-2.4]. Presented models in Table2 are random intercepts models. In the following sub-sections, we discuss the relevant independent variables and other control variables used in the regression models.

Sentiment Analysis

To capture emotional temperature and quantify them, we perform sentiment analysis. The measured sentiment is included in the regression models. Sentiment analysis is an increasingly popular way of analyzing social and behavioral data based on the development of machine learning algorithms and big data (O'Connor et al. 2010; Young and Soroka 2012). We use the VADER model (Hutto and Gilbert 2014; Elbagir and Yang 2020) as our primary measure of sentiment. VADER is a rule-based model for general sentiment analysis. This tool has been extensively validated in qualitative and quantitative ways and outperforms other machine learning algorithms and human evaluators in evaluating social and behavioral data of various kinds. VADER can capture complex expressions of tones in sentences and scale it from -1 to 1 as a measure of sentiment strength. It also generates polarity scores (e.g., -1,0,1) to capture valence of sentiment, which is negative, neutral, and positive respectively. We also present multiple sentiment scores for the robustness of sentiment analysis models. We use Bing and NRC to further examine sentiment models (Liu 2022; Mohammad and Turney 2013). While Bing and NRC are rather coarse ways of measuring sentiment based on dictionaries, they still provide different ways to measure sentiment. But for the main results of this article, we use VADER since it is the most sophisticated way to measure general sentiment in social communication. Bing lexicons quantify each word as -1 or 1, NRC captures emotions such as hope, fear, trust. These other lexicons can help us understand the overall distribution of sentiment in each game. [See Appendix 1.3 for more information and descriptive statistics of sentiment scores using different classifiers].

We take a dictionary-based approach instead of supervised learning approaches to measure the tone of communication for their efficiency when used on short texts such as tweets (Elbagir and Yang 2020). While the texts considered in the experiments reference specific game terms and mechanics, there is no specialized language in the text that would confound assessment of sentiment, and there is no game-specific shorthand for positive or negative attitudes or collapse that would contradict a more conventional interpretation based on lexicon. For instance, the word, “collapse,” while referencing a game outcome for Port of Mars, is a negative outcome and aligns with conventional classifications of the word as negatively balanced.

Structural Topic Model

In the regression models, we include proportion of identified topic in each round to estimate the relationship between topic and cooperation while controlling for relevant covariates. Topic models are an unsupervised machine learning approach that decomposes text corpora into a number of “topics”, which are collections of words that tend to appear together. In a broad sense, topic models enable the representation of a document as a composite of multiple 'topics,' and the estimation of these topic mixtures results in a distribution of topics within the document. This distribution serves as a descriptive framework for understanding the presence, prevalence, and temporal aspects of trends in language or communication within the document. A variety of approaches to topic modeling have been used for social science applications, including latent semantic analysis (LSA), probabilistic latent semantic analysis (PLSA), and latent semantic indexing (LSI). A foundational approach to performant topic models is the Latent Dirichlet Allocation (LDA) model and these models are applied to various social science topics (Blei, Ng, and Jordan 2003; Anzoise, Slanzi, and Poli 2020). The structural topic model (STM) is the development and extension of earlier models by adding more ‘structures’ to the topic models to improve predictive performance of models. The key component of STM is to include relevant metadata in topic calculation and use that metadata to serve as covariates in topic calculation (Roberts et al. 2014). While allowing for variance across dimensions like time and place, STM estimates topic prevalence and topic contents across documents. STM allows us to identify statistical correlation between topic prevalence and correlates of our interests. The key advantage of using STM is that 1) preemptive human coding is not necessary 2) fewer assumptions about labels and categories are made than supervised learning 3) we can estimate correlations between topics and variables of interests. STM has been used widely in areas including climate change behavior, police behavior, and radical groups because of its usefulness and reliability (Tvinnereim and Fløttum 2015; Mourtogos and Adams 2019; Karell and Freedman 2019).

