nature communications

Article

https://doi.org/10.1038/s41467-024-51990-7

Hyperscanning shows friends explore and strangers converge in conversation

Received: 29 September 2023

Accepted: 22 August 2024

Published online: 05 September 2024

Check for updates

Sebastian P. H. Speer[1], Laetitia Mwilambwe-Tshilobo[2,3], Lily Tsoi[4], Shannon M. Burns[5,6], Emily B. Falk[3,7,8,9] & Diana I. Tamir[1,2]

During conversation, people often endeavor to convey information in an understandable way (finding common ground) while also sharing novel or surprising information (exploring new ground). Here, we test how friends and strangers balance these two strategies to connect with each other. Using fMRI hyperscanning, we measure a preference for common ground as convergence over time and exploring new ground as divergence over time by tracking dyads' neural and linguistic trajectories over the course of semi-structured intimacy-building conversations. In our study, 60 dyads (30 friend dyads) engaged in a real-time conversation with discrete prompts and demarcated turns. Our analyses reveal that friends diverge neurally and linguistically: their neural patterns become more dissimilar over time and they explore more diverse topics. In contrast, strangers converge: neural patterns and language become more similar over time. The more a conversation between strangers resembles the exploratory conversations of friends, the more they enjoy it. Our results highlight exploring new ground as a strategy for a successful conversation.

A conversation is one of the quickest and most efficient ways to establish social connection. During conversation, people must convey their thoughts and feelings in a way their conversation partner can understand, thus finding common ground[1]. At the same time, people should explore new ground, providing novel ideas and surprising information[2]. This study explores how friends and strangers use these two strategies to connect with others.

People enjoy having conversations with others[3–5]. But people do not have a good sense of what defines a good one[5–7]. Is there a reliable path to a good conversation? And does this path depend on the relationship history?

People use conversations to find common ground. To establish common ground, conversation partners repeat each other's words, refer to objects using the same words, and adopt similar syntax[8,9]. With each new utterance, communicators converge on shared language and common knowledge unique to their idiosyncratic shared history[10]. Recipients rate partners that converge on common ground as more competent, warm, and cooperative[11]. This suggests that convergence may help people mutually understand each other[12]. In addition to examining alignment in language[12,13], common ground can be assessed with alignment in body movements[14,15], physiology[16], and neural activity during a conversation. For example, people display synchronous brain activity when they independently arrive at the same interpretation of a movie, speech, or other complex stimulus[17–20]. In contrast, neural alignment is absent when people are not on the same page about an experience[21,22]. Neural alignment is a marker of similar states of mind.

Here we test for common ground during a live conversation by measuring the extent to which dyads experience mental convergence, or increases in alignment over the course of a conversation. This mental convergence is associated with positive social outcomes such

[1]Princeton Neuroscience Institute, Princeton University, Princeton, NJ, USA. [2]Department of Psychology, Princeton University, Princeton, NJ, USA. [3]Annenberg School for Communication, University of Pennsylvania, Philadelphia, PA, USA. [4]Department of Psychology, Caldwell University, Caldwell, NJ, USA. [5]Department of Psychological Science, Pomona College, Claremont, CA, USA. [6]Department of Neuroscience, Pomona College, Claremont, CA, USA. [7]Department of Psychology, University of Pennsylvania, Philadelphia, PA, USA. [8]Wharton Marketing Department, University of Pennsylvania, Philadelphia, PA, USA. [9]Operations, Information, and Decisions Department, University of Pennsylvania, Philadelphia, PA, USA. e-mail: sspeer@princeton.edu

as emotional support[23], interpersonal liking[24–26], social influence[27], social cohesion[16], intimacy, compliance[28–30], perceptions of similarity[31], and cooperation[31–33]. This suggests that common ground fosters social connection between strangers and grows even stronger with friendship[34].

On the other hand, too much convergence may render a conversation too predictable and boring. Instead, conversation partners may want to engage and interest the other and, therefore, seek to explore new ground. Novelty increases engagement and interest. When people are surprised or encounter something new and unexpected, they are more likely to pay attention and are less likely to be bored[35]. Humans value information for its own sake and are willing to invest money to obtain information, even if it is irrelevant to the task at hand[36]. Socially, when engaged in their own thoughts or when reading others', people derive more pleasure when content spans diverse conceptual ground[37,38]. Conversations that are low in repetition[39], fast-paced[40], deep[41], cover novel topics[42], and allow conversation partners to share interesting experiences[35] are associated with greater enjoyment. A substantive conversation might thus have both depth (e.g., exploring one topic in many ways) and/or novelty (e.g., exploring many topics). Shallow conversations, in contrast, may be constrained by social norms and politeness. Indeed, conversations characterized by more exploration and novelty and less small talk are associated with higher well-being[43], strengthening of social ties[44], and relieving negative emotional experiences[45]. Therefore, conversation partners may be motivated to explore new ground and seek surprise and novelty in their interactions. Here we test for exploration of new ground by measuring the extent to which dyads experience mental divergence, or increasing distance in mental states over the course of a conversation.

People may pursue different conversation strategies depending on their social connection with their conversation partner. People converse differently when they know each other well than when they are just starting to get to know each other. Conversations with friends benefit from existing mutual knowledge, involve more self-disclosure, and are more unique, broad, and relaxed than conversations with strangers[46,47]. Long gaps in conversation are awkward for strangers but increase connection for friends[48]. Thus, friends have better conversations than strangers and may adopt different strategies to achieve them.

How does social connection shape the trajectories of conversations? Friends have shared history and common reference points, which allows them to draw upon a more diverse set of topics to discuss in conversation[49]. Friends make semantic associations that might appear distant to outsiders, allowing friends to change topics in conversation more rapidly[50]. Friends also generate more topics in conversation than strangers[51,52]. That said, friends do not necessarily communicate more accurately or efficiently than strangers, despite having a shared history and a larger body of common ground language[8,9,53]. Thus, while there is evidence to suggest that friends differ from strangers in how they rove through conversations, no studies have directly tested how they differ in implementing the two strategies and how this predicts conversation outcomes. We hypothesize that if friends build on their already established common ground, a preference for finding new ground and diverging should be a more beneficial strategy. Strangers, who do not have shared experiences and common reference points, should prefer converging on common ground. The two conversation strategies are not mutually exclusive; conversation partners may first find common ground before exploring new topics, or explore until finding a rich topic to exploit; people may also seek common ground on one dimension while exploring on another. But a greater inclination towards one strategy over the other could benefit different conversations differently depending on the existing relationship between the conversants.

This study investigates how finding common ground versus exploring new ground supports social connection during semi-structured intimacy-building conversations. We tested how a dyad's initial relationship (friends vs. strangers) shapes their use of each strategy. We measured finding common ground and exploring new ground as convergence and divergence, respectively, in mental state space and topic space using both neural and linguistic measures. This approach offers the unique opportunity to assess conversation strategy and mental experience in real time, across three diverse measures of conversation trajectories. We used fMRI hyperscanning to follow 60 dyads engage in a real-time conversation. Half of the dyads self-identified as friends, and half were strangers. This allowed us to test how an existing social connection influences the use of finding common ground versus exploring new ground strategies and how that relates to conversation outcomes.

The hyperscanning and conversation literature has pointed to the pivotal importance of mentalizing in establishing social connection (for review see refs. 54,55). Here we measured finding common ground versus exploring new ground by tracking the convergence and divergence of people's mental states. Previous research has demonstrated that three dimensions (social impact, rationality, and valence, termed the 3D mind model) capture the majority of variance in whole-brain activation underlying people's mental states[56–58]. Rationality represents whether people are inclined to act calmly and thoughtfully or react instinctively or rashly. Social impact captures whether mental states arise during intense social interactions or low energy solitary experiences. Finally, valence reflects whether a person is feeling good or bad. Knowing where one person is in this 3D space tells much about their internal mental state. Knowing if two people are moving toward or away from each other within this space tells you if their mental states are converging or diverging, respectively. By using neural decoding models[59–67] to track participants' mental states from whole-brain patterns of neural activity, we tested how convergence and divergence in the 3D mental state space change over the course of conversations for both friends and strangers.

To measure convergence/divergence in language data, we employ natural language processing (NLP) to decode positions in the same 3D mental state space from words used during the conversation. To understand how mental state dynamics relate to the content of conversations, we extracted participants' trajectories through topic space using topic modeling. We then tested how friends differ from strangers in their mental state convergence (neurally and linguistically) and topic exploration over the whole conversation.

Here we show that friends start more mentally aligned than strangers but then diverge in neural, linguistic, and topic space—evidence that friends tend to explore new ground in conversation. Strangers start more distant and become more aligned over time—evidence that strangers tend to find common ground in conversation. The more a conversation between strangers explored new ground, the better their conversation.

Results

Friends have higher quality conversations than strangers

As preregistered, we first tested if friends have better conversations than strangers. Participants completed a survey at the end of their conversation, measuring enjoyment of the conversation, closeness and similarity to the partner, anxiety while speaking and listening, desire to interact again, and desire to become friends. A factor analysis over these measures identified four metrics of conversation quality (Methods; Supplementary Methods). Friends had significantly better conversations than strangers on all four latent factors (Fig. 1): closeness ($t(57) = 7.56$, $p < 0.001$, two-tailed, $d = 1.97$, 95% CI [1.09, 1.87]), enjoyment ($t(57) = 5.67$, $p < 0.001$, two-tailed, $d = 1.48$, 95% CI [0.61, 1.27]), similarity ($t(57) = 10.81$, $p < 0.001$, two-tailed, $d = 2.82$, 95% CI [1.38, 2.00]), and reverse-coded negative affect ($t(57) = 3.23$, $p = 0.002$, two-tailed, $d = 0.84$, 95% CI [0.32, 1.36]). Negative affect had low reliability (Cronbach's $\alpha = 0.63$; interrater $r = 0.29$, $p = 0.03$), so was not analyzed further.

