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When and why does shared reality generalize?

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Abstract

Inspired by inductive reasoning models, we test whether generalized shared reality (i.e., the sense of being on the same page) arises through probabilistic inference about latent commonalities. Using a naturalistic text-based chat paradigm, we manipulated whether conversation partners discussed a belief they shared, a belief on which their opinions differed, or a random prompt. Participants discussing shared opinions reported experiencing greater shared reality compared to those discussing differences or random topics. Moreover, participants who made broader inferences about additional beliefs they might share with their partners also reported greater shared reality. While discussing shared opinions can induce an overall greater sense of shared reality, participants discussing differences leveraged their conversation to establish shared realities about other topics. We demonstrate that shared reality can emerge in multiple ways during initial interactions, establishing a foundation for future mechanistic investigations within an inductive inference framework.

Keywords: generalization; transfer; social cognition

Introduction

Our social interactions are guided by expectations about what we share in common with our partners (Stalnaker, 2002; Fussell & Krauss, 1992; Shteynberg et al., 2020; Thornton & Tamir, 2021), from our taste in music (Rentfrow & Gosling, 2006; Boer et al., 2011) to our deeply-held political values (Stern & Ondish, 2018; Skorinko & Sinclair, 2018). These expectations often extend far beyond our direct experiences. For example, we may watch a movie and think to ourselves that our best friend would surely like it just as much as we did, without ever consulting them about it. This kind of experience has been explored under the construct of generalized shared reality, "the experience of sharing a set of inner states (e.g., thoughts, feelings, or beliefs) in common with a particular interaction partner *about the world in general*" and measured through the Generalized Shared Reality (SR-G) self-report questionnaire (Rossignac-Milon et al., 2021).

Although shared reality is most commonly studied in long-term relationships (Rossignac-Milon & Higgins, 2018), it can also arise surprisingly quickly; we can "click" with someone we've just met (Templeton et al., 2022). Yet it is unclear how a sense of generalized shared reality arises from such a "thin slice" of concrete experiences with a communication partner (Anzellotti & Young, 2020; Cheong et al., 2023). Not all shared experiences seem to license the same degree of generalization, and interventions often fail to artificially induce generalized shared reality among strangers (Sedikides et al., 1999; Bebermeier et al., 2015; Echterhoff & Schmalbach, 2018; Ledgerwood & Wang, 2018). Intuitively, sharing a simple perceptual experience (e.g. spotting the same bird out the window) may not lead to the same feeling of generalized shared reality as, say, an intimate conversation about a shared religious or moral belief. However, accounts of shared reality have not typically specified the *mechanism* of how conversation partners generalize from a singular shared experience to a broader shared reality.

We explore the hypothesis that the experience of "being on the same page" with someone may be the product of *inductive inference* about a broader class of commonalities from relatively sparse evidence. If people maintain a generative model of the social world, they can leverage their rich knowledge of social structure (e.g. people who have X in common also tend to have Y in common) to form targeted expectations about what else they are likely to have in common with their conversation partner given sparse evidence (Fawcett & Markson, 2010). In the social domain, this kind of reasoning has been used to understand how people make informed predictions about the structure of social groups (Gershman & Cikara, 2020), about whether norms or conventions will be shared (Hawkins et al., 2023; Murthy et al., 2022), and about aspects of others' mental states such as emotions or desires (Houlihan et al., 2023; Baker et al., 2017). Understanding the inferential basis for the experience of shared reality may begin to unravel *when* and *why* it emerges.

In this paper, we developed a naturalistic text-based chat paradigm where pairs of strangers interacted after being matched based on pre-existing views expressed in an initial survey. By manipulating whether dyads were matched to discuss a prompt concerning a belief they shared, a belief where their opinions differed, or a random prompt, we observed the downstream effects on their experience of shared reality, and their expectations about what else they might have in common, elicited through a *Post-Chat Survey*. Matching on a shared belief led participants to report greater generalized shared reality, and the more participants believed they would share with their partners, the higher their reported SR-G score. Overall, our findings provide an empirical foundation for a mechanistic understanding of the social experience of "being on the same page".