By using R’s STM package, we first estimate topic contents for descriptive purposes to understand what kinds of topics are discussed and which themes are prevalent in a given document (Roberts, Stewart, Tingley 2019). For the purposes of this study, a document is operationalized as a chat session between rounds in each game. We first perform a data cleaning process that includes stemming, removing stop words, and other standard procedures. Then, those processed text is indexed and further prepared for analysis and these procedures include removing rarely used words from the corpus. The resulting corpus information is included in [Appendix 3.1] [Full analysis procedures are provided as R Markdown files in Appendix 3]. After that, we ran a series of models to estimate topic prevalence in documents for each game. In these models, we include variables including cooperation, the number of chat, Gini-chat, Stock levels, gender, visibility, variability and/or round depending on the game. We parameterize K=5 and use the spectral algorithm which is a standard initialization method that is stable (Roberts, Stewart, and Tingley 2019). We engage in topic labeling to understand topic contents. To do this, we combine model-based approach and document-based approach. Model-based approach uses certain parameters of the topic model itself and document-based approach uses reading documents selected completely at random to inform labeling (Grimmer, Roberts, Stewart 2022). We use Frequency and Exclusivity of the words (FREX; Airoldi and Bischof 2016), representative documents, and topic quality estimation. Based on multiple tools of topic labeling, we label topics of four games in Table 3. [Full results are provided in Appendix 3.4]. Topic prevalence is how much a document is associated with a topic. This measure is calculated based on the number of words assigned to the topic divided by total number of words for the document. Based on the topic labeling, we estimate the relationship between cooperation and topics. Statistical results are provided in Table 4. We demonstrate the extent to which estimated topics vary with levels of cooperation, while controlling for other covariates. [Full results are provided in Appendix 3.5].

To validate our results run in separate game, we run models with full text corpora in four games with varying number of topic parameterization (K=3, K=5, K=10) [Results are included in Appendix 3.6]. The results indicate that the models with full text corpora tend to identify game specific topics that are similar to models for each game. These additional tests validate our main topic clustering results in Table 3.

Covariates

We include variable 'stock' to control for the remaining shared resource levels in each round at the start of the game. In IRR, it is the infrastructure level. In GG, it is the % of remaining water. In POM, it is the level of system health. FOR's resources are typically completely harvested at the end of the round. We also control for resource dynamics – variability. It is coded as 1 if the round has variability. In POM, it is always 1 and in IRR, it is 1 for rounds 11-20. In other games, there is no variability. Limited visibility is included to take into account whether participants have limited information about others' actions and earnings. It is coded as 1 if there is limited visibility, otherwise, it is 0. Studies also show that a group's understanding about the game is an important predictor for cooperation so we include the number of chats as a proxy for such measure (Pavitt and Broomell 2016). Communication inequality is included and measured as Gini coefficient of the number of chats in round. Male percentage is also included as a control variable since it may affect cooperation outcomes (Cadsby and Maynes 1998). Game type and group identification is included to account for the multi-level effects.

Results

Sentiment Effect

Results section first offers statistical estimations examining the effects of sentiment on cooperation levels in full sample. We further report split sample analysis to disentangle the overall effect. After that, we fit topic contents model to label estimated topics and then run topic estimation models to examine correlation between topic contents and cooperation.

Table 2. The Effects of Sentiment on Levels of Cooperation in Full Sample

		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Primary Independent Variable	**Vader sentiment**	-0.051*** (0.014)	-0.012 (0.011)	0.003 (0.010)	0.011 (0.010)	0.002 (0.010)	0.008 (0.010)
Round-level covariates	**# chats**	N	-0.002** (0.001)	N	-0.002*** (0.001)	N	-0.002*** (0.001)
	Gini-chats	N	-0.010 (0.053)	N	-0.010 (0.039)	N	-0.005 (0.041)
	Stock	N	-0.002*** (0.001)	N	-0.002*** (0.000)	N	-0.002*** (0.000)
	Gender	N	0.000 (0.000)	N	0.000 (0.000)	N	-0.000 (0.000)

	Variability	N	0.002 (0.011)	N	0.002 (0.013)	N	0.002 (0.012)
	Limited visibility	N	-0.002 (0.017)	N	-0.002 (0.013)	N	-0.004 (0.024)
Model Specifications	Constant	0.688*** (0.011)	0.819*** (0.047)	0.600*** (0.088)	0.819*** (0.027)	0.593*** (0.086)	0.828*** (0.035)
	Wald Chi square(prob>chi2)	N	N	0.11 (0.7440)	599.99 (0.000)	0.03 (0.8596)	426.06 (0.000)
	LR test (prob>chi2)	N	N	390.47 (0.000)	0.00 (1.000)	457.34 (0.000)	60.26 (0.000)
	Random effects	N	N	Y(intercept)	Y(intercept)	Y(intercept)	Y(intercept)
	Nested levels	1	1	2	2	3	3
	Covariate adjustment	No	Yes	No	Yes	No	Yes
	N	1470	1470	1470	1470	1470	1470