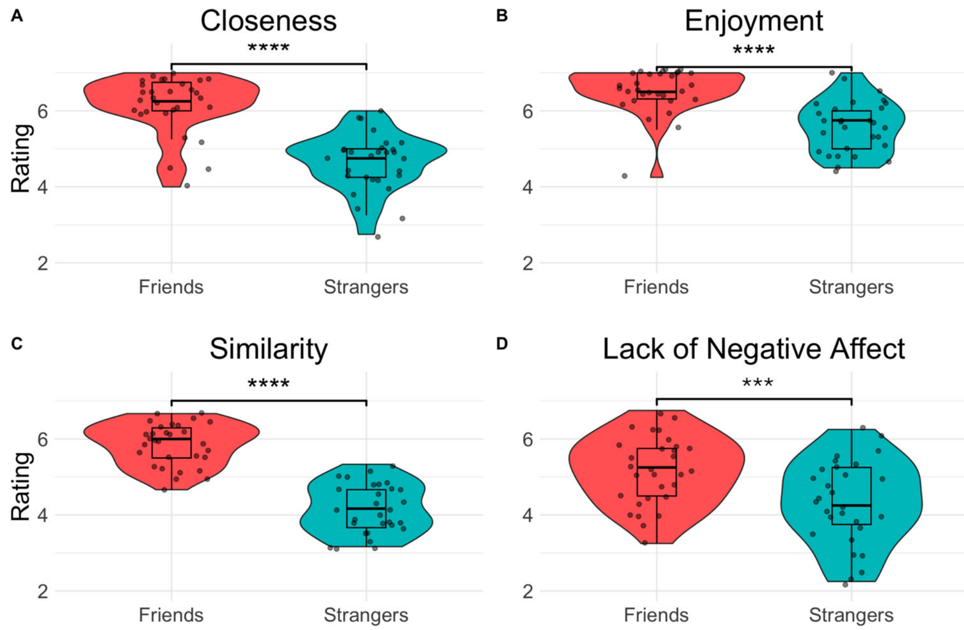

Fig. 1 | Friends have higher quality conversations as compared to strangers. Violin plots for the ratings on **A** closeness, **B** enjoyment, **C** similarity, and **D** negative affect (reverse-coded), for each dyad ($n = 59$) plotted separately for friends (Red) and strangers (Blue). * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.005$, **** = $p < 0.001$. P values were derived using two-tailed two-sample t-tests (no adjustments for multiple comparisons). The boxplots indicate the median (central line), the interquartile range (IQR; box edges), and the whiskers, which extend to 1.5 times the IQR from the first and third quartiles.

Friends diverge in mental state space while strangers converge

Friends enjoyed their conversation and their partner more than strangers. What conversation strategy-finding common ground or exploring new ground-supported these positive outcomes?

To answer this, we first measured, as preregistered, how dyads moved through mental state space with fMRI. We used a neural decoding model to locate and track each partner in mental state space over the course of the conversation. This decoding method was first developed and validated on four independent datasets where we knew both participants' neural patterns and the mental state under consideration at each time point. The model learned to translate whole-brain neural patterns into coordinates on the three dimensions that define mental state space using LASSO-PCR. The rationality dimension was best decoded by the right inferior frontal gyrus and medial prefrontal cortex (MPFC); social impact by the default mode network (posterior cingulate cortex, angular gyrus, MPFC); and valence by the vMPFC and MPFC[58] (Supplementary Methods, Supplementary Fig. 2). We applied these three models to the conversation data to locate each partner on each of the three dimensions. Using the decoded coordinates, we computed the distance between the two speakers in mental state space at each moment of time (Fig. 2), where a smaller distance represented a higher alignment of mental states between the dyad.

We used multilevel models to test if dyads converged or diverged within each conversation. Analyses of neural patterns showed that friends diverged in mental state space, while strangers converged (two-way interaction between time and relationship type: $\beta = -0.001$, 95% CI [−0.00034, −0.001], SE = 0.0003, $p = 0.001$; Fig. 3A). Friends started with higher mental state alignment than strangers and then diverged in mental state space until their distance was larger than strangers.

In a parallel exploratory analysis, we measured how dyads moved through linguistic space. We used natural language processing to locate each partner in mental state space based on the words they said on each turn (Supplementary Methods). This analysis likewise showed a trend in the same direction ($\beta = -0.02$, 95% CI [−0.05, 0.005], SE = 0.014, $p = 0.11$; Fig. 3B). We also found a significant three-way interaction such that the interaction between time and relationship type depends on the trial number ($\beta_{Friend:turns:trials} = -0.007$, 95% CI [−0.012, −0.002], SE = 0.003, $p = 0.006$; $\beta_{Stranger:turns:trials} = -0.005$, 95% CI [−0.013, 0.002], SE = 0.004, $p = 0.19$; $F_{overall} = 4.67$, $p = 0.009$). Initially, friends and strangers both converge, but after half of the trials, we start seeing the same effect as for the neural data: friends diverged, and strangers converged (Supplementary Note 2).

Finally, in a parallel exploratory analysis, we measured how dyads moved through topic space. We applied unsupervised machine learning to extract the topic of each turn and calculate the semantic difference between them (Supplementary Methods). Topic modeling analyses showed that friends explore more diverse topics, more rapidly than strangers ($\beta = -0.009$, 95% CI [−0.013, −0.005], SE = 0.002, $p < 0.0001$; Fig. 3C). Friends also generated significantly more topics ($t(57) = 3.00$, $p = 0.004$, two-tailed, $d = 0.78$, 95% CI [0.81, 4.14]; Fig. 4A), switched topics more often ($t(57) = 2.43$, $p = 0.019$, two-tailed, $d = 0.64$, 95% CI [1.06, 11.49]; Fig. 4B), and jumped longer distances between topics ($t(57)_{cosine} = 2.75$, $p_{cosine} = 0.008$, two-tailed, $d = 0.72$, 95% CI [0.005, 0.031]; Fig. 4C). Together, these findings show that strangers converged in mental state space and exploited topics for longer while friends diverged in neural and linguistic mental state space, and explored more topic space (for an overview of topics discussed see Fig. 5; for details on how the figure was created see Supplementary Methods).

Divergence is associated with better conversations among strangers

Friends have higher quality conversations than strangers. They also use different conversation strategies, opting to explore new ground while strangers focus on finding common ground. To what extent might exploring new ground be associated with beneficial outcomes in strangers? We tested this possibility with an exploratory analysis investigating whether divergence in mental state space and topic space was associated with better conversations among strangers.

For ratings of closeness, we fit three multilevel regression models to predict each of the three distance metrics, respectively: Mahalanobis distance in neural mental state space, Mahalanobis distance in linguistic mental state space, and cosine distance in topic space. Each

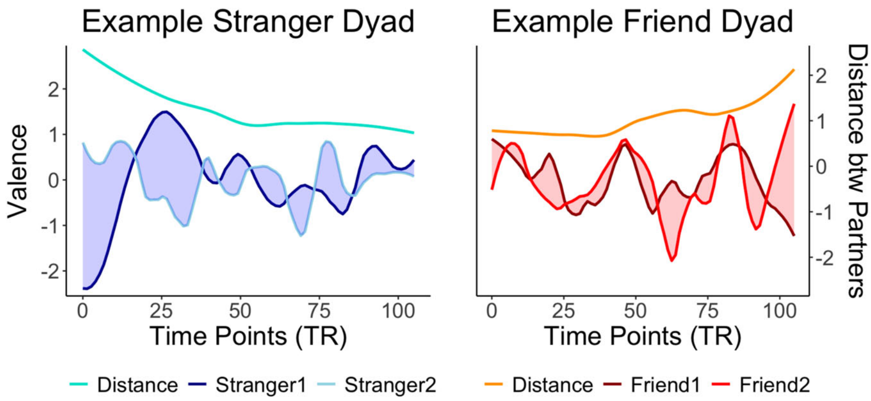

Fig. 2 | Example trajectories for a stranger dyad (left) and a friend dyad (right) along the valence dimension. Only one dimension is plotted to facilitate interpretation. Over the course of a trial, this stranger dyad converged along the valence dimension, whereas the friend dyad diverged. The trajectories and distance lines have been smoothed to facilitate interpretation. For smoothing, a loess regression was used with a 20% smoothing span for individual valence locations and a 70% smoothing span for distance between partners.

model includes closeness, trial number, and time points (within-dyads) as predictors. The analyses revealed significant interactions between time points and closeness, such that when strangers diverged more in linguistic mental state space ($\beta = 0.058$, 95% CI [0.03, 0.09], SE = 0.015, $p < 0.001$; Fig. 6D), they felt closer to their partner. For enjoyment, we again fit three multilevel models, this time using enjoyment as a predictor. These models revealed that when strangers diverged more in neural mental state space ($\beta = 0.0013$, 95% CI [0.0007, 0.0017], SE = 0.0003, $p < 0.001$; Fig. 6B), they enjoyed their conversations more. Lastly, we fit three models using similarity as a predictor. Here we found that when strangers diverged more in linguistic mental state ($\beta = 0.03$, 95% CI [−0.005, 0.06], SE = 0.018, = 0.10; Fig. 6F), neural mental state ($\beta = 0.0005$, 95% CI [−0.00009, 0.001], SE = 0.0002, = 0.10; Fig. 6C), and when they explored more topic space ($\beta = 0.007$, 95% CI [0.0008, 0.011], SE = 0.003, $p = 0.01$; Fig. 6I), they felt more similar to their partners. Together, these results suggest that when strangers have conversations that explore more ground, they have better conversations.

