How does shared reality generalize?

Wasita Mahaphanit (wasita.gr@dartmouth.edu)
Psychological & Brain Sciences Department, Dartmouth College
Hanover, NH, 03755, USA

Christopher L. Welker (christopher.l.welker.gr@dartmouth.edu)
Psychological & Brain Sciences Department, Dartmouth College
Hanover, NH, 03755, USA

Helen Schmidt (helen_schmidt@brown.edu)
Psychology & Neuroscience Department, Temple University
Philadelphia, PA, 19122, USA

Luke J. Chang (luke.j.chang@dartmouth.edu)
Psychological & Brain Sciences Department, Dartmouth College
Hanover, NH, 03755, USA

Robert D. Hawkins (rdhawkins@wisc.edu)
Department of Psychology, University of Wisconsin-Madison
Madison, Wisconsin, 53706, USA

Abstract

We use a Bayesian inductive reasoning model to 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 were assigned to discuss a belief they shared, a belief on which their opinions differed, or a random prompt. Subsequently, we asked participants to predict their conversation partner's beliefs and opinions on topics that were not assigned for discussion. We show that an inferential model that incorporates knowledge of the identified commonality from the chat phase captures participants' expectations of shared opinions with their chat partner. Our findings suggest that participants leverage the alignment of their opinions and the topic they share opinions on – a singular instance of shared experience – to infer other latent shared commonalities with their conversation partners, thereby generalizing to a broader shared reality. This work lays the foundation for a mechanistic understanding of generalized shared reality and its role in fostering a sense of connection between conversation partners.

Keywords: Shared reality; common ground; social learning; cognitive modeling; probabilistic modeling; Bayesian

Introduction

Our social interactions are guided by expectations about what we share in common with our partners (Stalnaker, 2002; Shteynberg et al., 2020), from our taste in music (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 recommend a new musical artist to a friend and, given our prior shared history of concerts attended together, expect our friend to like the artist as much as we do. 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 has been primarily measured through the Generalized Shared Reality (SR-G) self-report questionnaire (Rossignac-Milon et al., 2021).

Although shared reality has been studied extensively (Rossignac-Milon & Higgins, 2018), it is not clear how a sense of generalized shared reality arises from such a "thin slice" of concrete experiences with a communication partner (Anzellotti & Young, 2020). 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). Further, 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.

One helpful perspective for approaching this question comes from Bayesian accounts of inductive reasoning (Kemp & Tenenbaum, 2009; Griffiths, Chater, Kemp, Perfors, & Tenenbaum, 2010). 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), 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 *how* it emerges and clarify its role in social connection (Delgado et al., 2023).

Methods

Participants

We recruited participants (N = 676) through Prolific and paired them into 338 dyads. Participants were assigned 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). Dyads where either participant failed to participate during the chat phase were excluded, yielding our final sample (N = 640).

Task & Procedure

The experiment consisted of 3 phases (see Figure 1). Each participant completed a 35-question *Pre-Chat Survey* using a 5-point Likert scale.[1] to express their opinions across seven domains (Table 1). Participants were then matched into dyads according to a matching algorithm. This algorithm first identified *Pre-Chat* questions to which dyads responded in a highly

[1] Scale labels: "Definitely not", "Probably not", "Unsure", "Probably yes", and "Definitely yes".

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?

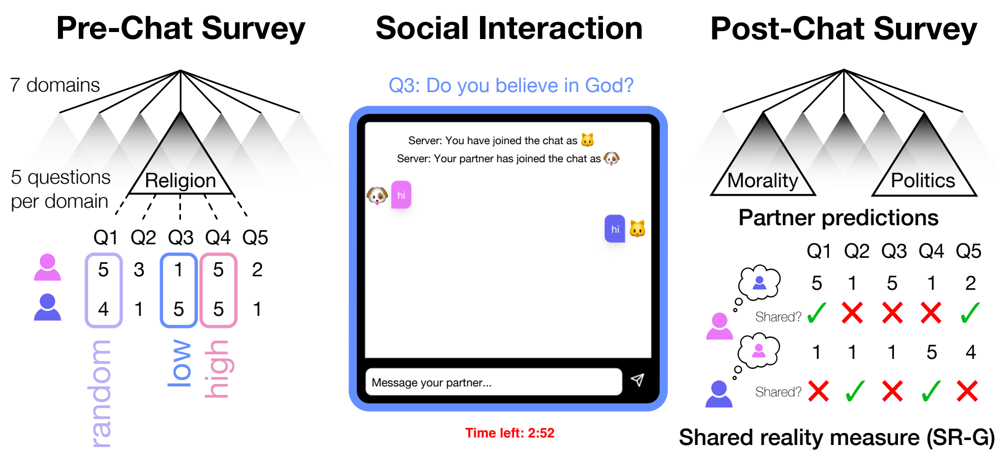

Figure 1: Participants first filled out a pre-chat survey and a discussion prompt was selected based on their assigned condition. After the chat phase, participants predicted their partner's responses to the same questions that they received in the pre-chat survey and were asked whether they would share the same thoughts. Participants then completed the SR-G questionnaire.

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. The interaction took place on a custom platform we developed with the web app framework Svelte and cloud database Firebase.

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 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." Participants also completed the interaction-specific Generalized Shared Reality questionnaire (SR-G), which is specifically designed to gauge state-level shared reality after an interaction between strangers.

Modeling

We consider three models of the information used by participants to make their *Post-Chat* judgments D.

Null Prior Only As a null model H_0, we assume participants make random responses in the post-chat survey, where each response is assigned an equal probability of occurring.

$$P(D \mid H_0) \sim \text{Categorical}([1/5, \dots, 1/5]) \tag{1}$$

where the likelihood is uniform over all possible domains, questions, and Likert response types.