Parentheses are clustered standard error that is appropriate in levels included in different models. *p< 0.10, **p<0.05, ***p<0.01

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Table 2 displays a series of models that systematically build up models that are nested in multiple levels. Model (1) is the most naïve model that does not include any fixed and random effects. Model (6) is the fully specified model with a full set of covariates and random effects at group and game level. Except for the most naïve models in Model (1) and (2), sentiment is positively associated with levels of cooperation from Model (3) to Model (6), but with no statistical significance at conventional levels. From the LR test, we identify that multilevel modelling is appropriate technique in a given data structure.

We further ran split sample analysis to identify heterogeneous effects of communication. Overall, results suggest that sentiment effect differs in different games. While most games tend to have positive correlations with cooperation, these estimates have little significant effect. Appendix 2.5 summarizes findings and shows relative importance of sentiment effect in four games. For different model specifications of each game, please see Appendix 2.1-2.4.

Among covariates, while the inequality of communication between players seems to have little effect on cooperation among players, the amount of communication itself has negative effects on cooperation in Model (2), (4), (6) (****p<.01)*. This suggests that low-performing groups tend to engage in more communication than high performing groups. The remaining shared resources are negatively correlated with cooperation because players tend to exploit resources more quickly when the resources are abundant(****p<.01*). Gender does have little impact on cooperation. Resource variability is positively associated with cooperation. Limited visibility is negatively associated with cooperation.

Topics and Cooperation

Building on sentiment analysis results, we further investigate the contents of the communication and how it relates to cooperation. Table 3 shows topic labels based on topic content models in the STM package. After preprocessing, we have 123 documents for the foraging game, 880 documents for the irrigation game, 199 documents for the groundwater game and 215 documents for Port of Mars game.

After running a series of structural topic models, we found that running a structural topic model with 4-5 topics yielded semantically coherent and distinct topics. The selected model is shown in Table 3. For the full model results, see Appendix 3.2-3.3 for word profiles and representative documents. Based on word profile and representative quotes and game running experience, we label each topic based on consensus among authors. A fuller description of topic labels is included in Appendix 3.4.

Table 3 shows the distinctive topic cluster captured by topic models. Here, we include topic proportion and the label. In the following, we describe each topic. We observe similarity and difference in topic contents. In terms of similarity, all four games tend to have 'coordination' activities tailored to each game – whether it be when, where, and/or how much to coordinate to accomplish common goals. Off-topic/socializing or related topics are also observed in most games in different parts of the game play. But we also observe differences in topics among games. In IRR, 'negotiation' topic is prominently observed, and 'evaluation of gameplay' is also a distinct topic that shows intense feelings between players with regards to power asymmetry and perceived inequality. GG models identify a 'long-term goal' topic that is less distinctively observed in other games. Players try to figure out how to act together in response to unknown rounds. In POM, 'dispute' is a prominent topic with 23.13% topic proportion that reflects tough game environment players face. 'Discussion about avoiding collapse' also shows the crisis situations that players frequently face during the game play.

Table 3. Suggested Topic Labels

Game	Topic	Topic proportion	Topic Label
Foraging	1	8.80%	Off-topic/socializing
	2	19.97%	Game clarification/Evaluation of past rounds
	3	27.40%	Coordination where to harvest
	4	20.08%	Coordination when to harvest
	5	23.75%	off-topic/socializing
Irrigation	1	22.80%	Coordination when to open and close gates
	2	24.80%	Coordination how much to invest in shared infrastructure
	3	13.97%	Negotiation between upstream vs downstream
	4	22.20%	Evaluation of game play
	5	16.23%	off-topic/socializing

Groundwater	1	19.62%	Crop choice coordination
	2	31.71%	Crop choice coordination/affirmation
	3	15.75%	Strategizing crop choice
	4	16.17%	Addressing uncertainty about game rules
	5	16.76%	Long-term goal
Port of Mars	1	11.44%	Sense making
	2	20.01%	Coordinating how much to invest in system health
	3	23.13%	Dispute
	4	28.90%	Coordination on trade
	5	16.53%	Discussion on avoiding collapse

Note: Full results of word profile analysis are included in Appendix 3.2. Topic proportion is the amount of words attributable to each topic that provides a measure of topic prevalence (Roberts et al. 2014).