Finally, in an exploratory analysis, we assessed the predictive accuracy of each measure of divergence – neural, linguistic, and topic— in predicting the conversation quality (Supplementary Note 3). A LASSO regression that reduced redundancy between predictors highlighted the contribution of the neural measure: the neural measure most robustly predicted out-of-sample conversation enjoyment ($\beta_{neural\_slope} = 0.14$, 95% $CI_{bootstrapped}$ [0, 0.33],,$\beta_{topic\_slope} = 0.02$, 95% $CI_{bootstrapped}$ [0, 0.20], $\beta_{ling\_slope} = 0$, 95% $CI_{bootstrapped}$ [0, 0.14], $p_{MSE} = 0.009$, $p_{RMSE} = 0.008$; Supplementary Note 3). In addition, a model comparison revealed that a model with just the neural measure had the lowest Bayesian Information criterion of 57.7, indicating the best trade-off between fit and complexity.

Discussion

One of the greatest joys of being human is connecting with others. How do people use conversations to establish these connections? Here, we investigated how two people align their mental states and rove through topics during conversation. We found robust evidence for two distinct strategies: exploring new ground and finding common ground. People used different strategies depending on their social connection. Friends start more mentally aligned than strangers but then diverge in mental state and topic space. In contrast, strangers start more distant and then converge over time. The more a conversation between strangers diverged like a conversation between friends, the more they enjoyed it and felt close and similar to their conversation partner. Thus, the more successful conversation explored more new ground.

Our findings test two complementary theories about what makes for a good conversation. On the one hand, previous literature has proposed that the goal of a conversation is to establish common ground. Common ground is established through physiological, linguistic, postural, and neural synchrony[12–19] and is associated with positive social outcomes such as interpersonal liking, intimacy, cooperation, and social influence[23–28,31,33]. A different stream of literature has emphasized the importance of novelty and exploration in conversations[35,40–42]. Conversations that explore new ground are associated with higher well-being and stronger social ties[43–45]. Our findings demonstrate the merit of both accounts by suggesting that the default strategy depends on whether a social connection exists or the goal is to form a new one. The default tendency when strangers interact is to establish common ground. This is achieved by building mental and linguistic convergence—even if this strategy does not lead to a better conversation. In contrast, when friends converse, they tend to explore new frontiers.

We found convergent evidence for this effect across three distinct measures. To understand the neurocognitive dynamics underlying this difference, we developed models that can decode mental states from conversation partners' neural patterns. This allowed us to track both participants' mental states and their relative distance in mental state space. This preregistered analysis revealed that friends drift apart, whereas strangers converge in neural mental state space. We replicated these findings in linguistic mental state space in parallel exploratory analysis using natural language processing. We derived mental state locations based on participants' words in the conversation. Friends consistently diverge in conversation, whereas strangers converge in linguistic mental state space in later trials. We replicated these findings again in an exploratory analysis using topic modeling to investigate how dyads rove through topic space. Friends generated more topics, switched between topics more frequently, and switched to more distant topics than strangers. Thus, across three distinct measures (neural, linguistic, and topics), we find that friends begin with greater levels of common ground and then explore while strangers begin with less common ground and then converge, or at least diverge more slowly over the course of a conversation. This convergent evidence highlights the robustness of this effect.

Strangers predominantly seek common ground in their conversations. Why might strangers not default to exploring if it has such clear benefits? Conversations can be thought of as spatial foraging, where dyads search for topics found in clusters (like berries on bushes) within an environment abundant with such clusters (e.g., dispersed patches). People should persist in exploring a specific patch until it becomes challenging to locate desired items there. At this point, they

https://doi.org/10.1038/s41467-024-51990-7

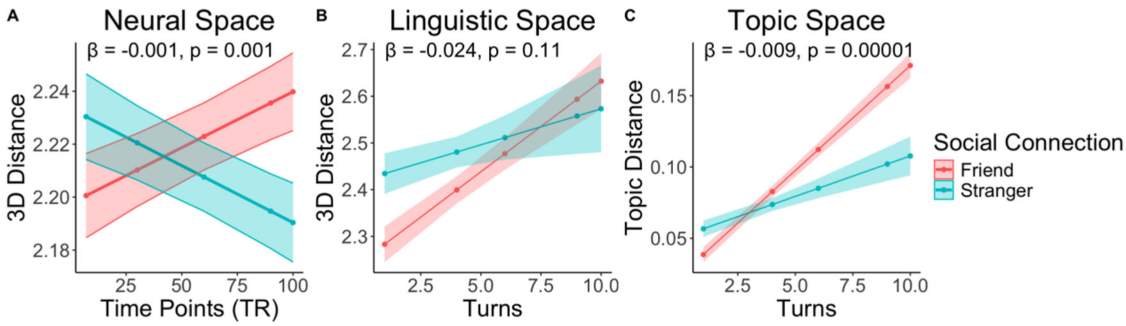

Fig. 3 | Friends ($n = 30$ dyads) diverged more than strangers ($n = 29$ dyads) over time. Two-way interactions between social connection (friend vs. stranger) and time on distance are found across **A** neural space, with time as time points within trials; **B** linguistic space, with time as turns within trials; and **C** topic space, with time as turns within trials. *P* values were derived from multilevel models (no adjustments were made for multiple comparisons). Error bands represent the standard error around the fitted values.

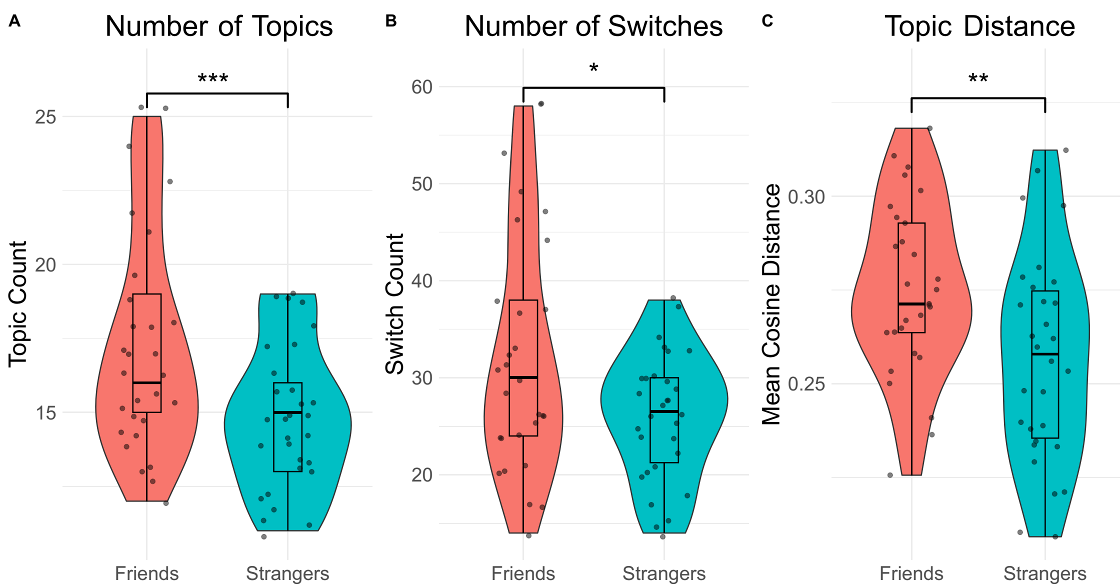

Fig. 4 | Friends ($n = 30$) explored more topics than strangers ($n = 29$) during conversation. Violin plots overlaid on boxplots for **A** the number of topics generated, **B** the number of switches generated, and **C** the mean cosine distance for each dyad are plotted separately for friends (Red) and strangers (Blue). * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.005$. *P* values were derived using two-tailed two-sample t-tests (no adjustments were made for multiple comparisons). The boxplots indicate the median (central line), the interquartile range (IQR; box edges), and the whiskers, which extend to 1.5 times the IQR from the first and third quartiles.

should abandon the current patch to locate a fresh, untouched one. There are risks to exploring—there is no guarantee of finding a new rich patch. In conversation, strangers may exploit topics longer than friends because they are less certain of finding another fruitful topic. By establishing common ground, strangers may learn more about the landscape of potential topics, thus reducing the risk of exploration. This suggests that in the context of the affiliative conversations within this study the two strategies are not mutually exclusive but might be implemented *sequentially*. In fact, preliminary research suggests that strangers in longer conversations begin exploring after a period of converging[62]. Our findings suggest that strangers who take the risk of foraging more may discover more rewarding topics and have more enjoyable conversations. However, it is also possible that strangers who find common ground quickly and feel safe exploring do so because they are already a good match. That is, their initial connection facilitates both exploration and enjoyable conversations.

