Conversational Linguistic Features Predict Social Network Learning

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Abstract

Whether it is the first day of school or a new job, individuals often find themselves in situations where they must quickly and accurately learn novel social networks. However, the mechanisms through which this learning occurs remain unclear. We posit that individuals use linguistic features of conversations to identify the valence and strength of social relationships. Across three studies using a naturalistic behavioral task (57 adults; 34,735 observations), we employ novel person- and stimulus-focused approaches to investigate social network learning success, examine how distinct linguistic features predict network learning, and explore the association between semantic similarity and relationship formation. We found that participants learned similar network structures, linguistic features uniquely predicted network learning, and greater semantic similarity was associated with perceived friendship formation. These findings suggest that naturalistic conversational content is both a potential mechanism of social network learning and a promising avenue for future research on social relational inference.

Keywords: social cognition, judgment and decision making, language, relational learning

Introduction

The first day at a new school or job can be remarkably challenging. Not only does one have to navigate a new building and adjust to new responsibilities, but one must also learn a complex new social structure. Success in learning new social structures is critically important for health and well-being, as an individual's position and linkage within a social network has been associated with both positive (e.g., prosocial behavior, physical and mental health) (Bond et al., 2012; van den Bos et al., 2018) and negative (e.g., propensity for depression, tobacco use) (Rosenquist et al., 2011; Ennett & Bauman, 1994) outcomes. Moreover, having a more accurate representation of one's network is associated with better social outcomes (Yu & Kilduff, 2020) and positively impacts professional and academic performance (Marineau, 2017; Lee et al., 2017). To date, relatively little is known as to how we dynamically learn these relational associations (Tompson et al., 2019). It is also unclear how conversations, a foundational form of social connection between individuals, inform social network learning.

The majority of research characterizing social network learning has either aimed to identify the consequences of accurate knowledge of existing social network positions and structures (Yu & Kilduff, 2020; Mobasseri, Stein, & Carney, 2022; Alt et al., 2022), or examine how individuals learn experimenter-generated networks that manipulate specific network features (Tompson et al., 2020; Son, Bhandari, & FeldmanHall, 2021). The present research bridges these two areas by examining how individuals learn – in real time – the structure of a novel social network through passive observation using naturalistic stimuli (Grall & Finn, 2022; Nastase, Goldstein, & Hasson, 2020). We focus on passive observation given its importance in relational learning across species (Seyfarth & Cheney, 2013) and in early development (Hamlin, Wynn, & Bloom, 2007). Moreover, it is likely one of the key modalities through which novel social networks are learned in the real world. Here, we examine how individuals learn two types of dyadic associations – relational and non-relational learning – in the context of a competitive game. Relational learning (Liberman & Shaw, 2018) refers to whether individuals are friends or rivals; this association is the basis for a social network (Alt et al., 2022; Baek, Porter, & Parkinson, 2021). Non-relational, or game-based, learning refers to who is more likely to beat another person to win the game. While both are social in nature, the former involves integrating information about individuals while *also* focusing on the nature of their interactions with each other. We hypothesize that this more complex assessment will make relational learning more difficult than game-based learning.

This hypothesis is rooted in prior work regarding the efficiency of social learning (i.e., learning about social entities or structures) and its relationship to non-social learning (Hackel et al., 2022). Specifically, research regarding the speed of social learning is mixed. In the early stages of network learning, non-social learning was faster than social learning, but social learning became faster with time and caught up with non-social learning rates (Tompson et al., 2019). Another group saw no differences in social and non-social learning rates during recall, but they did not investigate learning rates at the time of viewing (Kumaran, Melo, &

Duzel, 2012). Other groups have investigated naturalistic social learning rates, but these have been on the magnitude of days or weeks (Farroni et al., 2005; Benítez-Andrades et al., 2021). The present research instead evaluates social relational learning over a relatively brief time course (approximately 1 hour of observation) and compares two different types of social learning.

This approach allows us to gain more nuanced knowledge of what specific factors are associated with relational, and correspondingly social network, learning. Psychologists have argued that linguistic analysis should be used more frequently to study the underlying psychological mechanisms behind interpersonal interactions (Jackson et al., 2021; Boyd & Schwartz, 2021). Prior work has found that multidimensional features of interpersonal interactions, including personality, emotion, and verbal content, provide information about social relationships (Son, Bhandari, & FeldmanHall, 2021; Alt et al., 2022; Tong et al., 2020).

However, there is a meaningful knowledge gap in how features from communicative channels *specifically* contribute to learning the structure of a larger social network. There is reason to suspect that they might play a large role. People who tell secrets to each other are more likely to be perceived as friends (Liberman & Shaw, 2018) and differences in linguistic styles can reliably reflect personality characteristics (Slatcher et al., 2007). Verbal cues can indicate friendly or hostile attitudes between speakers (Argyle, Alkema, & Gilmour, 1971), and verbal indicators of positive emotions can evoke signals of trustworthiness (Anderson & Thompson, 2004) and are predictive of more enjoyable social interactions (Berry & Hansen, 1996) and closer friendships (Berry, Willingham, & Thayer, 2000). Finally, verbal content has been shown to be the best predictor of perceived conversational affect relative to non-verbal and tonal cues (Krauss et al., 1981).

While many linguistic features have psychological relevance (Cambria et al., 2017; Zhang, Wang, & Liu, 2018), linguistic similarity may be particularly important for social network learning (Kovacs & Kleinbaum, 2020). For example, couples who speak more similarly to each other early in their relationships are more likely to be together in the long term (Ireland et al., 2011), and language style-matching and positive emotion words are seen in supportive conversations with friends (Cannava & Bodie, 2017). Dyads involving two members in a conversation also exhibit language style-matching, that is, having coordinated and stylistically similar conversations (Babcock, Ta, & Ickes, 2014). Notably, however, the association between closeness and linguistic similarity may be moderated by the overarching relational context. Therefore, linguistic similarity may be a marker of multiple features related to social network learning in real-world contexts.

Across three studies, participants took part in a naturalistic behavioral experiment and learned about a novel social network via passive observation. In Study 1, we took a person-focused approach to evaluate how well participants learned this complex network. In Study 2, we took a stimulus-focused approach to examine how participants used information from conversations to learn the structure of the network. This information consisted of three distinct linguistic features – semantic similarity, sentiment, and clout. These features were selected based on prior research on language similarity, tone, and authority and implemented using a variety of natural language processing techniques. Finally, in Study 3, we investigated how conversational features related to relationship inferences over time.

Study 1

Method

Participants. Fifty-seven participants were recruited from a large city in the northeastern United States. Informed consent was obtained for all participants, and participants received course credit for their time. Experimental procedures were approved by the university's Institutional Review Board. Demographic information for the first ten participants was not collected due to an administrative error, but information was collected for all subsequent participants (45 female; 2 other; 23 non-White; M_{age} = 19.08, SD_{age} $\pm$ 1.48). The goal sample size was 50 participants due to time and resource constraints, and due to oversampling, data from 57 participants was collected (Brysbaert & Stevens, 2018). Two included participants missed responses to 50 or more trials, but this did not greatly impact the total number of observations collected ($N_{observations}$ = 34,735, $M_{participant}$ = 609.4 responses, $SD_{participant}$ $\pm$ 19.7 responses). Participants were verbally screened about their familiarity with this *Survivor* season and episode, and none reported being familiar with it.