Based on topic content models, we estimate regression models to examine the relationship between the expected proportion of a document and covariates. Table 4 shows the correlations between identified topics and levels of cooperation, controlling for covariates.

Table 4: Correlation between Topics and Cooperation in Four Games

Game Type	Topics	Estimate	Standard Error	T-value	Pr(>|t|)
Foraging	T1: off-topic/socializing	0.213	0.416	0.511	0.6101
	T2: game clarification/evaluation of past rounds	-0.154	0.562	-0.274	0.785
	T3: coordination where to harvest	1.085	0.623	1.742	0.084
	T4: coordination when to harvest	0.698	0.566	1.234	0.220
	T5: off-topic/socializing	-1.868	0.591	-3.161	0.002
Irrigation	T1: coordination when to open and close gates	0.037	0.049	0.750	0.454
	T2: coordination how much to invest in shared infrastructure	0.034	0.035	0.961	0.337
	T3: negotiation between upstream vs downstream	-0.018	0.034	-0.537	0.591
	T4: evaluation of game play	0.058	0.045	1.295	0.196
	T5: off-topic/socializing	-0.111	0.037	-2.998	0.003
Groundwater	T1: crop choice coordination	0.047	0.049	0.959	0.339
	T2: crop choice coordination/affirmation	-0.268	0.055	-4.871	0.000
	T3: strategizing crop choice	0.025	0.063	0.403	0.687
	T4: addressing uncertainty about game rules	0.066	0.067	0.974	0.331
	T5: long-term goal	0.131	0.069	1.918	0.057
Port of Mars	T1: sense making	-0.046	0.060	-0.751	0.453
	T2: coordinating how much to invest in system health	-0.020	0.061	-0.322	0.748
	T3: dispute	0.008	0.071	0.117	0.907
	T4: coordination on trade	0.014	0.079	0.181	0.856
	T5: discussion on avoiding collapse	0.044	0.067	0.653	0.515

Note: We estimate regressions where the dependent variables are the proportion of each document about a topic and the main covariate is cooperation. Covariates include cooperation, stock levels, the number of chats, Gini-chats, gender, variability, limited visibility, and game fixed effects. We use the recommended "Global" option that uses an approximation to the average covariance matrix formed using the global parameters instead of parameters based on individual document to calculate the estimation uncertainty (Roberts, Stewart, Tingley 2019). Full regression results for each game are included in Appendix 3.4. We use estimateEffect in R's stm package.

In foraging games, our results in Table 4 suggest that coordination topics – when and where to harvest – are more actively discussed in rounds with higher levels of cooperation among players. Discussions around where to harvest are particularly significantly correlated with game rounds with high levels of cooperation (*p<.10*). Off-topic/Socializing tends to be negatively associated with levels of cooperation and Topic 5 shows particularly strong negative correlation with levels of cooperation. Game clarification/evaluation of past rounds seems to have little effect.

Results in the irrigation game suggest that coordination topics – coordination about gate operation and coordination about how much to invest in shared infrastructure – are not statistically significantly different between high cooperation and low cooperation rounds. Negotiation between upstream and downstream users is not significantly correlated with cooperation. Evaluation of gameplay tends to be correlated with high cooperation but with no statistical significance. Off-topic/socialization is negatively and significantly correlated with cooperation (*p<.01*).

Topic prevalence model in groundwater game suggests that while coordination on crop choice itself is positively associated with cooperation, 'crop choice affirmation' topic is more significantly observed in low cooperation rounds (*p<.01*). These results suggest that 'affirmation' topic is more discussed when initial crop choice coordination plan is not properly implemented so these running behind groups want to ensure that everyone is taking proper action as is planned. Results also suggest that when groups talk more about long-term goals, they tend to be more cooperative in their crop choice (*p<.10*). Strategizing and coordinating crop choice decisions is not significantly associated with high cooperation. Groups' chat about addressing game rule ambiguity is positively associated with cooperation, but with little significance.