Exploratory analyses suggest that the neural measure was the best predictor of conversation enjoyment (Supplementary Note 3). This points to an advantage of fMRI hyperscanning measures for predicting the success of a conversation. Words alone may not capture all the psychological drivers of conversation success. The linguistic measures can only capture a speaker's language production, whereas the neural measure has the advantage of continuously tracking both conversation partners' mental states, including during gaps in the conversation and in listeners as they consume language. fMRI also offers advantages over other neuroimaging modalities such as EEG and fNIRS, such as high spatial resolution and detecting activity in midline and subcortical regions. Mentalizing, reward processing, and decoding all three mental state dimensions rely on exactly these regions[54,63]; Figure A1). Nevertheless, future research may benefit from exploring how our findings generalize to other neuroimaging modalities.

Future research should also investigate mental state convergence/divergence in other types of social interactions. Here, we investigated dynamics in mental state alignment during affiliative conversations specifically, with the goal of establishing and strengthening social bonds. This begs the question, how might conversation strategies change when the goals of the conversation change? Do people likewise try to find common ground or explore new ground when trying to persuade, or teach, or learn from another person?[64]. The conversations in this experimental paradigm were somewhat

https://doi.org/10.1038/s41467-024-51990-7

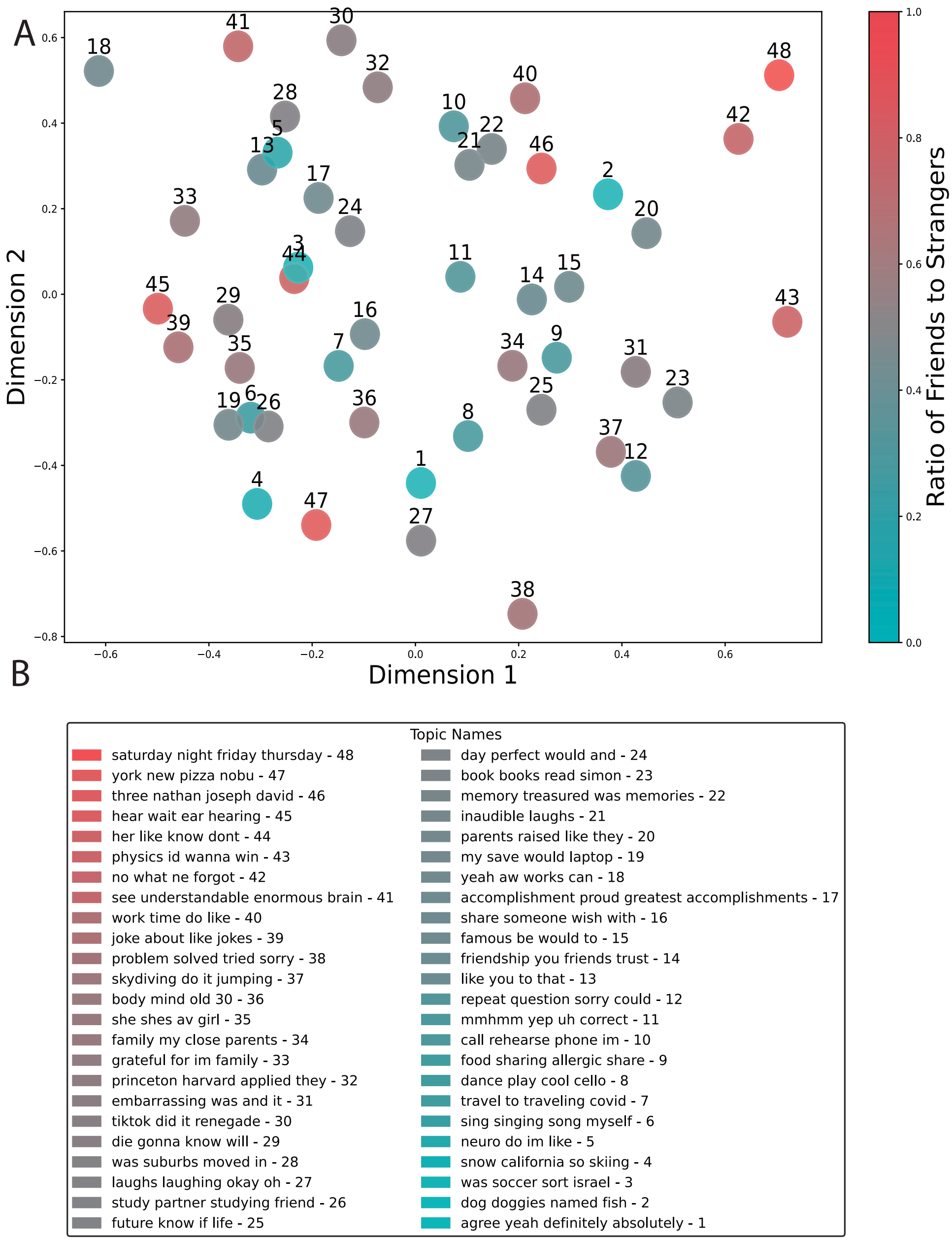

Fig. 5 | Conversation topics discussed by friends vs. strangers. A In this two-dimensional space (created by multidimensional scaling), topics closer together are more semantically related. Topics differed in how frequently friends and strangers discussed them. Topics discussed more by friends (Red) are located more on the fringes of the plot, whereas the topics discussed more by strangers (Blue) tend to be located more towards the center. **B** The topic descriptions are arranged by how frequently friends vs strangers discussed them.

contrived: people were stuck in the scanner and had no choice but to talk to each other. What happens in the real world outside the scanner when strangers talk to each other? People often avoid talking to strangers because they underestimate others' interest in talking to them[3,5]. Investigating how the choice to interact impacts the conversational strategies described here would further illuminate the mechanisms of effective social interaction.

This study helps to answer a perennial question in social life: What makes a good conversation? Across all the analyses, we consistently find that friends explore new ground, whereas strangers focus on finding common ground. When strangers explore like friends, they have more successful conversations. Although people may think they should focus on finding common ground with new acquaintances, transitioning to exploring new ground could help people form relationships more effectively. These findings inform longstanding discussions about the best way to converse and generate insight into how to satisfy people's universal need to connect with others.

Methods

This study aimed to investigate what characterizes a good conversation. Previous research identified two possible routes to success: convergence on shared mental states versus exploration of a wide array of topics and perspectives. In this study, we focused on testing whether the optimal pattern of convergence (finding common ground) and divergence (exploring new ground) differs depending on the dyad's initial relationship (friends vs. strangers). To this end, we used fMRI hyperscanning: 60 dyads engaged in a real-time conversation with discrete prompts and demarcated turns. Half of the recruited dyads self-identified as friends, whereas the other half were strangers.

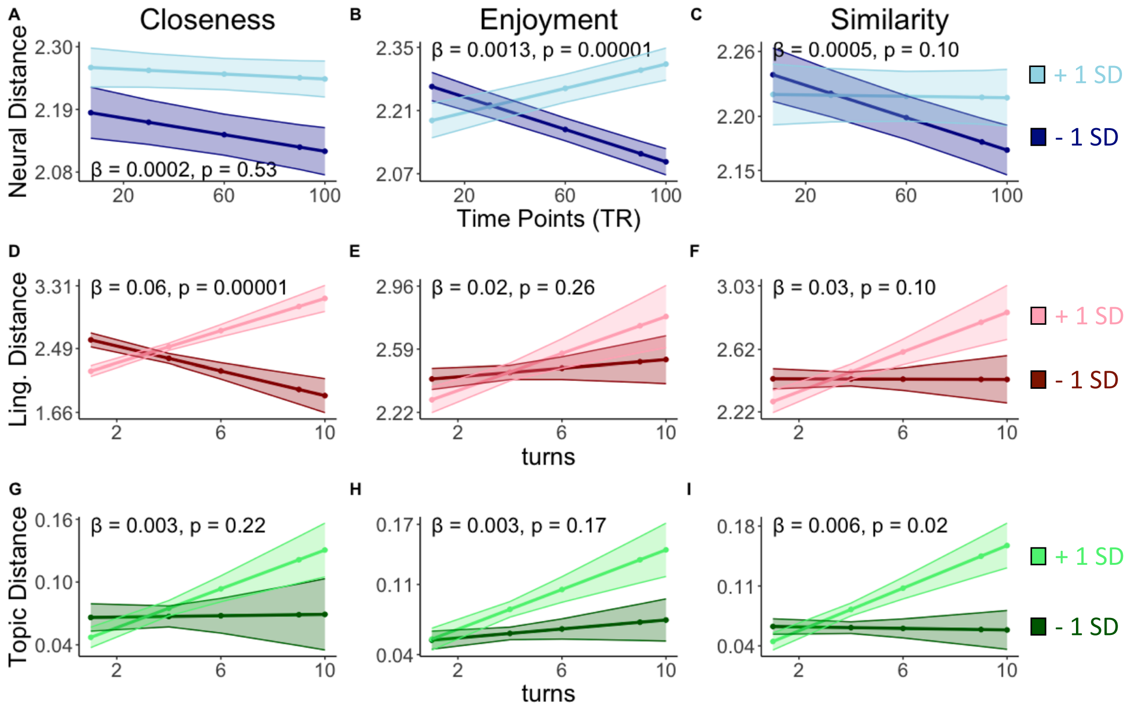

Fig. 6 | Strangers ($n = 29$ Dyads) who explored new ground had better conversations than strangers who found common ground. These plots show the fitted values from nine multilevel models relating the quality of strangers' conversations to the change in distance over time. Quality was measured in three ways: closeness (**A**, **D**, **G**), enjoyment (**B**, **E**, **H**), and similarity (**C**, **F**, **I**), at +1 SD and −1SD for each outcome). Divergence was measured as change in distance on three metrics: neural (blue), linguistic (red), and topic (green). Error bands represent the standard error around the fitted values. SD Standard Deviation.