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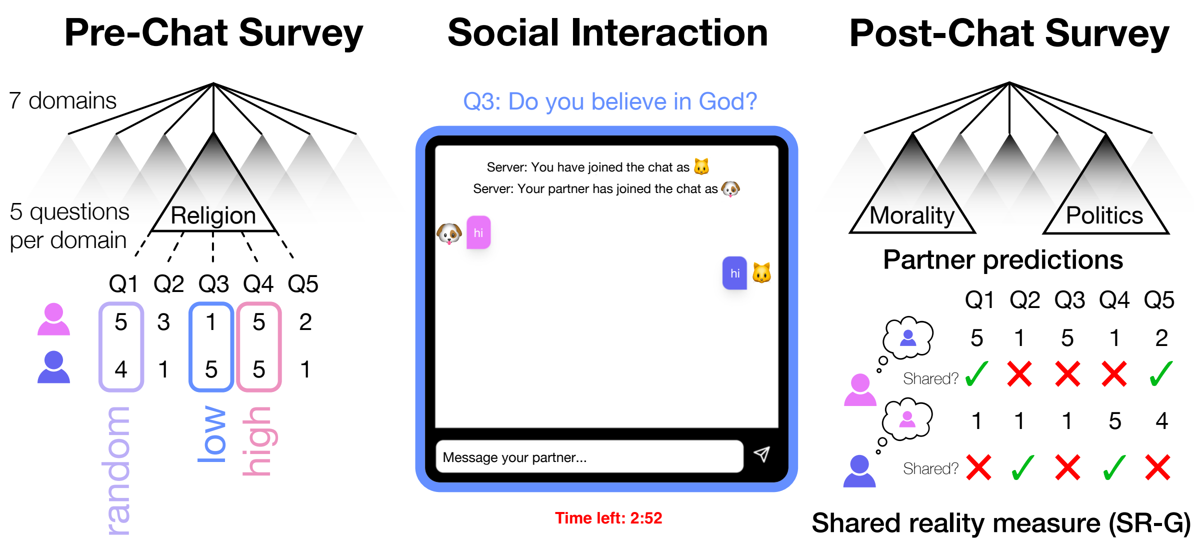

Figure 1: *Design schematic*. Participants first completed a Pre-Chat Survey and a discussion prompt was selected based on the condition they were assigned to (low match, random match, or high match). During the chat phase, users freely exchanged messages based on the prompt. Each user was represented by an emoji avatar and a red timer below the chatbox indicated how much time the dyad had remaining. After the chat phase, participants predicted their partner's responses to the same questions that they received in the Pre-Chat Survey and were asked whether they would share the same thoughts. Participants then completed the SR-G questionnaire to report their sense of shared reality.

Methods

Participants. We recruited 676 participants through Prolific and automatically paired them into $N = 338$ dyads. Building on prior work which implemented a correlational design when studying shared reality development in online chats (Rossignac-Milon et al., 2021), we used a between-subjects design, assigning pairs of participants to either discuss a question they both responded to in the same way (high match condition), a question they responded to in the complete opposite way (low match condition), or a random question (random match condition). Participants were required to live in the United States and be fluent in English. Several dyads in each condition (8 in low match, 9 in random match, and 6 in high match) were excluded because at least one person in that dyad did not complete a portion of the study due to a technical issue or disconnection. Dyads were also excluded if either participant failed to participate during the chat phase. Our final sample consisted of 210 participants in the high match condition, 212 in low match, and 218 in the random match.

Procedure. The experiment consisted of three phases (see Figure 1). In the *Pre-Chat* phase, each participant completed a 35-question survey designed to elicit their opinions and beliefs across seven domains (Table 1) using a 5-point Likert scale.[1] After completing this survey, participants were automatically matched with another participant based on their responses. To balance the distribution of pairs discussing each survey question, we employed a matching algorithm. This algorithm initially identified questions to which dyads responded in a highly similar (high match) or opposing (low match) manner. Following this, the algorithm prioritized questions that the fewest number of pairs had discussed up to that point. In the random match condition, dyads were assigned a randomly chosen question from the *Pre-Chat Survey*. Once assigned a discussion question, pairs entered a chatroom.