Results from Port of Mars suggest that groups' communication about how to coordinate actions is not significantly correlated with cooperation. Topics such as disputes and how to avoid collapse have little meaningful relationship with cooperation. POM's identified topics are not significantly correlated with cooperation.

In all, we find significant variations of topics between high cooperation and low cooperation rounds in several games. Coordination topics that are observed in all games seem to have differential effects in different games. Further, the specific contents of coordination seem to have significantly different effects on each game. The results also show that off-topic communication is associated with less cooperation in several games.

Discussion

This study offers a quantitative analysis of group chats by building on previous studies of communication in shared resource governance experiments (DeCaro, Janssen, Lee 2021; Osborne, Sundström, Bodin 2019; Pavitt 2011; Pavitt 2018). Our analyses suggest that four different shared resource dilemma games share important similarities to one another, despite their differences in biophysical complexity and rules of the game. While identified topics have similarities between games, we found that its effect on levels of cooperation is varied significantly. Those different effects of discussion topics on cooperation warrant further explanation about each game's rules, biophysical characteristics, and uncertainties.

In FOR, coordination on where to harvest is more important to cooperation and off-topic socializing is negatively associated with cooperation. FOR runs in relatively specific spatial and temporal scale with clear visualization. Thus, coordination processes can be readily facilitated compared to other games and those processes tend to yield immediate positive outputs. However, in IRR, we find that coordinating through communication is much harder due to structural inequality built into the game – upstream vs downstream dynamics and other game rules including allowing chat with only nearby players. Our manual chat reading suggests that addressing such inequity tends to involve negatively valanced 'emotional' engagement between players, which further undermines coordinating actions.

In GG, while coordination strategies are similarly found like other games, these tend to explain little of cooperation. Even, crop-choice affirmation topic is associated with low cooperation. Manual chat reading suggests that groups with low performance tend to check each other's decisions more frequently due to the previous failure of rule enforcement and resultant distrust among players. Instead, we find that chatting about long-term goals – since the end round is not known to players and hydrological uncertainty exists in the game – is associated with higher levels of cooperation. Successful groups are more likely to talk about fundamental uncertainty that impacts every player in the game and then coordinate their actions accordingly. They tend to devise a comprehensive game plan and have less enforcement issues.

POM shares similarities with other games by having coordination and sense-making topics, but we also find that POM has unique topics, including disputes among players and discussions on avoiding collapse. Inferential statistics suggest that when there is overwhelming unpredictability and disturbances, ordinary coordinating strategies and/or figuring out what to do type topics tend to have little impact on cooperation levels. These results suggest that uncertainties built into the POM ~~game~~ make coordination harder and discussions are not likely to enhance cooperation in the short term.

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Specific coordination strategies that are found to be the important factors in previous analyses (Pavitt 2011; Pavitt 2018) are not necessarily the enabling factors for cooperation in IRR, GG, and POM. Why does coordination have a heterogeneous effect in different games? We posit that biophysical condition, rules of the game, and uncertainties must affect the way players talk to each other (Ostrom 2005; Poteete, Janssen, Ostrom 2010; Emerson and Nabatchi 2015). In IRR, the power asymmetry and struggle are more pronounced and make coordination difficult to be effective. When power struggle is not effectively managed between participants, the effectiveness of coordination strategies may vary by how players respond to and cope with such situations through social interactions. In GG, instead of coordination topics, addressing uncertainty about long-term goals is a more important factor that shapes coordination. Unless the group addresses such uncertainty, cooperation strategy and relevant actions are difficult to emerge from communication. In POM, negative disturbances and events may disturb strategizing a game and make cooperation challenging. Even when players discuss various coordination plans, effective cooperation rarely emerges due to unpredictability of situations.