Previous research has demonstrated that people use three dimensions, namely social impact, rationality, and valence, termed the 3D mind model, to represent the mental states of themselves and others[56–58]. Here, we used this model to assess to what extent dyads converge or diverge in mental state space. To this end, we developed predictive models to decode mental state representations from whole-brain activity patterns, using four previous (independent) fMRI data sets that used mental state judgment tasks designed to evoke neural patterns that vary across the three mental state dimensions. With these models, we decoded participants' 'location' on each dimension at each moment in time (Supplementary Methods).

We subsequently applied these three models to the conversation data (https://osf.io/qsnyj/) to decode to what extent these three dimensions are expressed in each participant's mind. For our primary analyses, we computed the Mahalanobis distance between the two speakers in 3D mental state space at each moment of time across the whole conversation, where a smaller distance represented a higher alignment of mental states between the dyad. These decoded neural metrics of distance in mental state space served as our primary dependent variable. We replicated these analyses using NLP to decode mental state dimensions from text data. Specifically, we used affectR, an NLP algorithm that decodes mental state locations based on the words participants use in conversation (Supplementary Methods). Speech turns were used here, as they are the smallest meaningful unit of analysis at which distance in mental state space between speakers can be computed using linguistic data. We subsequently tested to what extent friends differ from strangers in their mental state alignment (neural and linguistic) over the whole conversation, how alignment changes over time, and how these two factors (friends vs. strangers and time) interact with each other. In addition, we tested how friends and strangers differ in their exploration of different topics throughout the conversation using topic modeling. The analysis plan and all materials for this study were preregistered on the Open Science Framework at: https://osf.io/5d3r7/.

Participants

A total of 63 dyads (126 participants) engaged in a real-time conversation while they were simultaneously scanned using fMRI hyperscanning. Due to technical issues, the data for 4 dyads remained incomplete and were excluded from further analysis. So the final dataset consisted of 30 friend dyads ($n = 60$ participants; age 18–33, $M_{age} = 20.4$, $SD_{age} = 2.8$; 36 women, 24 men, 0 non-binary, African American = 3, Asian = 23, Caucasian = 24, Other = 10), who self-identified as friends and attested that they interact with each other at least four days a week for at least three months and 29 stranger dyads ($n = 58$ participants; age 18-36, $M_{age} = 20.72$, $SD = 3.46$; 41 women, 17 men, 0 non-binary, African American = 8, Asian = 19, Caucasian = 26, Other = 5), who were randomly paired and were unacquainted before the study. All participants had to be at least 18 years old to be eligible for the study. All participants provided informed consent in a manner approved by the Princeton University Institutional Review Board. Sex and gender were not considered in the study design, since this was not part of our preregistered research question. At the point of preregistration, we had no strong hypothesis that conversational strategies and their neural correlates differ systematically across sex or gender. The sample size was determined based on a power analysis to detect a main effect of condition in the neural data ($f = 0.2$) and to replicate the behavioral relation between social content and connection pilot data (power: >95%; alpha: 0.05). Participants received $62 for participating in the study.

Tasks and stimuli

During the scanning session, dyads engaged in a conversation while lying in separate fMRI scanners in two adjacent rooms. The conversations were freeform, which meant that participants could say whatever they wanted, but also scaffolded in that they were given prompts to discuss to ensure that every dyad walked through similar topics. Specifically, in our conversation task, dyads discussed several topic prompts (e.g., If you could wake up tomorrow with one new

Fig. 7 | An example trial as seen from each participant's perspective. Dyads view the discussion prompt for 9 s. Subsequently, they are assigned speaker and listener roles and the speaker starts speaking. The speaker can then press a button to "pass the mic" to the listener. In addition, participants see how much time there is left in the current trial at the bottom of the screen.

ability, what would it be?) from an established social task termed the fast friends procedure[44]. The prompts in our conversation task (i.e., the fast friends procedure) were designed to foster a social connection between conversation partners. This was accomplished by gradually increasing the level of intimacy of the prompts over time. Specifically, there were 20 prompts in total (Supplementary Methods): eight prompts with low intimacy (e.g., Would you like to be famous? In what way?), six prompts with medium intimacy (e.g., What do you value most in a friendship?), and six prompts with high intimacy (e.g., "Share with your partner an embarrassing moment in your life."; Aron et al. [44]). Participants took turns responding. Within each prompt, participants were randomly assigned to who would start as the speaker and who would start as the listener. Once any speaker finished talking, they would press a button to indicate that they finished their turn and that it was the other person's turn to speak. Participants were instructed to fill the full three minutes of each prompt (Fig. 7). It is also important to note that participants saw each other briefly before they went into the scanner and also met briefly after as they went to complete the post-scan questionnaires.

There were two between-dyad conditions, which constitute the primary independent variable: (1) *Friends*: Half of the recruited dyads ($N = 30$) self-identified as friends and attested that they interact at least four days a week for at least 3 months. (2) Strangers: The other half of the participants were strangers. Stranger dyads were paired randomly. This allows us to explore how an existing social connection influences the mental state alignment of dyads during their conversations.

In addition, there were two within-dyad conditions: (i) Generate: On these trials, dyads provided their personal responses to the prompts; this allowed on-the-fly generation, expression, reception, and response to each other's words. (ii) Read: On these trials, dyads read a script provided by experimenters–text from another pair's conversation for a previous study; this preserves the structure of a conversation (speaking, listening, and turn-taking) but prevents participants from generating relevant self or social information or responding accordingly. In all analyses reported in the main text we focus exclusively on the generate condition as participants were only able to form social bonds in this condition. We compare the two conditions in terms of mental state trajectories in the Supplementary Methods. The investigators were not blinded to allocation to the between-dyad and within-dyad conditions during experiments and outcome assessment.

Dyads completed 20 trials, randomly assigned to condition; condition orders were randomized across dyads. Each run included 2 Generate and 2 Read trials. Trials began with the conversation prompt and condition cue (9 s), followed by 180 s of turn-taking. Runs began and ended with a fixation cross (12 s). The protocol included 5 runs, each lasting 13.6 minutes (544 TRs).

Speech recording

We recorded the content of the conversations during the fMRI scan using a customized MR-compatible recording system (FOMRI II; Optoacoustics Ltd). The MR recording system uses two orthogonally oriented optical microphones. The reference microphone records the background noise, whereas the source microphone records both background noise and the speaker's speech utterances (signal). A dual-adaptive filter subtracts the reference input from the source channel (using a least mean squares approach). To guarantee an optimal subtraction, the reference signal is adaptively filtered, where the filter gains are learned continuously from the residual signal and the reference input. To prevent divergence of the filter when speech is present, a voice activity detector is integrated into the algorithm. Lastly, a speech enhancement spectral filtering algorithm further preprocesses the speech output to achieve real-time speech enhancement.

fMRI acquisition

The fMRI images for the dyads were collected using a 3 T Siemens Skyra MRI system and a 3 T Siemens Prisma MRI system. The same scanning parameters were used for both scanners. Functional scans were acquired with whole brain coverage in interleaved order (3.0 mm slice thickness, 3.0 × 3.0 mm in-plane resolution, flip angle = 80°). TE was 28 ms, and TR was 1500 ms. A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 176 sagittal slices, flip angle = 9°, TE = 2.98 ms, TR = 2300 ms). To minimize head movement, participants' heads were stabilized with foam padding.

Preprocessing

The fMRI data was preprocessed using fMRIPrep version 20.2.0, a Nipype-based tool[65] (https://fmriprep.org/en/latest/workflows.html). We chose fMRIPrep because it addresses the challenge of robust and reproducible preprocessing as it automatically adapts a workflow based on best-in-class algorithms to virtually any dataset, enabling high-quality preprocessing without the need for manual intervention[66]. Each T1w volume was corrected for intensity non-uniformity and skull stripped. Spatial normalization to the International Consortium for Brain Mapping 152 Nonlinear Asymmetrical template version 2009c[67] was performed through nonlinear registration, using brain-extracted versions of both T1w volume and template. Brain tissue segmentation of cerebrospinal fluid (CSF), white matter (WM), and gray matter was performed on the brain-extracted T1w. Field map distortion correction was performed by coregistering the functional image to the same-participant T1w image with intensity inverted[68] and constrained with an average field map template[69]. This was followed by coregistration to the corresponding T1w using boundary-based registration[70] with 9 degrees of freedom. Motion correcting transformations, field distortion correcting warp, blood oxygen level-dependent images-to-T1w transformation, and T1w to template Montreal Imaging Institute (MNI) warp were concatenated and applied in a single step using Lanczos interpolation. Physiological noise regressors were extracted using CompCor[71]. Principal components were estimated for the two CompCor variants: temporal (tCompCor) and anatomical (aCompCor). Six tCompCor components were then calculated, including only the top 5% variable voxels within that subcortical mask. For aCompCor, six components were calculated within the intersection of the subcortical mask, and the union of CSF and WM masks was calculated in T1w space, after their projection to the native space of each functional run. Frame-wise displacement[72] was calculated for each functional run using the implementation of Nipype.