In the *Chat* phase, pairs were prompted with their assigned question and were instructed to discuss their responses with their conversation partner for 3 minutes. Apart from the prompt, no structure was imposed on the conversations, allowing participants to interact naturally with their partners. To enhance ecological validity and encourage responsiveness, users were provided with real-time indications when their partner was typing. The interaction took place on a custom platform we developed using the web application framework Svelte and the backend cloud computing service Firebase. The chat interface included a timer so that participants could keep track of their remaining time, and participants were assigned either a cat or dog emoji avatar to represent themselves anonymously.

After the interaction, participants entered the *Post-Chat* phase in which they completed another 35-question survey. It was similar to the *Pre-Chat Survey* except that participants were asked to predict their *partner's opinion* instead of reporting their own. Participants were also asked for an explicit

[1] The scale was labeled "Definitely not", "Probably not", "Unsure", "Probably yes", and "Definitely yes".

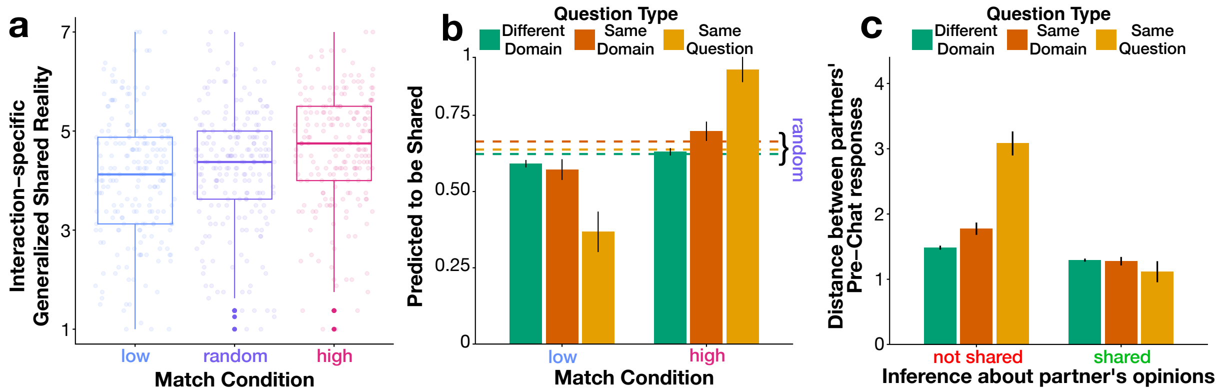

Figure 2: (a) Boxplots showing interaction-specific generalized shared reality scores (SR-G) for participants in each match condition. (b) Barplots showing the proportion of questions in the Post-Chat Survey that participants expected to have in common with their conversation partner. Low and high match categories are displayed along the x-axis, results from the random match condition are shown with dashed lines. Color represents question type (i.e. whether the question was the topic of their chat ["Same Question"], in the same domain as the discussed question ["Same Domain"], or in a different domain). Error bars show two times the standard error. (c) Barplots showing the absolute difference between conversation partners' responses to each question in the pre-survey. Distances between questions that participants did not expect to have in common with their partner are shown on the left, while those between questions which they did expect to have in common are shown on the right. Color represents question type. Error bars show two times the standard error.

commonality judgment, "Do you think you and your partner share the same thoughts/opinions about this question?" with a binary, forced-choice response of "Yes" or "No." We randomized the presentation order of questions in both the *Pre-Chat Survey* and *Post-Chat Survey* to guard against participants, at the *Post-Chat* phase, being primed by their earlier responses from the *Pre-Chat* phase. To validate how well our task evoked a sense of generalized shared reality, participants also completed the interaction-specific Generalized Shared Reality questionnaire (SR-G) (Rossignac-Milon et al., 2021), which is specifically designed to gauge state-level shared reality after an interaction between strangers.