Procedure. Participants took part in a naturalistic experiment wherein they learned about the structure of a novel social network via passive observation of a mid-season television episode. *Survivor* is a particularly fitting stimulus to examine these questions – it captures unscripted, real-life conversations between individuals in a context where the goal is forming different types of relationships (i.e., forming alliances and rivalries) to win the game. We selected a mid-season episode that came right after previously separated teams merged, ensuring a mix of friendships and rivalries.

Participants watched a full episode from the television show, *Survivor* (Season 8, Episode 13; aired April 22, 2004, CBS Television), which was divided into six clips (M_{length} = 6.50 minutes, SD_{length} $\pm$ 0.03 minutes). In a within-subjects design, participants watched each clip with closed captioning in chronological order and made a series of keyboard responses after each clip finished playing. The task was designed and displayed using PsychoPy (Peirce et al., 2019). Each episode clip and subsequent keyboard responses comprised one experimental block, with each block falling into one of three decision categories: friendship, rivalry, or win (Fig. 1). Participants completed each decision category twice, and decision blocks were presented in a random order. When making responses, participants were presented with three photos of contestants from the episode. One photo, displayed at the top of the screen, was the target, and the other two photos, displayed below the target photo, were possible choices. Above the target photo, a question was displayed that changed depending on the decision category. For friendship blocks, participants were asked "Who has a stronger friendship with X?", where X was the name of the contestant in the target photo. In rivalry blocks, participants were asked “Who has a stronger rivalry with X?”, and in win blocks, participants were asked “Who is more likely to beat X?” Participants selected one of the two choice contestants per trial using the keyboard. Once a response was made, a new target photo and two new choice photos were displayed. Participants repeated these responses for every possible pairwise combination (105 possible responses per block). Participants had up to five seconds to make each response.

Analysis. Statistical analyses were performed using R. Multilevel models were performed using the *lme4* package in R (Bates et al., 2015). Network graphs were created using the *igraph* package in R (Csardi & Nepusz, 2005).

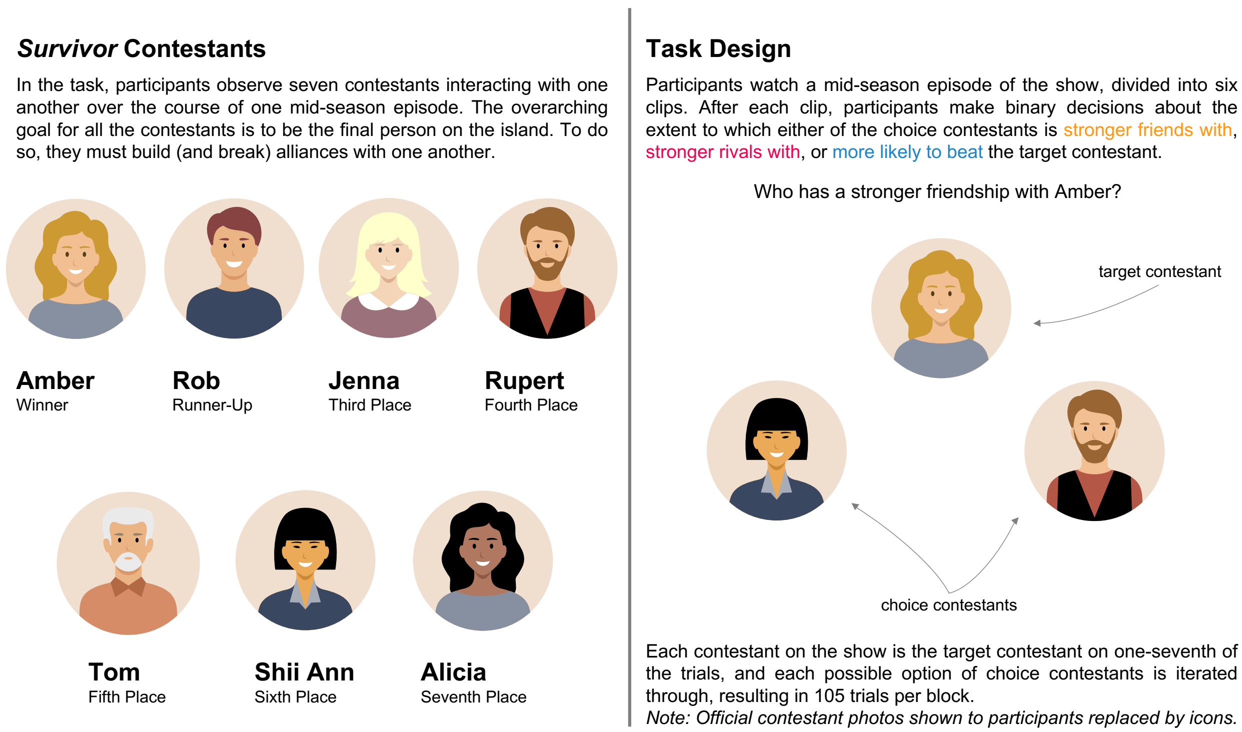
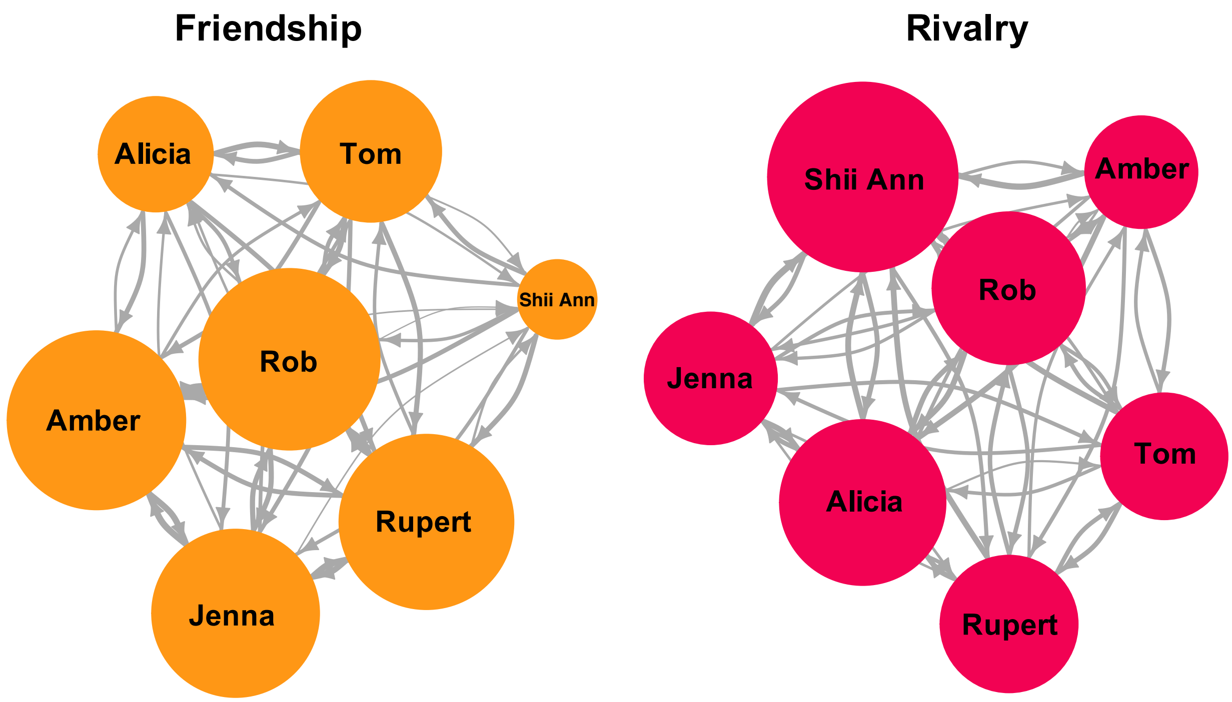