Because speaking induces motion artifacts and potential distortions in the magnetic field, an additional denoising step was necessary to clean the data after preprocessing. As a consequence, we performed additional confound regression on the preprocessed data using the six head motion regressors, their cosine, their first derivatives, their squares, the white matter signal, its derivative, its square, the square of its derivative, the cerebrospinal fluid signal, its derivative, its square and the square of its derivative as regressors of no interest. The residuals of this regression (the cleaned data) were then used for further analysis. These regressors were chosen based on a systematic analysis comparing the efficiency of different confound models (Supplementary Methods). The cleaned data were segmented into individual prompts to be able to contrast the generate and the read conditions and to investigate the effect of trials across time.

Exploring differences in the quality of conversations between friends and strangers

After the conversation, participants completed a survey to measure their perceptions of social connection. This survey included questions about enjoyment of the conversation, similarity to the partner, anxiety while speaking and listening, closeness to their partner, desire to interact again, and desire to become friends. We used factor analyses to identify latent clusters that more parsimoniously explain how conversations can differ in terms of the social connection established (Supplementary Methods). We then tested the differences in ratings between friends and strangers on the resulting latent factors using two-sample t-tests. We ensured that the assumptions of the t-test were met. In cases in which the assumption of equal variances was not met we conducted a Welch test instead.

Tracking dyadic distance

Investigating how social connection and time shape neural mental state alignment. For our main analysis, we wanted to investigate how social connection and time interact to shape alignment (convergence vs. divergence) in mental state space. To this end, we needed to track each participant's mental state at each moment in the conversation. We wanted to explore how participants converged (or diverged) in mental state space over the course of the conversation. To achieve this, we developed predictive models to decode mental state representations from whole-brain activity patterns, using four previous independent fMRI data sets that used mental state judgment tasks designed to evoke neural patterns that vary across the three mental state dimensions. The decoding models were trained and tested on four fMRI datasets that are independent of the conversation data. We tested the generalizability of our models using cross-validation and cross-task prediction and, in both cases, found significant prediction accuracy (Supplementary Methods). After the models for each of the three dimensions were trained and validated, our primary analysis applied these three models to each volume of the preprocessed and denoised data from the conversation task for each conversation for each participant to decode to what extent these three dimensions are expressed, and thus which mental states are represented in each participant's mind. We also tested whether the mental state representation we decoded represents participant's own mental states or the mental states of their conversation partner, and found that they represent participant's own mental states (see Supplementary Note 4). After we obtained the values for the three dimensions for each participant and time point, we computed the Mahalanobis distance between the two speakers at each timepoint and computed the average distance across time points within each trial. The Mahalanobis distance was chosen because it is insensitive to the scale of the variables entered, it removes redundant information from correlated variables. As a result, it has become the standard distance measure used for multivariate fMRI analyses[73–75]. All the fMRI analyses reported up until this point were conducted using custom Python (version 3.9) scripts (https://osf.io/qsnyj/). To avoid confounding our analysis with the BOLD response to the onset and offset of the discussion prompt, we truncated each trial by removing the first and last 7 TRs (10.5 s) as recommended by previous research[76].

Given the nested structure of our data (time points within trials within participants), we then conducted a multilevel analysis to test the effect of friendship (friends vs. strangers) and time (time points and trials) on mental state alignment. Since each discussion prompt constituted an independent conversation, we were particularly interested in time points within each prompt. Thus, together with social connection (friend vs. stranger), time points within trials were considered the primary independent variable. The dependent variable was the continuous Mahalanobis distance with a Gaussian link. Friendship served as a dyad-level predictor, whereas time served as a trial-level (trials) and a within-trial-level (time points) predictor. We mean-centered the trial variable to facilitate the interpretation of three-way interaction effects. The models allowed for random intercepts within participants. The multilevel models were implemented in R[77] (version 4.2.1) using the nlme package[78]. We ensured that the assumptions of the models were met.

Investigating how social connection and time shape linguistic mental state alignment. Beyond the preregistered analysis (https://osf.io/5d3r7/), we can also assess dyads' alignment trajectories through mental state space by analyzing their language. This was done to test for convergent evidence across measurement modalities. Specifically, we used a natural language processing (NLP) algorithm, termed affectr (https://github.com/markallenthornton/affectr), to decode mental state location in 3D space based on the words participants chose to say during the conversation (Supplementary Methods). To test whether there is internal consistency between the neural and mental state decoding procedure we used a distance correlation approach and found that the two measures of mental states are internally consistent (Supplementary Note 6).

Subsequently, similar to the neural analysis, to make the two analyses using the 3d mind model comparable, we computed the Mahalanobis distance between each turn in each trial for each conversation. We only used trials with more than three turns, since the number of samples must be larger than the number of dimensions ($N = 3$: rationality, social impact & valence) to compute the covariance matrix needed to calculate the Mahalanobis distance. Speech turns were used here as they are the smallest meaningful unit of analysis at which distance in mental state space between speakers can be computed using linguistic data. As described above, the turns are demarcated by the participants pressing a button to indicate that their turn has ended and the other person can speak. Two dyads only had trials with 3 turns or less; these dyads could not be analyzed using this method. For the remaining 57 dyads, we removed trials with an extreme number of turns, as these trials had turns that were too short to be meaningfully analyzed with our NLP tools. The 1.5 * interquartile range (IQR) rule was used to determine outliers. This rule identified trials with more than 12 turns as outliers. As a consequence, all trials with more than 12 turns were removed from the NLP analysis (529 trials, 17%). To further account for the effects of words per turn, we added the number of words per turn as an additional predictor in our regression models. We also conducted robustness checks with the model without this additional confound regression, which revealed similar results (see Supplementary Note 5).

Similar to the neural analyses, given the nested structure of our data (turns within trials within participants), we then conducted a multilevel analysis to test the effect of friendship (friends vs. strangers) and time (turns and trials) on mental state alignment in the linguistic data. The dependent variable was the continuous Mahalanobis distance with a Gaussian link. The models allowed for random intercepts within participants. Again, trials were mean-centered. This modeling approach enabled us to test whether mental state convergence/divergence in the brain is associated with similar patterns in language. As before, the multilevel models were implemented in R[77] using the nlme package[78]. We ensured that the assumptions of the models were met.

Investigating how social connection and time shape alignment in topic space. In addition to what was preregistered in our analysis plan (https://osf.io/5d3r7/), we also conducted topic analysis. The two previous analyses focused on how distant the conversation partners are in mental state space, but they do not provide insights into what people are talking about that leads to different trajectories in mental state space. To address this question, we used topic modeling to explore how the neural and linguistic mental state dynamics relate to the content of the conversations. We applied BERTopic to our conversation data to extract topic embeddings for each turn in each conversation across all dyads (Supplementary Methods). We then investigated how exploring the content space differs between friends and strangers in several ways. We analyzed the topic data on both the between-dyad and within-dyad level to test to what extent between-dyad versus within-dyad heterogeneity contribute to differences in how friends and strangers explore content space.

We used four different measures of content space exploration. First, we used the difference in the number of topics generated. Second, we investigated the number of switches between topics. This measure also includes switching back to a previous topic discussed within a trial. Third, we computed the pairwise cosine distance between each topic within a dyad and calculated the average across distance to measure how large the explored content space for each dyad was. The cosine distance was used here because topics are encoded in a high-dimensional embedding space (>300 dimensions), which outnumbers the number of samples (in this case, the number of participants), which makes it impossible to compute the Mahalanobis distance. Cosine distance is chosen over the Euclidean distance because the Euclidean distance encounters problems in high dimensional space[79]. In addition, the cosine similarity has been established as the standard distance measure for NLP. It is also the default metric in BERTopic because it does not take into the magnitude of vectors, which is helpful when working with text data where word counts are influenced by the length of the documents, which often vary considerably in NLP analyses. Fourth, to test for the robustness of the distance measure, we performed the same analysis with the Euclidean distance. We applied a two-sample t-test to test whether these measures of content exploration differ between friends and strangers.

Lastly, to mirror the previous analysis on mental state convergence/divergence, we also entered the turn-by-turn topic embeddings into a multilevel model to test the effect of friendship (friends vs. strangers) and time (turns and trials) on divergence in content space in the topic data. The dependent variable was the continuous cosine distance with a Gaussian link. The models allowed for random intercepts within participants. This allowed us to test how time and social connection interact to shape exploration of content space in conversations. We also conducted additional between-dyad topic modeling analysis, which can be found in Supplementary Note 1. We also tested whether mental state divergence is directly associated with topic exploration, and found significant correlations both with the linguistic and the neural measures (see Supplementary Note 7).