Stimuli. The questions in the *Pre-* and *Post-Chat Surveys* were carefully chosen to elicit participants' opinions in 7 distinct domains (Table 1). We ran a series of studies to ensure that the questions were both relevant and specific to their respective domain. To generate a set of potential survey questions, we recruited a group of participants on Prolific ($N = 49$)

Table 1: Example Question Stimuli

Domain	Example
Lifestyle	Do you exercise regularly?
Background	Do you live in a city?
Identity	Are you a parent or caregiver?
Morality	Is lying acceptable?
Politics	Will you vote in the next election?
Preferences	Do you prefer TV shows over movies?
Religion	Do you believe in an afterlife?

and asked them to imagine a scenario in which they encountered a stranger and had to ask them questions (1) to get to know them better or (2) to find something in common. For each prompt, we asked participants to generate questions related to each of our 7 domains. The study team reviewed participants' responses and selected the top 10 questions from each domain that appeared most frequently.

To prune down our stimuli set to the desired total of 5 questions per domain and establish domain specificity, we designed another study to identify which set of questions from each domain were most tightly associated with each other, and least associated with questions from other domains. To this end, we recruited an independent group of $N = 70$ participants from Prolific to complete a triplet odd-one-out task (Hebart, Zheng, Pereira, & Baker, 2020). This task has been proven to reliably measure mental representations while being agnostic to the specific domains in which these representations exhibit similarity. In each task trial, participants were presented with three question items: 2 questions from the same domain and 1 oddball, a question from another domain. Participants were instructed to select which question in the set was most unlike the others. All participants completed one practice trial with performance feedback followed by 45 trials of the main task. To select the final set of 5 questions for each domain, we calculated the participant's accuracy at identifying the oddball for all possible 5-question subsets from each domain. We selected the subsets with the highest average accuracy in each domain to make up our final question set. By selecting questions with the highest perceived similarity, we successfully constructed domains comprised of specific and highly related questions.

Results

Discussing shared beliefs induces greater shared reality. First, to assess the effectiveness of our experimental manipulation, we compared self-reported SR-G scores from participants in the high match, random match, and low match conditions. We hypothesized that participants in the high match condition would report higher SR-G scores, followed by those in the random match condition, and then those in the low match condition. First, we calculated a composite SR-G score for each participant by averaging their responses across the eight questionnaire items, where higher composite scores reflect stronger feelings of shared reality. Then, we ran a linear mixed-effects model with a linear contrast applied to match type, controlling for the discussion question's domain and including random intercepts for each dyad. As predicted, we found a significant linear effect of condition ($\beta = 0.25$, 95% CI $= [0.11, 0.39], p < 0.001$) with the highest SR-G reported in the high match condition ($M = 4.61$), followed by the random match condition ($M = 4.25$) and the low match condition ($M = 4.05$; Figure 2a).

Participants accurately infer latent commonalities. Next, we assessed the degree to which participants generalized from their singular shared experience with their conversation partner to other potential commonalities. As our primary dependent variable, we calculated the proportion of questions in the *Post-Chat Survey* that participants expected to have in common with their conversation partner (i.e., degree of generalization). We built a linear mixed-effects model predicting this proportion of questions expected to be shared as a function of match condition (low match, random match, or high match). We also included a fixed effect of the discussed question's domain and random intercepts for each pair. We found that participants made broader generalizations in the high match condition ($M = 0.65$) than in the low match condition ($M = 0.58$), with the random condition falling between the other two ($M = 0.63$), $\beta = 0.03$, 95% CI $= [0.01, 0.06], p = 0.024$.

Although generalization increased in the high match condition compared to the low match condition, we wondered whether the *scope* of generalization also changed across conditions. Did participants make broader, cross-domain generalizations in the high match condition, or were changes in generalization relatively domain-specific? To address this question, we categorized participants' responses to the *Post-Chat Survey* questions into one of three *question types*: *same question* (the question they discussed), *same domain* (the other four questions from the domain of the discussed question), and *different domain* (all the remaining questions). We built a logistic mixed-effects model predicting whether participants thought they shared an opinion about a question with their partner. We included fixed effects of match condition and question type as well as the interaction between those terms and the domain of the discussed question. The model included random intercepts for each participant and dyad. We found a significant interaction between the linear contrasts on question type and condition (odds ratio: $= 2.39$, 95% CI = $[2.05 - 2.78], p < 0.001$). As seen in Figure 2b, participants in the high match condition were more likely to expect that they would have the same opinions about the discussed question and questions from the same domain, while the opposite pattern was observed for the low match condition.