Fig. 1. Overview of task design. Participants observed seven contestants interacting with each other on an episode of *Survivor* and made binary decisions about the extent to which contestants were friends with, rivals with, or more likely to win over other contestants.

In Study 1, we evaluated how well participants were able to learn this complex network. To visualize the social networks that participants inferred based on friendship and rivalry responses, we plotted the average directed friendship and rivalry networks (Fig. 2). Node size reflects a calculated PageRank value for each contestant. PageRank refers to the extent to which a node receives links from other well-connected nodes, and it is a metric of network importance for an individual node (Page et al., 1999). Larger nodes indicate higher PageRank values for those contestants while smaller nodes indicate lower PageRank values. The lines between nodes (i.e., edges) reflect the percentage of time contestants were selected as a better friend or bigger rival of the target contestant (denoted by an arrow pointing away from the node) or the percentage of time they were selected as a better friend or rival of another contestant. The thickness of the line (i.e., edge weight) reflects the relative percentage of time chosen as friends or rivals. We also calculated the average percent of time that each contestant was chosen as a friend and as a rival. These average percentages, along with the calculated PageRanks, are displayed in the table in Figure 2. Moreover, we noted the order that each contestant in the episode we showed to participants were voted off in each subsequent episode as the season progressed.



Names	Order Voted Off	Friend PageRank	Rival PageRank	Average Time Chosen as Friend (%)	Average Time Chosen as Rival (%)	Average Time Chosen as Winner (%)
Amber	Winner	0.172	0.111	62.1	35.7	60.5
Rob	6th	0.174	0.150	61.6	51.5	78.1
Jenna	5th	0.162	0.130	56.0	43.3	49.8
Rupert	4th	0.168	0.135	61.6	46.2	68.8
Tom	3rd	0.136	0.125	49.1	42.8	29.8
Shii Ann	2nd	0.076	0.186	21.6	70.9	31.5
Alicia	1st	0.111	0.163	36.9	59.5	31.5

chosen more often

chosen less often

Fig. 2. Average directed friendship and rivalry networks as identified by participants. Node size (circles) is based on a calculated PageRank value for each contestant, a measure of the extent to which each node is connected to other well-connected nodes. Larger nodes indicate higher PageRank values. The edge weight (thickness of the lines between nodes) reflects the relative percentage of time chosen as friends or rivals. Node sizes tend to reflect the order in which contestants were voted off the show, with the exception of Shii Ann, who won immunity in this episode. The contestant with the highest PageRank in the friendship network (Amber), ultimately won the show. The table denotes the order each contestant was voted off the show in this and subsequent episodes by their fellow contestants, and the relative average percentage of time each contestant was chosen as someone's friend, someone's rival, or the predicted season winner.

To assess how response times (RTs) varied between relational (friendship, rivalry) and non-relational game evaluations (win), we compared participant RTs across block categories. To investigate if participants are learning contestant relationships over time, we compared how RTs changed as a function of block category and time. Faster RTs as the task progressed indicate learning (Tompson et al., 2020). Because all questions pertain to gathering more social information, we would expect to see a similar pattern of decreased response times as time passes for all questions. However, if learning relational structures is more difficult than assessing other types of interpersonal associations (Tompson et al., 2020), then we would expect to see slower response times for relational questions as compared to game-based questions.

Finally, to assess whether participants learned the structure of the social network similarly to one another, we compared how often each participant agreed with the group average (i.e., responded the same way) about which contestants were friends and which were rivals. If participants accurately learned these networks, that is, learned the same relational information as the group, we would expect them to agree with the group more often than chance (50%, given that each decision is a binary choice). The percentage of time each contestant pair was chosen as friends or as rivals was averaged across all participants and blocks to get a group average. Each participant's percentage of time chosen was also averaged for each contestant pair. If both the group and the participant agreed that those contestants were friends or rivals 50% of the time or greater, that participant was scored as successfully learning the relationship. Contestant pairs that both the group and the participant agreed were friends or rivals less than 50% of the time were also scored as successfully learning the relationship. A disagreement between each participant and the group (e.g., the group said a given contestant pair was friends 60% of the time but a given participant said they were friends only 40% of the time) was scored as unsuccessfully learning the relationship. An overall accuracy score was calculated across all relationships for each participant. For example, say Rob and Amber are chosen as friends greater than 50% of the time across all participant responses. If participant A selects Rob and Amber as friends greater than or equal to 50% of the time across all of their friendship responses, we would say that participant A successfully learned the friendship relationship for this dyad. If participant B selects Rob and Amber as friends less than 50% of the time across all of their friendship responses, participant B would *not* have successfully learned the friendship relationship for this dyad. We can repeat this for every contestant dyad across friendship and rivalry responses.

Modeling. To investigate the response times for relational (friendship and rivalry) questions compared to non-relational game questions (win), we fit a multilevel model with decision category as the predictor, z-standardized response times as the outcome variable, and a random effect of participant. To investigate how response times for relational questions compared to non-relational game questions changed as the task progressed, we fit a multilevel model with trial number as the predictor, z-standardized response times as the outcome variable, trial number * decision category as an interaction term, and a random effect of participant. Finally, we ran two one-sample t-tests to examine participant response accuracy compared to chance (50%).

Results

We found a significant main effect of the friendship decision category on participant response times, such that participants took more time to answer friendship questions than win questions, b = .45, SE = .01, t(34676.15) = 37.60, p < .001, 95% CI [.43, .48], despite both questions relying on the same episode information (Fig. 3a). We also found a significant main effect of rivalry questions on participant response times, such that participants took more time to answer rivalry questions than win questions, b = .48, SE = .01, t(34676.20) = 39.76, p < .001, 95% CI [.46, .50]. Finally, we found that participants took more time to answer rivalry questions than friendship questions, b = .03, SE = .01, t(34676.27) = 2.14, p = .03, 95% CI [.002, .05]. A likelihood-ratio test confirmed that the decision category model predicted significantly more variance, $\chi^2(2)$ = 1949.10, AIC = 92910.56, BIC = 92952.84, p < .001, compared to the null model (random effect of participant only), AIC = 94855.66, BIC = 94881.03.