Citation diversity statement

Recent work in several fields of science has identified a bias in citation practices such that papers from women and other minority scholars are under-cited relative to the number of such papers in the field[80–83]. Here we sought to proactively consider choosing references that reflect the diversity of the field in thought, form of contribution, gender, race, ethnicity, and other factors. First, we obtained the predicted gender of the first and last author of each reference by using databases that store the probability of a first name being carried by a woman[83]. By this measure and excluding self-citations to the first and last authors of our current paper), our references contain 14.63% woman(first)/woman(last), 17.07% man/woman, 25.32% woman/man, and 42.98% man/man. This method is limited in that a) names, pronouns, and social media profiles used to construct the databases may not, in every case, be indicative of gender identity and b) it cannot account for intersex, non-binary, or transgender people. Second, we obtained predicted racial/ethnic category of the first and last author of each reference by databases that store the probability of a first and last name being carried by an author of color[83]. By this measure (and excluding self-citations), our references contain 3.56% author of color (first)/author of color(last), 12.74% white author/author of color, 18.05% author of color/white author, and 65.64% white author/white author. This method is limited in that a) names and Florida Voter Data to make the predictions may not be indicative of racial/ethnic identity, and b) it cannot account for Indigenous and mixed-race authors, or those who may face differential biases due to the ambiguous racialization or ethnicization of their names. We look forward to future work that could help us to better understand how to support equitable practices in science.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The preprocessed neural data can be obtained by contacting the authors while additional studies using the same dataset are still ongoing. Once access is granted the preprocessed data will be available interminably. The processed output of the neural data needed to reproduce the results in the main text are available on OSF (https://osf.io/qsnyj/, https://osf.io/qsnyj/, https://doi.org/10.17605/OSF.IO/QSNYJ). The raw text data are not available to protect participant privacy. The processed output of the text data are available on OSF (https://osf.io/qsnyj/, https://osf.io/qsnyj/, https://doi.org/10.17605/OSF.IO/QSNYJ). This repository also contains a minimum dataset that can be used to interpret, verify, and extend the research in the article.

Code availability

All code to reproduce the analyses and results reported in this manuscript is available on: https://osf.io/qsnyj/ (https://doi.org/10.17605/OSF.IO/QSNYJ).

References

1. Wray, A. & Grace, G. W. The consequences of talking to strangers: evolutionary corollaries of socio-cultural influences on linguistic form. *Lingua* **117**, 543–578 (2007).
2. Van Burgsteden, L., Te Molder, H. & Raymond, G. The turn-by-turn unfolding of "dialogue": examining participants' orientations to moments of transformative engagement. *Lang. Commun.* **82**, 64–81 (2022).
3. Epley, N. & Schroeder, J. Mistakenly seeking solitude. *J. Exp. Psychol. Gen.* **143**, 1980–1999 (2014).
4. Sandstrom, G. M. & Dunn, E. W. Social interactions and well-being: the surprising power of weak ties. *Pers. Soc. Psychol. Bull.* **40**, 910–922 (2014).
5. Schroeder, J., Lyons, D. & Epley, N. Hello, stranger? Pleasant conversations are preceded by concerns about starting one. *J. Exp. Psychol. Gen.* **151**, 1141–1153 (2022).
6. Mastroianni, A. M., Gilbert, D. T., Cooney, G. & Wilson, T. D. Do conversations end when people want them to? *Proc. Natl Acad. Sci.* **118**, e2011809118 (2021).
7. Boothby, E. J., Cooney, G., Sandstrom, G. M. & Clark, M. S. The liking gap in conversations: do people like us more than we think? *Psychol. Sci.* **29**, 1742–1756 (2018).
8. Pollmann, M. M. H. & Krahmer, E. J. How do friends and strangers play the game *Taboo*? **37**, 497–517 (2018).
9. Fussell, S. R. & Krauss, R. M. The effects of intended audience on message production and comprehension: reference in a common ground framework. *J. Exp. Soc. Psychol.* **25**, 203–219 (1989).
10. Clark, H. H. & Brennan, S. E. Grounding in communication. in *Perspectives on socially shared cognition*. (eds. Resnick, L. B., Levine, J. M. & Teasley, S. D.) 127–149 https://doi.org/10.1037/10096-006 (American Psychological Association, Washington, 1991).
11. Giles, H., & Ogay, T. Communication accommodation theory. In B.B. Whaley & W. Samster (Eds.) *Explaining Communication: Contemporary Theories and Exemplars*, 293–310 (Routledge, 2007).
12. Garrod, S. & Pickering, M. J. Why is conversation so easy? *Trends Cogn. Sci.* **8**, 8–11 (2004).
13. Garrod, S. & Pickering, M. J. Joint action, interactive alignment, and dialog. *Top. Cogn. Sci.* **1**, 292–304 (2009).
14. Church, R. B., Kelly, S. & Holcombe, D. Temporal synchrony between speech, action and gesture during language production. *Lang. Cogn. Neurosci.* **29**, 345–354 (2014).
15. Shockley, K., Santana, M.-V. & Fowler, C. A. Mutual interpersonal postural constraints are involved in cooperative conversation. *J. Exp. Psychol. Hum. Percept. Perform.* **29**, 326–332 (2003).
16. Konvalinka, I. et al. Synchronized arousal between performers and related spectators in a fire-walking ritual. *Proc. Natl. Acad. Sci.* **108**, 8514–8519 (2011).
17. Hasson, U., Nir, Y., Levy, I., Fuhrmann, G. & Malach, R. Intersubject synchronization of cortical activity during natural vision. *Science* **303**, 1634–1640 (2004).
18. Schmälzle, R., Häcker, F. E. K., Honey, C. J. & Hasson, U. Engaged listeners: shared neural processing of powerful political speeches. *Soc. Cogn. Affect. Neurosci.* **10**, 1137–1143 (2015).
19. Stephens, G. J., Silbert, L. J. & Hasson, U. Speaker–listener neural coupling underlies successful communication. *Proc. Natl. Acad. Sci.* **107**, 14425–14430 (2010).
20. Yeshurun, Y. et al. Same story, different story: the neural representation of interpretive frameworks. *Psychol. Sci.* **28**, 307–319 (2017).
21. Leong, Y. C., Chen, J., Willer, R. & Zaki, J. Conservative and liberal attitudes drive polarized neural responses to political content. *Proc. Natl. Acad. Sci.* **117**, 27731–27739 (2020).
22. Hasson, U. et al. Shared and idiosyncratic cortical activation patterns in autism revealed under continuous real-life viewing conditions. *Autism Res.* **2**, 220–231 (2009).
23. Doré, B. P. & Morris, R. R. Linguistic synchrony predicts the immediate and lasting impact of text-based emotional support. *Psychol. Sci.* **29**, 1716–1723 (2018).
24. Ireland, M. E. et al. Language Style Matching Predicts Relationship Initiation and Stability. *Psychol. Sci.* **22**, 39–44 (2011).
25. Putman, W. B. & Street, R. L. The conception and perception of noncontent speech performance: implications for speech-accommodation theory. *Int. J. Sociol. Lang.* **1984**, (1984).
26. Street, R. L., Brady, R. M. & Putman, W. B. The influence of speech rate stereotypes and rate similarity or listeners' evaluations of speakers. *J. Lang. Soc. Psychol.* **2**, 37–56 (1983).
27. Ludwig, S. et al. More than words: the influence of affective content and linguistic style matches in online reviews on conversion rates. *J. Mark.* **77**, 87–103 (2013).
28. Jacob, C., Guéguen, N., Martin, A. & Boulbry, G. Retail salespeople's mimicry of customers: effects on consumer behavior. *J. Retail. Consum. Serv.* **18**, 381–388 (2011).
29. Ramseyer, F. & Tschacher, W. Nonverbal synchrony in psychotherapy: coordinated body movement reflects relationship quality and outcome. *J. Consult. Clin. Psychol.* **79**, 284–295 (2011).
30. Tanner, R. J., Ferraro, R., Chartrand, T. L., Bettman, J. R. & Baaren, R. V. Of chameleons and consumption: the impact of mimicry on choice and preferences. *J. Consum. Res.* **34**, 754–766 (2008).
31. Valdesolo, P. & DeSteno, D. Synchrony and the social tuning of compassion. *Emotion* **11**, 262–266 (2011).
32. Tunçgenç, B. & Cohen, E. Interpersonal movement synchrony facilitates pro-social behavior in children's peer-play. *Dev. Sci.* **21**, e12505 (2018).
33. Wiltermuth, S. S. & Heath, C. Synchrony and cooperation. *Psychol. Sci.* **20**, 1–5 (2009).
34. Parkinson, C., Kleinbaum, A. M. & Wheatley, T. Similar neural responses predict friendship. *Nat. Commun.* **9**, 332 (2018).
35. Westgate, E. C. & Wilson, T. D. Boring thoughts and bored minds: The MAC model of boredom and cognitive engagement. *Psychol. Rev.* **125**, 689–713 (2018).
36. Bennett, D., Bode, S., Brydevall, M., Warren, H. & Murawski, C. Intrinsic valuation of information in decision making under uncertainty. *PLOS Comput. Biol.* **12**, e1005020 (2016).
37. Mason, M. F. & Bar, M. The effect of mental progression on mood. *J. Exp. Psychol. Gen.* **141**, 217–221 (2012).
38. Pronin, E. & Jacobs, E. Thought speed, mood, and the experience of mental motion. *Perspect. Psychol. Sci.* **3**, 461–485 (2008).
39. See, A., Roller, S., Kiela, D. & Weston, J. What makes a good conversation? How controllable attributes affect human judgments. Preprint at http://arxiv.org/abs/1902.08654 (2019).
40. Templeton, E. M., Chang, L. J., Reynolds, E. A., Cone LeBeaumont, M. D. & Wheatley, T. Fast response times signal social connection in conversation. *Proc. Natl Acad. Sci. USA* **119**, e2116915119 (2022).
41. Kardas, M., Kumar, A. & Epley, N. Overly shallow? Miscalibrated expectations create a barrier to deeper conversation. *J. Pers. Soc. Psychol.* **122**, 367–398 (2022).
42. Cooney, G., Gilbert, D. T. & Wilson, T. D. The novelty penalty: why do people like talking about new experiences but hearing about old ones? *Psychol. Sci.* **28**, 380–394 (2017).
43. Mehl, M. R., Vazire, S., Holleran, S. E. & Clark, C. S. Eavesdropping on happiness: well-being is related to having less small talk and more substantive conversations. *Psychol. Sci.* **21**, 539–541 (2010).
44. Aron, A., Melinat, E., Aron, E., Vallone, R. & Bator, R. The experimental generation of interpersonal closeness: a procedure and some preliminary findings. *Pers. Soc. Psychol. Bull.* **23**, 363–377 (1997).
45. Slepian, M. L. & Moulton-Tetlock, E. Confiding secrets and well-being. *Soc. Psychol. Personal. Sci.* **10**, 472–484 (2019).