We next wondered whether participants made *accurate* inferences about their partners. If so, did their inferences become less accurate for questions that were less similar to the topic of their discussion? In addressing these questions, we first calculated the Manhattan distance (i.e. absolute difference) between pairs' responses to each question of the *Pre-Chat Survey*. These distances served as a ground truth measure of the degree of commonality between conversation partners' beliefs. Then we built a Poisson mixed-effects regression model with the absolute difference between partners' responses to each question in the *Pre-Chat Survey* as the outcome measure and binary generalization responses (shared or not shared), question type (with a linear contrast), and the interaction between generalization responses and question type as predictor variables. The domain of the discussed question and match type were included as control variables and random intercepts were included for each participant and pair. The model revealed a significant interaction between question type and generalization responses, such that participants' generalization responses were most accurate for the question they discussed with their partner, less so for other questions within the same domain, and least for questions outside of that domain ($IRR = 0.81, 95\% CI = [0.79 - 0.83], p < 0.001$ Figure 2c). A post-hoc simple contrast between generalization responses within the "different domain" question type revealed that, despite it being the least accurate question type, participants' inferences still reflected actual similarities ($M_{diff} = 0.16, z = 12.36, p < 0.001$). Consistent with an inductive inference account of generalized shared reality, we find evidence for a relationship between the participants' match domain and the degree to which they accurately infer similarities with their chat partner. This suggests a pattern of inductive inference, where participants leverage partner-related knowledge learned during the chat phase to inform predictions about other commonalities.

Generalization predicts greater shared reality. Having established that participants both generalized more and experienced greater shared reality when matched on commonalities than when matched on differences, we wondered if the extent to which participants generalized might predict the extent to which they reported feelings of shared reality. Based on concerns that the range of generalization would be restricted in the high and low match conditions, we decided to first model the relationship between generalization and SR-G score in only the random match condition. We built a linear mixed effects model predicting participants' reports of shared reality based on the proportion of questions that they selected as having in common with their partner and included the domain of the discussed question as a control

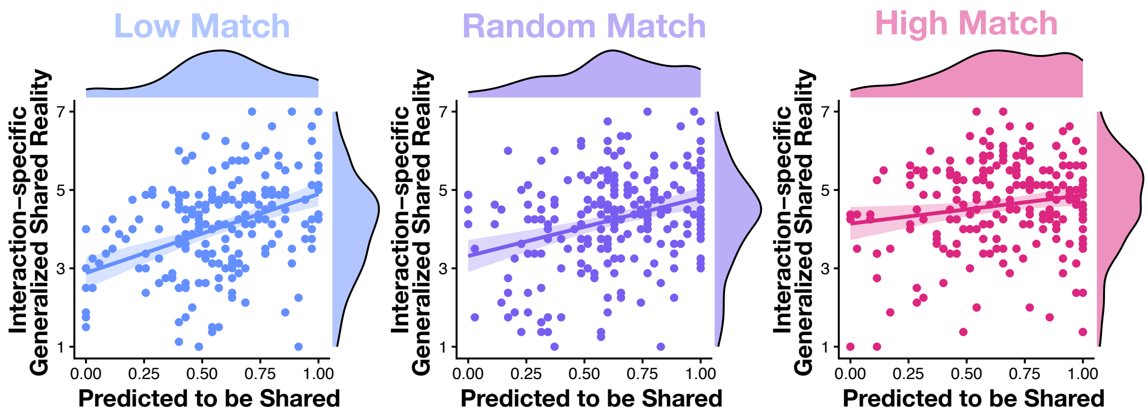

Figure 3: Scatter plots with regression lines showing the relationship between interaction-specific generalized shared reality scores and the proportion of questions in the *Post-Chat Survey* that participants thought they would have in common with their conversation partner. Left plot shows data from the low match condition, middle plot from the random match condition, and right plot from the high match condition. In all plots, each point represents data from a single participant.