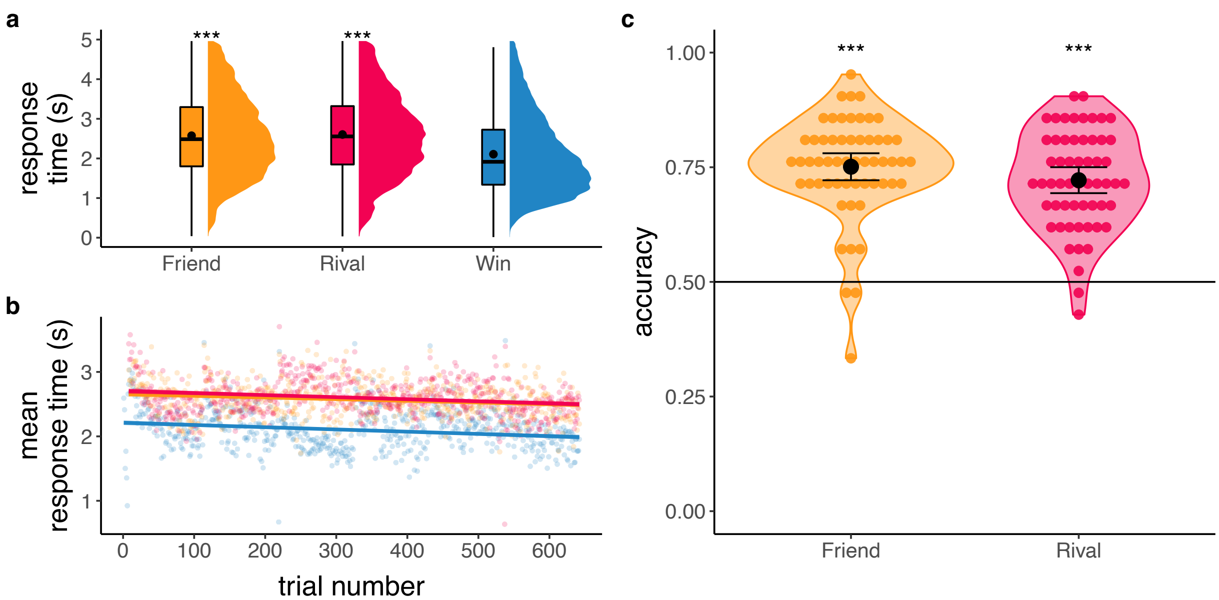


Fig. 3. Successful learning of a complex social network via passive observation. Distribution of response times (RTs) in seconds for each decision category (a) indicates that participants respond slower to friend and rival trials than to win trials, ps < .001. Mean RT is denoted by a black point in the boxplot, median RT is denoted by a black line in the boxplot, and lower and upper edges of the boxplot correspond to the 25th and 75th percentiles, respectively. Distribution of RTs is denoted to the right of each box plot. Mean RTs across participants in seconds over time (b) indicate that participants respond faster as time passes. Points denote the mean RT across participants per decision category for every trial. Lines denote fitted linear regressions to the data per decision category. Shading reflects 95% confidence intervals. Response accuracy for friend and rival trials (c) shows significantly greater than chance (50% accuracy) learning of the social network in the episode, ps < .001. Points denote mean accuracy per participant across all *Survivor* contestant pairs. Accuracy is determined by quantifying the amount of time each participant agreed with the group average. Error bars reflect 95% confidence intervals. *Note: Figure reflects unstandardized beta coefficients.*

We found a significant two-way interaction between the win and friend decision categories and trial number on response times, b = .06, SE = .01, t(34669.27) = 4.55, p < .001, 95% CI [.03, .09] (Fig. 3b). We observed a non-significant two-way interaction between the win and rival block categories and trial number on response times, b = .003, SE = .01, t(34720) = .24, p = .81, 95% CI [-.02, .03]. A likelihood-ratio test confirmed that the interaction model predicted significantly more variance, $\chi^2(2) = 25.28$, AIC = 92768.18, BIC = 92835.83, $p < .001$, compared to the null model (i.e., main effects of block category and trial order without the interaction term), AIC = 92789.47, BIC = 92840.20. Simple slopes analysis indicated that this was due to a significant negative association between the win block category and trial number, b = -.08, SE = .01, t(34727.25) = 8.61, $p < .001$. This was also due to a significant negative association between the rivalry block category and trial number, b = -.07, SE = .01, t(34728.47) = 7.72, $p < .001$, and due to a non-significant negative association between the friend block category and trial number, b = -.016, SE = .01, t(34713.89) = 1.69, p = .09. While response times for all decision categories decreased over time, relational responses (i.e., friendship and rivalry) were always slower than non-relational responses (i.e., win).

A one-sample t-test for friend trials revealed that participant accuracy for friendship responses was significantly above chance, t(56) = 17.08, $p < .001$ (Fig. 3c). A one-sample t-test for rival trials revealed that participant accuracy for rivalry responses was also significantly above chance, t(56) = 15.68, $p < .001$.

Discussion

These results suggest that participants rapidly learned similar social information via passive observation. In Study 2, we tested the hypothesis that participants used distinct linguistic features – greater semantic similarity, more positive emotional tone, and higher confidence – to inform their relational judgments.

Study 2

Method

Materials. Behavioral responses from participants who took part in the Survivor task in Study 1 were used for analyses in Study 2.

Episode Transcriptions. Two independent coders transcribed dialogue from the episode, noting all spoken dialogue, the speaker name, the recipient name (to whom the speaker is talking), and block number (1 – 6). The transcriptions were further organized at the sentence level, such that each sentence had a corresponding speaker name, recipient name, and block number. In all analyses, we included only the contestants (Amber, Rob, Jenna, Rupert, Tom, Shii Ann, and Alicia) as speakers. Dialogue spoken by the host (Jeff Probst) was not included.

Natural Language Processing. In Study 2, we evaluated how participants used verbal information from conversations between *Survivor* contestants to learn about social dynamics and relationships. To assess to what extent participants used this information to inform their relationship decisions, we used natural language processing on the transcribed episode dialogue to quantitatively represent three distinct linguistic features – semantic similarity, sentiment, and clout – and analyze to what extent participants used each feature to inform their choices about friendship and rivalry.

Semantic Similarity. Semantic similarity was calculated using Google's pre-trained Universal Sentence Encoder (USE), available on TensorFlow Hub and implemented in Python (Cer et al., 2018). This dimensional analysis measures to what extent two pieces of text have the same meaning using text embeddings, which is an advancement from the prior work that investigates to what extent pieces of text use similar words or have similar styles (Kovacs & Kleinbaum, 2020). USE converts text into vectors in high-dimensional space (512 dimensions). The distance between these vectors can then be used to determine the semantic similarity of the two texts. We computed pairwise semantic similarity for each unique contestant pair, with values ranging from 0, which indicates no similarity, to 1, which indicates perfectly similar.