Empirical Prior Only Our next model H_1 assumes participants are using background knowledge of how the population of partners would *generally* respond, but do not use any partner-specific information.

$$P(D_i \mid H_1) \sim \text{Categorical}([\hat{p}_i^1, \dots, \hat{p}_i^5]) \tag{2}$$

where we estimated $\hat{p}_i$ from the empirical distribution of responses to that item from the *Pre-Chat Survey*.

Inferential Cognitive Model Our final model H_2 assumes participants are using Bayesian inference to infer their partner's likely *Pre-Chat* responses *conditioned on matching on item j*:

$$P(D_i|H_2) = P(D_i|\text{match}_j) \tag{3}$$

Intuitively, this model can account for the covariance structure in the empirical prior – observing a match on a given item reduces uncertainty about other items.

Results

We used the Watanabe–Akaike information criterion (WAIC; (Gelman et al., 2013)) to perform model comparison. Our inferential model H_2, which incorporates both knowledge of how responses to questions covary with each other *and* knowledge of how a chat partner responded to the assigned discussion topic, demonstrated a superior overall fit to participants' *Post-Chat* judgments (ΔWAIC = –969.1), compared to the alternative models (see Table 2).

Table 2: Model Comparison

Model	WAIC
H_0: Null Prior Only	69908
H_1: Empirical Prior Only	56532
H_2: **Inferential Model**	**55563**

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References

Anzellotti, S., & Young, L. L. (2020). The acquisition of person knowledge. *Annual Review of Psychology*, *71*, 613–634.

Baker, C. L., Jara-Ettinger, J., Saxe, R., & Tenenbaum, J. B. (2017). Rational quantitative attribution of beliefs, desires and percepts in human mentalizing. *Nature Human Behaviour*, *1*(4), 0064.

Bebermeier, S., Echterhoff, G., Bohner, G., & Hellmann, J. H. (2015). The generalization of shared reality: When communication about one target shapes evaluations of other targets. *European Journal of Social Psychology*, *45*(5), 623–640.

Boer, D., Fischer, R., Strack, M., Bond, M. H., Lo, E., & Lam, J. (2011). How shared preferences in music create bonds between people: Values as the missing link. *Personality and Social Psychology Bulletin*, *37*(9), 1159–1171.

Delgado, M. R., Fareri, D. S., & Chang, L. J. (2023). Characterizing the mechanisms of social connection. *Neuron*, *111*(24), 3911–3925. doi: 10.1016/j.neuron.2023.09.012

Echterhoff, G., & Schmalbach, B. (2018). How shared reality is created in interpersonal communication. *Current opinion in psychology*, *23*, 57–61.

Fawcett, C. A., & Markson, L. (2010). Children reason about shared preferences. *Developmental psychology*, *46*(2), 299.

Gelman, A., Hwang, J., & Vehtari, A. (2013, 07). Understanding predictive information criteria for bayesian models. *Statistics and Computing*, *24*. doi: 10.1007/s11222-013-9416-2

Gershman, S. J., & Cikara, M. (2020). Social-structure learning. *Current Directions in Psychological Science*, *29*(5), 460–466.

Griffiths, T. L., Chater, N., Kemp, C., Perfors, A., & Tenenbaum, J. B. (2010). Probabilistic models of cognition: Exploring representations and inductive biases. *Trends in cognitive sciences*, *14*(8), 357–364.

Hawkins, R. D., Franke, M., Frank, M. C., Goldberg, A. E., Smith, K., Griffiths, T. L., & Goodman, N. D. (2023). From partners to populations: A hierarchical bayesian account of coordination and convention. *Psychological Review*, *130*(4), 977.

Houlihan, S. D., Kleiman-Weiner, M., Hewitt, L. B., Tenenbaum, J. B., & Saxe, R. (2023). Emotion prediction as computation over a generative theory of mind. *Philosophical Transactions of the Royal Society A*, *381*(2251), 20220047.

Kemp, C., & Tenenbaum, J. B. (2009). Structured statistical models of inductive reasoning. *Psychological review*, *116*(1), 20.

Ledgerwood, A., & Wang, Y. A. (2018). Achieving local and global shared realities: Distance guides alignment to specific or general social influences. *Current Opinion in Psychology*, *23*, 62–65.

Rossignac-Milon, M., Bolger, N., Zee, K. S., Boothby, E. J., & Higgins, E. T. (2021). Merged minds: Generalized shared reality in dyadic relationships. *Journal of Personality and Social Psychology*, *120*(4), 882.

Rossignac-Milon, M., & Higgins, E. T. (2018). Epistemic companions: Shared reality development in close relationships. *Current opinion in psychology*, *23*, 66–71.

Sedikides, C., Reeder, G. D., & Campbell, W. K. (1999). The relationship closeness induction task. *Representative Research in Social Psychology*, *23*, 1–4.

Shteynberg, G., Hirsh, J. B., Bentley, R. A., & Garthoff, J. (2020). Shared worlds and shared minds: A theory of collective learning and a psychology of common knowledge. *Psychological Review*, *127*(5), 918.

Skorinko, J. L., & Sinclair, S. (2018). Shared reality through social tuning of implicit prejudice. *Current opinion in psychology*, *23*, 109–112.

Stalnaker, R. (2002). Common ground. *Linguistics and philosophy*, *25*(5/6), 701–721.

Stern, C., & Ondish, P. (2018). Political aspects of shared reality. *Current Opinion in Psychology*, *23*, 11–14.