variable. Random intercepts were included for each pair. The proportion of questions participants expected to share with their conversation partner was a significant, positive predictor of SR-G score ($\beta = 1.18, 95\%CI = [0.60, 1.75], p < 0.001$). To further explore the difference in slopes between match types, we included participants from all conditions in another linear mixed effects model predicting reports of shared reality based on the proportion of questions that they predicted to have in common with their partner, match type (with a linear contrast), and the interaction between these two terms. We included the domain of the discussed question as a control variable and random intercepts for each pair. The model's results included a significant negative interaction term, suggesting that the relationship between generalization and shared reality was strongest in the low match condition, and weakest in the high match condition ($\beta = -0.15, 95\%CI = [-0.26, -0.4], p = 0.007$). The more participants generalized, the greater the shared reality they experienced (see Figure 3).

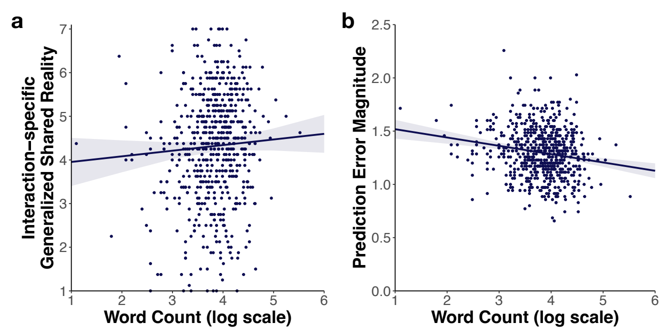

Figure 4: (a) Although all participants had three minutes to chat with their partner, as people exchanged more words with their partner (measured in log-scaled word count), participants reported higher shared reality, as measured with the SR-G. (b) As people exchanged more words with their partners, the magnitude of error for predicted partner responses decreased. Shaded areas reflect 95% confidence intervals and points reflect individual participants.

Conversational facets of shared reality. While all chat conversations were limited to three minutes, we examined the impact of conversation length (measured using log-scaled word count) on the sense of shared reality. We fit a Poisson mixed-effects regression model with each participant's conversational word count as the outcome measure, match type as a predictor (with a linear contrast), and a random effect of participant. Participants in the low match condition had the longest exchanges ($M = 52.88$ words) compared to high ($M = 51.57$) and random ($M = 48.20$), but linear contrasts revealed no significant difference by match condition ($ps > .05$). Therefore, our experimental manipulation did not impact how long the conversations were. To examine whether longer conversations were associated with increased feelings of generalized shared reality, we examined the relationship between total conversational word count and SR-G composite scores (Figure 4a). We fit a linear mixed-effects model with SR-G score as the outcome, log-scaled word count as the predictor, and included a random effect of dyad, but there was not a significant effect of conversation length on reported shared reality for responses pooled across match conditions ($b = 0.13, 95\%CI = [-0.07, 0.33], p = 0.19$) nor for randomly-matched participants only ($b = 0.17, 95\%CI = [-0.15, 0.49], p = 0.29$).

We also examined whether longer conversations were associated with the accuracy of predictions that participants made about their partner's responses in the *Post-Chat Survey* (Figure 4b). Using *Post-Chat* responses from each participant and *Pre-Chat* responses from their partner, we calculated the prediction error magnitude per question. The values ranged from 0 (perfectly matched prediction) to 4 (perfectly opposite prediction), and we hypothesized that longer conversations would be associated with lower prediction errors. We fit a linear mixed-effects model with prediction error magnitude as the outcome, log-scaled word count as a predictor, and included a random effect of dyad, and there was a significant effect of conversation length on prediction errors for responses pooled across match condition ($b = -0.09, 95\% CI = [-0.11, -0.05], p < 0.001$) and for randomly-matched participants ($b = -0.06, 95\% CI = [-0.12, -0.01], p = 0.02$). The more participants spoke to their partners, the more accurate they were in their predictions.