For the purposes of this study, we entered all dialogue spoken by each contestant during each episode clip (including when speaking to another contestant, to the host, to the team, and to the camera during a confessional interview) as text into the USE embedding model (Fig. 4a). This pre-trained USE model supports text analysis that is longer than single words, such as sentences and short paragraphs, and concatenates dialogue to compare speaker similarity directly (Cer et al., 2018). We then converted the text into vectors in 512-dimensional space. Finally, to measure pairwise semantic similarity, we correlated each contestant's vector space with every other contestant and calculated an r^2 (a measure of how semantically similar the text is between contestants) for each unique contestant pair. This was repeated six times for dialogue from each episode clip (see Supplemental).

Sentiment. For each sentence of dialogue spoken by a contestant, we calculated a sentiment score using the *sentimentR* package (Rinker, 2021). *sentimentR* uses a machine learning algorithm that analyzes each word from the sentence and compares it to a dictionary of positive and negative words. Positive words in the sentence are given a score of 1 and negative words are given a score of -1. These are known as polarized words, and when these polarized words are combined with four words before and two words after in the same sentence, the group of words together is known as a polarized context cluster (Rinker, 2021). The words in this cluster are tagged as neutral, negator, amplifier, or de-amplifier. Each polarized word's score (1 for positive words, -1 for negative words) is then adjusted based on the tags on other words in the cluster. Amplifiers increase polarity (more positive) and de-amplifiers decrease polarity (more negative). Neutral words do not affect the polarized word's score. The scores for all polarized words in a sentence are then averaged to get one sentiment score per sentence (Fig. 4b). Generally, scores that are greater than zero represent positive sentiment while scores that are less than zero represent negative sentiment. We mean-centered sentiment scores within the Target category for plotting and statistical analysis.

In order to understand how sentiment related to relationship choices, we calculated mean sentiment (using the mean-centered sentiment scores) for each unique speaker-recipient pair per episode clip. These mean sentiment scores represent the average sentiment in a speaker's dialogue when talking to a given recipient in each segment of the episode. We could then match these mean sentiment scores to the relationship judgment data for plotting and statistical analysis.

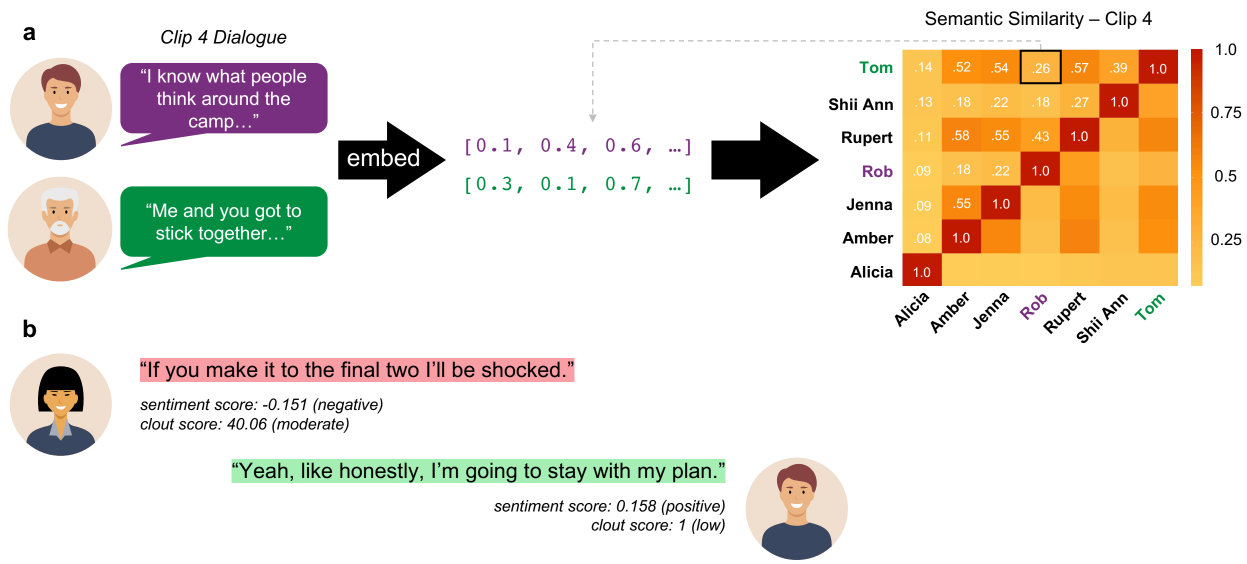


Fig. 4. Calculating pairwise semantic similarity, sentiment, and clout from contestant dialogue. Converting text vectors (a) using the Universal Sentence Encoder. Text strings are fed into the embedding model. These strings contain all sentence-level dialogue spoken by contestants in each episode clip. Text is converted to vectors in 512-dimensional space. Vectors are correlated (correlations represent pairwise semantic similarity) and plotted in a heatmap. Correlated vectors represent how semantically similar the dialogue is from two contestants. Example dialogue from conversation between two characters on the show (b) with corresponding sentiment and clout scores. Text highlighted in green indicates a positive tone while text highlighted in red indicates a negative tone. Displayed sentiment and clout scores reflect scores for each highlighted sentence.

Clout. We calculated a clout score for each sentence of dialogue spoken by a contestant using the LIWC software (Boyd et al., 2022). Clout refers to relative social status, confidence, and self-assurance conveyed in dialogue. Clout scores are calculated using an algorithm that was developed based on research that identified language features that were relevant to individuals' social positions or ranks (Kacewicz et al., 2014). Like sentiment, we calculated a clout score per sentence of dialogue, and scores ranged from 1 – 100 (Fig. 4b). Scores greater than 50 indicate higher clout while scores less than 50 indicate lower clout. We mean-centered clout scores within the Target category for plotting and statistical analysis.

In order to understand how clout related to relationship choices, we calculated mean clout (using the mean-centered clout scores) for each unique speaker-recipient pair per episode clip. These mean clout scores represent the average clout in a speaker's dialogue when talking to a given recipient in each segment of the episode. We then matched these mean clout scores to the relationship judgment data for plotting and statistical analysis.

Analysis. Statistical analyses were performed using R and Python. Linguistic analyses were performed using the Universal Sentence Encoder in Python (Cer et al., 2018), *sentimentR* package in R (Rinker, 2021; Naldi, 2019), and Linguistic and Inquiry Word Count (LIWC) software (Boyd et al., 2022). Beta generalized linear models were performed using the *glmmTMB* package in R (Brooks et al., 2017).