Null findings from SA analyses also imply that the context in which communication occurs matters. One study suggests that capturing the function of positive statement is important only when positive statement is aligned with group identity and sympathy. In these conditions, positive sentiment can mobilize shared experiences and thus increase healthy cooperation (Lopez and Villamayor-Tomas 2017). They also suggest that the effects of negative statements of disapproval or criticism effect on cooperation are robust in the field setting. Null findings could also stem from the methodological limitations. Studies caution us against using dictionary-based approach since many SA classifiers (even well-developed ones) have limitations in capturing granular functions of sentiment in shared resource governance (Naldi 2019).

Likewise, STM also has limitations because it cannot identify topics with small text segments which may be a significant factor explaining outcomes, although we do not expect that this to be the case in our analyses. Our previously published studies with these datasets suggest that such important but less-likely captured topics were not identified with current datasets. While we are not naïve to believe that findings from the laboratory game experiments will be directly transferrable to real-world resource governance, we still believe that these findings will be relevant parameters and discussion points for real-world stakeholders.

To the authors' knowledge, this paper is the first study to use approaches from natural language processing for analyzing chat as text data to examine the effect of communication on cooperative behaviors specifically in shared resource dilemma games. Building on existing content analysis studies (Pavitt 2011; Lopez and Villamayor-Tomas 2017; Pavitt 2018; Osborne, Sundström, Bodin 2019; DeCaro, Janssen, Lee 2021), future studies can further build granular ways to use computational models by including more detailed understandings based on human coding and supervised learning methods if sufficient amount of data is collected. Computational institutional analysis is one such approach that advances the study of governing commons (Rice et al. 2020; Frey et al. 2022; Yin, Zhang, Filkov 2023). In this study, we show low cost and efficient solutions for analyzing communication data in shared resource governance and collective action study.

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Future studies may also employ varying definitions of cooperation in different games and how these types of definitions – whether it be investments in shared resources/infrastructure or earned tokens – may be systematically associated with participant's perceptions about games. Depending on the design of experimental collective action games, future studies can consider multi-dimensional construct that captures a variety of aspects of cooperation including perceptions, cooperation in specific tasks, benefit and cost distributions (Koontz et al. 2019; Naime et al. 2022). The research outlined in this paper emphasizes that cooperation is a contested term with no singular definition that is normalized across studies.

Finally, we want to emphasize that our analyses and interpretations of results play out within a small group resource dilemma context. While we draw general and particular conclusions from different games, real world resource dilemmas tend to involve legal and normative constraints or mis- and dis-information recently (Jerit and Zhao 2020) and thus the role of communication to resolve social dilemmas is somewhat limited. While these findings focus on micro-scale communication in small groups, communication analysis can be further developed in other controlled or real-world cases where there are larger groups with different underlying institutional context and information complexity. Future studies may consider the current era of mis- and dis-information as an important institutional context in collective action. To some extent, communication can even more polarize or exacerbate coherent decision making through mis- and dis-information (Jerit and Zhao 2020). Thus, it is imperative to understand what kinds of communication are more beneficial than others in forging cooperative outcomes.

Conclusion

This article applies quantitative text analysis methods to game chat data from four resource dilemma games to provide a more generalizable set of observations about the role of communication content in promoting cooperation in shared resource governance. Our results suggest that four shared resource dilemma games identify similar discussion topics –strategizing actions, coordination on choices, socialization, but that they also differ in whether and how these similar and dissimilar topics are associated with levels of cooperation defined as the investment to shared resources in each game. Discussion topics enhancing cooperation include coordination in FOR and long-term goals in GG. But topics that are negatively associated with cooperation include off-topic/socialization in FOR and IRR and crop choice affirmation in GG. We further compare four different games in-depth and specifically examine the differences in contextual factors. Our results reinforce the idea that only when we fully understand the decision context in each resource dilemma settings, we can find leverages to improve sustainable resource management through enhanced cooperation.

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Ethical Approval

Ethical approval was not required as the data of this study is based on past studies and the data is publicly available.

Informed Consent

We use information from past published studies, and they are publicly available. Informed consent was obtained in those previous studies.

Competing Interests

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

Author Contributions

MJ and MA contributed to the conception and design of the study. MA took the lead in writing and analysis and RB, MS, MJ provided substantial contributions to the drafts and revisions. All authors participated in the interpretation of the results.

Data availability

The datasets generated during and/or analysed during the current study are available in the repository, https://osf.io/spvga/