Discussion

Shared reality, the experience of "being on the same page," is the keystone of social connection. Therefore, studying how shared reality is established in novel relationships can help us understand how people form social connections and engage in enjoyable conversations. Here, we investigated whether generalized shared reality emerges through inferences regarding latent commonalities. Our approach leveraged a naturalistic text-based chat paradigm in which pairs of strangers discussed either a shared opinion, an opposing opinion, or a randomly assigned discussion question. Although all participants underwent the shared experience of a chat interaction, our approach demonstrates that the *content* of shared experience matters. Participants who discussed shared opinions subsequently made broader inferences about which other opinions they might share with their partner and reported a stronger sense of shared reality compared to those who discussed differences or a random topic (Figure 2a and b).

Critically, we observed a gradient of generalization: participants who discussed shared opinions (high match condition) anticipated sharing more opinions within the same domain as their discussed topic than in other domains. Moreover, participants who believed they shared more beliefs with their conversation partner also experienced a stronger sense of shared reality (Figure 3). Our data suggests that discussing shared opinions fosters a stronger shared reality (Figure 2a), and that participants discussing differences may actively seek other commonalities to build a shared reality. In summary, while a greater shared reality is felt *when* discussing a shared opinion, generalizing more, potentially due to actively seeking common ground, is an additional factor as to *why* shared reality is felt.

We also examined how different aspects of the chat influenced participants' reported sense of shared reality. Notably, while the conversation length did not directly affect feelings of shared reality, participants who exchanged more words with their chat partners demonstrated higher accuracy in predicting their partners' responses from the *Pre-Chat Survey* (see Figure 4b).This suggests that more extensive interactions allow conversation partners to search for other shared beliefs and learn about each other, enabling more informed inferences and, consequently, greater accuracy. Taken together, our results deepen our understanding of the intricate interplay between common ground, conversation dynamics, and the emergence of generalized shared reality. In future work, we seek to identify time points in the chat when conversation shifts from assigned topics, to measure the extent to which dyads discuss other potential commonalities.

Limitations and future directions. Drawing inspiration from evidence accumulation models, where decisions are made after reaching a threshold of sampled information (Huk, Katz, & Yates, 2013), we aim to explore how the chat phase duration affects participants' SR-G and partner predictions. 8% of participants reported that our three-minute conversation duration was too short to allow for a comprehensive understanding of their partner's stance on the discussion question and subsequent generalization. Allocating more time for participants to engage with their partners might lead to fewer "unsure" responses in the *Post-Chat Survey* and facilitate greater out-of-domain transfer, as the dyad would have more time to discuss opinions less relevant to their assigned topic. Moreover, we predict that longer chat durations could foster a stronger sense of shared reality.

While we identified questions that people perceived as more similar in order to construct domains of shared reality (see Table 1), we acknowledge that multiple factors may contribute to this perceived similarity, which are presently unknown. The next step in our research will involve collecting data on how people perceive these questions along various dimensions. Specifically, we aim to explore factors such as the extent of self-disclosure each question allows during discussion, as the literature highlights self-disclosure as a significant precursor to the construction of shared reality (Rossignac-Milon & Higgins, 2018). Identifying features in our question stimuli that contribute to a stronger sense of shared reality can provide a more nuanced understanding of the conditions under which shared reality generalizes.

Our findings are consistent with the idea that participants engage in inductive reasoning to deduce latent commonalities shared with their conversation partners. Specifically, when inferring the alignment of their beliefs across various domains, participants base their predictions on their interactions with their partners. Moving forward, we aim to construct a generative Bayesian model to offer a mechanistic account of this reasoning process. We will use this model to make predictions about the expected degree of commonalities people anticipate, taking into consideration the identified commonality domain from the chat phase. We expect a model with an understanding of how answers to questions covary with each other, both within and across domains, will outperform a null model lacking this knowledge. The null model either lacks such correlational knowledge or only generalizes within a domain, not across. Our proposed model will help pin down precisely *how* shared reality generalizes and licenses more wide-ranging social behaviors such as warmth and social closeness.

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