Relationship Choices. To understand how these distinct linguistic features impacted social network learning, we calculated the percent of time each contestant was chosen as a friend, rival, or likely winner relative to a given target across each episode clip. Importantly, this percentage of time chosen value is not the amount of time each contestant was chosen, but rather this value captures the amount of time that, for any target-choice pair of contestants, the choice contestant was selected when paired with the target contestant. In all results for Study 2, percent of time chosen is the dependent variable, while each linguistic feature is the independent variables. For example, if we examine only responses from episode clip #4 and only trials when Rob is presented as the target contestant, we can calculate the percent of time that Amber was chosen as Rob's friend, Rob's rival, or someone that would beat Rob for each participant. We can repeat this for every episode clip and every combination of contestants presented as targets and possible choices.

Modeling. To investigate the effect of each linguistic feature on relationship judgments, we fit three beta generalized linear models with the linguistic feature (dyadic-level semantic similarity, sentiment, or clout) as the predictor, percent of time chosen by participants as a friend or rival as the outcome variable, feature * decision category as an interaction term, and participant as a random effect. We also include a random effect of dyad in the semantic similarity model and a random effect of both speaker (i.e., who spoke the dialogue) and recipient (i.e., to whom the speaker is talking) in the sentiment and clout models.

Results

We observed a significant two-way interaction between the pairwise contestant-contestant semantic similarity in conversational dialogue and relationship type on the percent of time that contestants were chosen either as friends or rivals, $b = -1.47$, $SE = .18$, $z = -8.13$, $p < .001$, 95% CI [-1.82, -1.12] (Fig. 5a). A likelihood-ratio test confirmed that the model containing the interaction term predicted significantly more variance, $\chi^2(1) = 65.99$, $AIC = -11171.25$, $p < .001$, compared to the null model (i.e., main effects of similarity and block category without the interaction term), $AIC = -11107.26$. A contrast to examine the significant interaction revealed a significant difference between relationship types (friend – rival), $b = 1.47$, $SE = .18$, $t(9493) = 8.13$, $p < .001$.

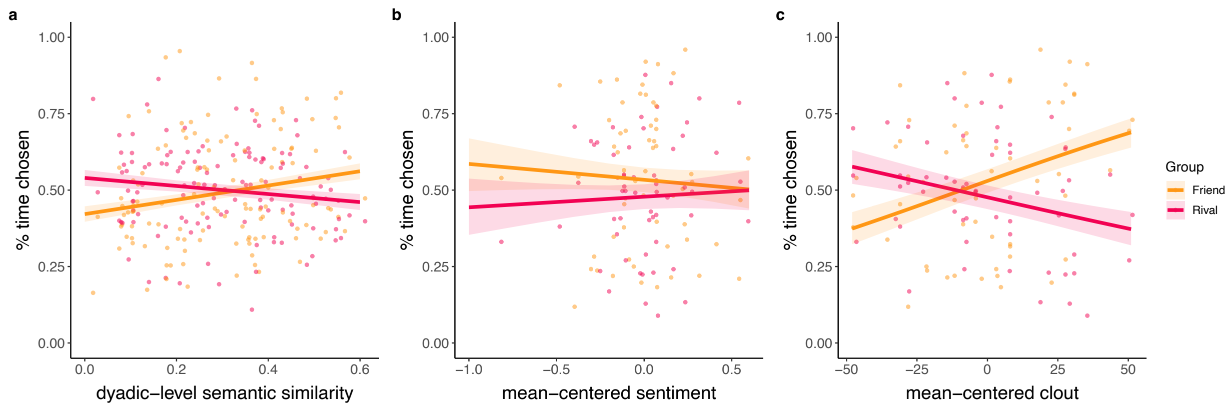


Fig. 5. Relationship between conversational linguistic features and the amount of time chosen as friends or rivals. A beta generalized linear mixed model reveals that pairwise semantic similarity (a) positively predicts friendship choices and negatively predicts rivalry choices. Each point represents mean semantic similarity and mean percent of time chosen as friends or rivals for each dyad per episode clip. A generalized linear mixed model with a beta distribution reveals that sentiment (b) is not predictive of relationship choices. Each point represents the mean-centered average sentiment and mean percent time chosen as friends or rivals for each contestant pair per episode clip. A generalized linear mixed model with a beta distribution reveals that clout (c) positively predicts friendship choices and negatively predicts rivalry choices. Each point represents the mean-centered average clout and mean percent time chosen as friends or rivals for each contestant pair per episode clip. *Note: Shading represents 95% confidence intervals*.

We did not find a significant two-way interaction between sentiment and relationship type on the percent of time that contestants were chosen as either friends or rivals, *b* = .35, *SE* = .24, *z* = 1.49, *p* = .14, 95% CI [-.11, .81] (Fig. 5b). A likelihood-ratio test showed that the model containing the interaction term did not predict significantly more variance, $\chi^2(1) = 2.20$, *AIC* = -4032.54, *p* = .138, compared to the null model (i.e., main effects of sentiment and decision category without the interaction term), *AIC* = -4032.34. Examining the main effects model, there was a significant main effect of rivalry (relative to friendship) decisions on percent of time chosen, *b* = -.22, *SE* = .06, *z* = -3.91, *p* < .001, 95% CI [-.33, -.11], but there was not a significant main effect of sentiment on percent of time chosen, *b* = -.05, *SE* = .12, *z* = -.39, *p* = .70, 95% CI [-.29, .19]. This suggests that sentiment in conversations may be less informative relative to other linguistic features.

We observed a significant two-way interaction between clout and relationship type on the percent of time that contestants were chosen as either friends or rivals, *b* = -.02, *SE* = .002, *z* = -9.43, *p* < .001, 95% CI [-.03, -.02] (Fig. 5c). A likelihood-ratio test confirmed that the model containing the interaction term predicted significantly more variance, $\chi^2(1) = 88.77$, *AIC* = -4124.70, *p* < .001, compared to the null model (i.e., the main effects of clout and block category without the interaction term), *AIC* = -4037.93. A contrast to examine the significant interaction revealed a significant difference between relationship types (friend – rival), *b* = .02, *SE* = .002, *t*(2242) = 9.43, *p* < .001.

Discussion

These results indicate that people use conversational linguistic information to inform relationship inferences (see Supplemental). However, these relationships unfolded over time, and it's unclear if increased similarity precedes or follows friendship formation (Parkinson, Kleinbaum, & Wheatley, 2018). In Study 3, we employed a dyadic approach to test the hypothesis that individuals who were more often selected as friends in Study 1 were also more semantically similar at the start of the *Survivor* season, which would be consistent with research on friendship formation (Kovacs & Kleinbaum, 2020). We also tested the hypothesis that, given the constrained contextual environment of *Survivor*, semantic similarity between contestants would generally increase over time (Kovacs & Kleinbaum, 2020).

Study 3

Method

Materials. Behavioral responses from participants who took part in the Survivor task in Study 1 were used for analyses in Study 2.

Episode Transcriptions. Two coders transcribed dialogue from all episodes of *Survivor* that preceded the episode used in Studies 1 and 2 (Season 8, Episode 1 – Episode 8, Episode 10 – Episode 12; CBS Television). We did not transcribe Episode 9 as it was a recap episode. All other episode transcriptions, in addition to the previously transcribed Episode 13, were used in Study 3 analyses ($N_{episodes}$ = 12). As in Study 2, the transcriptions noted all spoken dialogue, the speaker name, and the recipient name. The transcriptions were further organized at the sentence level, such that each sentence had a corresponding speaker and recipient. While we transcribed all episode dialogue, we only included the contestants that appear in Episode 13 as speakers in Study 3.

Analysis. Statistical analyses were performed using R and Python. Linguistic analyses were performed using the Universal Sentence Encoder in Python (Cer et al., 2018). Multilevel models were performed using the *lme4* package in R (Bates et al., 2015).

In Study 3, we investigated if the verbal features that participants used to learn the social network structure later in the season could be used to predict relationship inferences over time (e.g., across the season of television). We calculated pairwise semantic similarity for all contestants and across all episodes using the same technique outlined in Study 2. Episode 9 was not included as it was a recap of the events of the prior episodes. Twelve episodes were used in total. We calculated similarity for the entirety of Episode 13, rather than calculating similarity for each block like we did in Study 2. Each episode was treated like a progressive time point (e.g., Time 0 = Episode 1, Time 1 = Episode 2), to allow us to examine semantic similarity over time. Importantly, due to the team structure of *Survivor*, wherein the season starts off with three separate teams that do not communicate with each other and ends with one team that is formed by merging remaining members of the original teams, we only included semantic similarity scores for dyads who were in the same team at each time point in the model (Fig. 6).

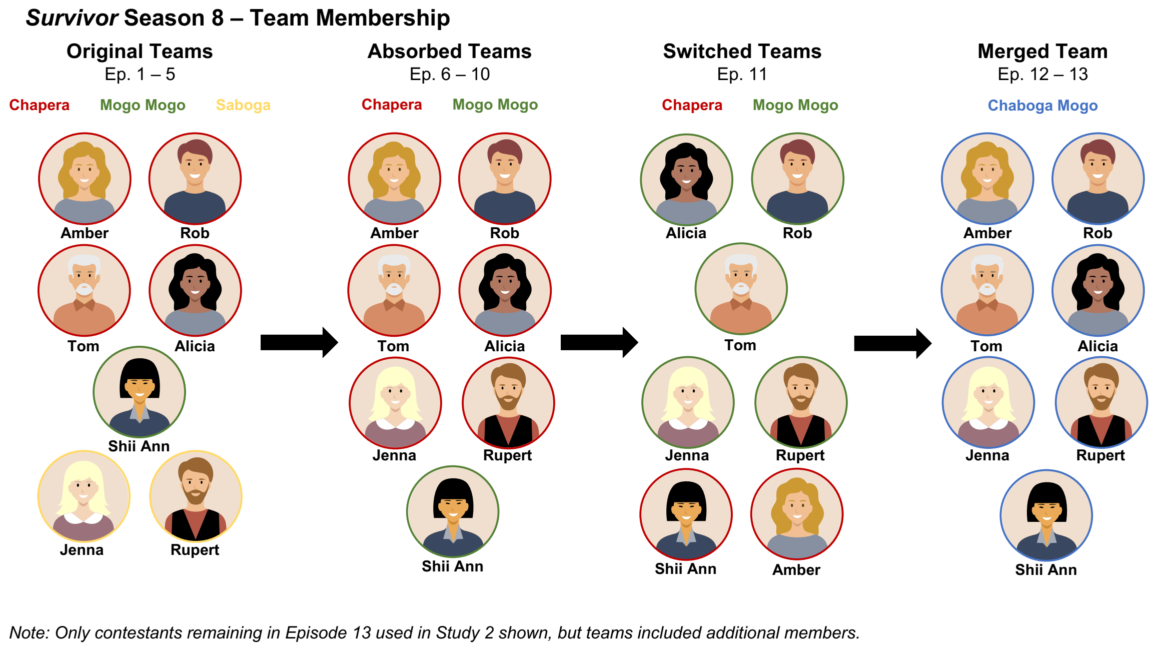


Fig. 6. Team structure throughout season 8 of *Survivor*. All episodes in the season leading up to Episode 13, the episode that is shown to participants in Study 2, are shown. Only contestants who remain in Episode 13 are shown, but teams included additional team members that were voted off over the course of the season. During the first five episodes of the season, contestants are split into three teams – Chapera, Mogo Mogo, and Saboga. In Episode 6, teams are merged and the Saboga team is eliminated, and two teams remain for episodes six through ten – Chapera and Mogo Mogo. In Episode 11, contestants are randomly swapped, with all but one Chapera member (Amber) moving over to Mogo Mogo. Finally, in Episode 12, Chapera and Mogo Mogo teams are merged into one team – Chaboga Mogo. This merged team structure remains up to Episode 13, the episode that participants in Study 2 view during the experimental task. Chapera team members denoted with red circular outline. Mogo Mogo team members denoted with green circular outline. Saboga members and Chaboga Mogo team members denoted with yellow and blue circular outlines, respectively.

Results

We observed a significant three-way interaction between z-standardized percent of time chosen, relationship type, and z-standardized time on z-standardized dyadic semantic similarity, β = .10, *SE* = .01, t(16862.28) = 6.54, p < .001, 95% CI [0.07, 0.13] (Fig. 7). A likelihood-ratio test confirmed that the interaction model predicted significantly more variance, $\chi^2(4)$ = 44.89, *AIC* = 44242.72, *BIC* = 44327.79, p < .001, compared to the null model (i.e., main effects of percent of time chosen as friends or rivals, block category, and time without the interaction term), *AIC* = 44279.61, *BIC* = 44333.74. Simple slopes analysis indicated that contestants who were more often chosen as friends later in the season were initially more similar, β = .05, *SE* = .01, t(16858.02) = 3.67, p < .001, and contestants who were more often chosen as rivals were initially less similar, β = -.04, *SE* = .02, t(16856.19) = 2.74, p = .006. Additionally, contestants who were chosen as friends one standard deviation (SD) below the mean showed a greater increase in semantic similarity over time, β = .17, *SE* = .02, t(16864.00) = 10.72, p < .001, compared to contestants chosen as friends at the mean, β = .12, *SE* = .01, t(16863.86) = 10.80, p < .001, and one SD above the mean, β = .06, *SE* = .01, t(16852.90) = 4.93, p < .001 (Fig. 7a). Conversely, contestants who were chosen as rivals one SD below the mean showed a lower increase in semantic similarity over time, β = .07, *SE* = .01, t(16853.31) = 5.58, p < .001, compared to contestants chosen as rivals at the mean, β = .12, *SE* = .01, t(16863.87) = 10.64, p < .001, and one SD above the mean, β = .16, *SE* = .02, t(16863.68) = 9.35, p < .001 (Fig. 7b).

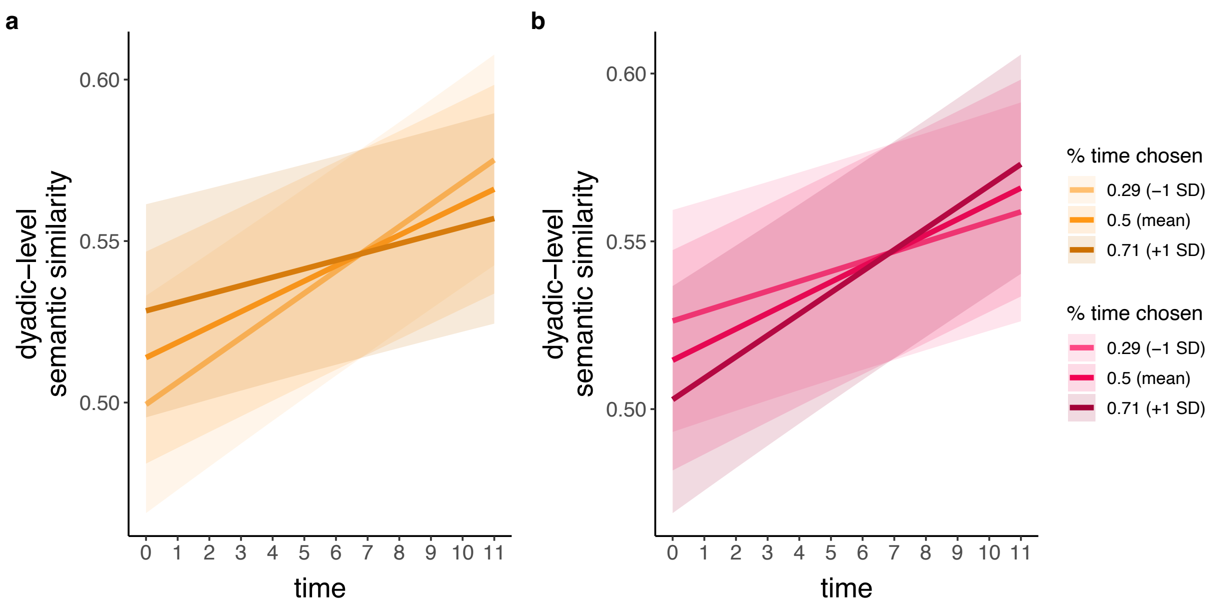


Fig. 7. Dyadic semantic similarity over time as predicted by the percentage of time dyads are chosen as friends (a) or rivals (b). Dyads who are less often chosen as friends (-1 SD) are predicted to have lower semantic similarity at the start of the season, compared to dyads who are chosen as friends more often. Dyads who are more often chosen as friends (+1 SD) are predicted to have higher semantic similarity at the start of the season, compared to dyads who are chosen as friends less often. Dyads who are chosen less often as rivals (-1 SD) are predicted to have higher semantic similarity at the start of the season, compared to dyads who are chosen as rivals more often. Dyads who are chosen more often as rivals (+1 SD) are predicted to have lower semantic similarity at the start of the season, compared to dyads who are chosen as rivals less often. *Note: Figure reflects unstandardized beta coefficients. Shading represents 95% confidence intervals.*

Discussion

Individuals must synthesize complex, multi-stream information to learn novel social networks. Our results across three studies suggest that information from one stream – conversations – provides important information that people may use to learn about social relationships. This potentially meaningful empirical advancement would allow for examining naturalistic social network learning in a relatively brief laboratory session.

Because of the naturalistic nature of our stimuli, it is difficult to determine a “true” social network structure of the episode. However, we saw a high level of network agreement amongst participants, and the weighted nodes in our network graphs indicated that participants incorporated social-relational information when making their responses. The subsequent order of contestants voted off the show (except for Shii Ann, who won immunity) corresponds to the amount of time that contestant was chosen as a friend of another contestant (from least to most). These friendship judgments were more consistent with the results of the show than the win assessments (Fig. 2). Moreover, unbeknownst to the participants, the two contestants who were perceived as being the closest friends (Rob and Amber) got married at the end of the season, indicating that participants learned features of the network that are related to real-world relationship qualities.

These findings support prior work underscoring language’s informative value for individual and social judgments (Tong et al., 2020). We found that contestants who had higher semantic similarity were perceived as friends while those with lower similarity were perceived as rivals by external viewers (Ireland et al., 2011; Babcock, Ta, & Ickes, 2014). However, we did not find evidence for positive sentiment supporting friendship judgments (Cannava & Bodie, 2017). This may be because the friendships in the social network on *Survivor* reflect strategic alliances rather than natural contributors to friendship outside of competitive environments. Future work should examine how relationship inferences are made using a non-competitive naturalistic stimulus.

Notably, we found that contestants who were selected most often as friends were those who started off most semantically similar to each other, and that contestants who were selected most often as rivals were the least semantically similar. This is consistent with prior work that suggests friends are more similar to each other (Bahns et al, 2017). Our findings go even further because we were able to identify past levels of semantic similarity and relate those to relational inferences made during later evaluation. These results also present compelling evidence of interpersonal communication similarity acting as a precursor to relationship formation (Parkinson, Kleinbaum, & Wheatley, 2018), and is among the first to address whether homophily is a cause or consequence of friendship. These are particularly exciting results, as they suggest that linguistic features may predict relational inferences and relational inferences may also predict linguistic features. Future work should continue to examine this bidirectional relationship.

Although *Survivor* was an excellent naturalistic stimulus to use to explore these research questions, the competitive nature of the show may also influence participant behavior such that win judgments were easier to make than friendship or rivalry judgments. Participants gather more salient rivalry and win information upon learning who is voted out by their peers, and thus may have more ambiguity about friendships. However, a key strength is that reality television contains unscripted conversations (Grall & Finn, 2022). In particular, the unique and dynamic relationships between *Survivor* contestants allow us to more closely simulate the social network learning experience that people encounter in everyday life, wherein affiliative, adversarial, and competitive aspects may be similarly intertwined (rather than isolated) in relationships. Moreover, television is made with the viewer in mind, which complements our perceiver-directed NLP methods.

Taken together, this work combines naturalistic stimuli with innovative language analysis methods to understand how conversations inform people of the underlying psychology and structure of social networks.

Data Availability Statement

Deidentified data and code for all three studies are publicly accessible at https://osf.io/8wqhb/.

Declarations

Funding: The authors did not receive support from any organization for the submitted work.
Conflicts of interest/Competing interests: The authors have no competing interests to declare that are relevant to the content of this article.
Ethics approval: The research discussed in this article was reviewed and approved by the Institutional Review Board (IRB) at Temple University, protocol ID: 28451.
Consent to participate: Informed consent was obtained from all participants included in the study.
Consent for publication: Participants consented to having their de-identified data published in this article.
Availability of data and materials: De-identified data for all three studies is publicly available at https://osf.io/8wqhb/.
Code availability: Code for all three studies is publicly available at https://osf.io/8wqhb/.

Open Practices Statement

Data and materials for all three studies are available at https://osf.io/8wqhb/.

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