46. Knapp, M. L., Ellis, D. G. & Williams, B. A. Perceptions of communication behavior associated with relationship terms. *Commun. Monogr.* **47**, 262–278 (1980).
47. Planalp, S. & Benson, A. Friends' and acquaintances' conversations i: perceived differences. *J. Soc. Pers. Relatsh.* **9**, 483–506 (1992).
48. Templeton, E. M., Chang, L. J., Reynolds, E. A., Cone LeBeaumont, M. D. & Wheatley, T. Long gaps between turns are awkward for strangers but not for friends. *Philos. Trans. R. Soc. B Biol. Sci.* **378**, 20210471 (2023).
49. Clark, H. H. & Marshall, C. R. Definite reference and mutual knowledge. In Joshi, A. K., Webber, B. L. & Sag, I. A. (eds) Elements of Discourse Understanding, 10–63 (Cambridge University Press, 1981).
50. Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K. & Harshman, R. Indexing by latent semantic analysis. *J. Am. Soc. Inf. Sci.* **41**, 391–407 (1990).
51. Hornstein, G. A. Intimacy in conversational style as a function of the degree of closeness between members of a dyad. *J. Personal. Soc. Psychol.* **49**, 671–681 (1985).
52. Planalp, S. Friends' and acquaintances' conversations II: coded differences. *J. Soc. Pers. Relatsh.* **10**, 339–354 (1993).
53. Tsang, S., Lipson, J., Snyder, A. & Wood, A. People constrain their semantic associations when talking to both friends and strangers. *J. Exp. Psychol. Gen.* **153**, 1407–1413 (2024)
54. Kelsen, B. A., Sumich, A., Kasabov, N., Liang, S. H. Y. & Wang, G. Y. What has social neuroscience learned from hyperscanning studies of spoken communication? A systematic review. *Neurosci. Biobehav. Rev.* **132**, 1249–1262 (2022).
55. Redcay, E. & Schilbach, L. Using second-person neuroscience to elucidate the mechanisms of social interaction. *Nat. Rev. Neurosci.* **20**, 495–505 (2019).
56. Tamir, D. I., Thornton, M. A., Contreras, J. M. & Mitchell, J. P. Neural evidence that three dimensions organize mental state representation: Rationality, social impact, and valence. *Proc. Natl. Acad. Sci. USA* **113**, 194–199 (2016).
57. Tamir, D. I. & Thornton, M. A. Modeling the predictive social mind. *Trends Cogn. Sci.* **22**, 201–212 (2018).
58. Thornton, M. A. & Tamir, D. I. People represent mental states in terms of rationality, social impact, and valence: validating the 3d Mind Model. *Cortex* **125**, 44–59 (2020).
59. Kragel, P. A., Koban, L., Barrett, L. F. & Wager, T. D. Representation, pattern information, and brain signatures: from neurons to neuroimaging. *Neuron* **99**, 257–273 (2018).
60. Huth, A. G., Nishimoto, S., Vu, A. T. & Gallant, J. L. A continuous semantic space describes the representation of thousands of object and action categories across the human brain. *Neuron* **76**, 1210–1224 (2012).
61. Huth, A. G., de Heer, W. A., Griffiths, T. L., Theunissen, F. E. & Gallant, J. L. Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature* **532**, 453–458 (2016).
62. Sened, H., Speer, S. P. H., Cooney, G., Reece, A. G. & Tamir, D. I. The temporal arc of successful conversations. *Soc. Personal. Soc. Psychol. 2024 Conference San Diego CA* (2024).
63. Alkire, D., Levitas, D., Warnell, K. R. & Redcay, E. Social interaction recruits mentalizing and reward systems in middle childhood. *Hum. Brain Mapp.* **39**, 3928–3942 (2018).
64. Maës, E., Blache, P. & Becerra-Bonache, L. Shared knowledge in natural conversations: can entropy metrics shed light on information transfers? In *Proc. 26th Conference on Computational Natural Language Learning (CoNLL)*, 213–227 (Association for Computational Linguistics, 2022).
65. Gorgolewski, K. et al. Nipype: a flexible, lightweight and extensible neuroimaging data processing framework in Python. *Front. Neuroinform.* **5**, (2011).
66. Esteban, O. et al. fMRIPrep: a robust preprocessing pipeline for functional MRI. *Nat. Methods* **16**, 111–116 (2019).
67. Esteban, O. et al. Surface-driven registration method for the structure-informed segmentation of diffusion MR images. *NeuroImage* **139**, 450–461 (2016).
68. Caballero-Gaudes, C. & Reynolds, R. C. Methods for cleaning the BOLD fMRI signal. *NeuroImage* **154**, 128–149 (2017).
69. Tustison, N. J. et al. Pulmonary kinematics from tagged hyperpolarized helium-3 MRI. *J. Magn. Reson. Imaging* **31**, 1236–1241 (2010).
70. Smith, S. M. et al. Accurate, robust, and automated longitudinal and cross-sectional brain change analysis. *NeuroImage* **17**, 479–489 (2002).
71. Cox, R. W. & Hyde, J. S. Software tools for analysis and visualization of fMRI data. *NMR Biomed.* **10**, 171–178 (1997).
72. Treiber, J. M. et al. Characterization and correction of geometric distortions in 814 diffusion weighted images. *PLOS ONE* **11**, e0152472 (2016).
73. Allefeld, C. & Haynes, J.-D. Searchlight-based multi-voxel pattern analysis of fMRI by cross-validated MANOVA. *NeuroImage* **89**, 345–357 (2014).
74. Nili, H. et al. A toolbox for representational similarity analysis. *PLoS Comput. Biol.* **10**, e1003553 (2014).
75. Bobadilla-Suarez, S., Ahlheim, C., Mehrotra, A., Panos, A. & Love, B. C. Measures of neural similarity. *Comput. Brain Behav.* **3**, 369–383 (2020).
76. Nastase, S. A., Gazzola, V., Hasson, U. & Keysers, C. Measuring shared responses across subjects using intersubject correlation. *Soc. Cogn. Affect. Neurosci.* nsz037 https://doi.org/10.1093/scan/nsz037 (2019).
77. R Core Team. R: A Language and Environment for Statistical Computing (2022).
78. Pinheiro, J., Bates, D. & R. Core Team. nlme: linear and nonlinear mixed effects models. R package version 3.1–165, https://CRAN.R-project.org/package=nlme (2024).
79. Aggarwal, C. C., Hinneburg, A. & Keim, D. A. On the surprising behavior of distance metrics in high dimensional space. In *Database Theory — ICDT 2001* (eds. Van den Bussche, J. & Vianu, V.) vol. 1973, 420–434 (Springer Berlin Heidelberg, Berlin, Heidelberg, 2001).
80. Dworkin, J. D. et al. The extent and drivers of gender imbalance in neuroscience reference lists. *Nat. Neurosci.* **23**, 918–926 (2020).
81. Dworkin, J., Zurn, P. & Bassett, D. S. (In) citing action to realize an equitable future. *Neuron* **106**, 890–894 (2020).
82. Kozlowski, D., Larivière, V., Sugimoto, C. R. & Monroe-White, T. Intersectional inequalities in science. *Proc. Natl. Acad. Sci. USA* **119**, e2113067119 (2022).
83. Zhou, D. et al. Gender diversity statement and code notebook v1.0. https://github.com/dalejn/cleanBib (2020).

Acknowledgements

This work was supported by NIMH grant R21MH127284 and PNI Research Innovator Award to D.I.T. and NIH fellowship grant F32MH120951 to L.T. This publication was supported by the Princeton University Library Open Fund Access Fund. The authors thank Zaid Zada and Uri Hasson for their feedback on earlier versions of this manuscript, and members of the Princeton Social Neuroscience Laboratory for helpful discussions. Funding for the acquisition of the data was provided in part by the Regina and John Scully '66 Center for the Neuroscience of Mind and Behavior.

Author contributions

Conceptualization: S.P.H.S., L.M.T., E.B.F., D.I.T. Methodology: S.P.H.S., L.M.T., L.T., S.M.B., E.B.F., D.I.T. Investigation: L.T., S.M.B. Formal analysis: S.P.H.S., L.M.T. Visualization: S.P.H.S. Funding acquisition: L.T., D.I.T., E.B.F. Project administration: E.B.F., D.I.T. Supervision: E.B.F., D.I.T.

Writing—original draft: S.P.H.S. Writing—review & editing: S.P.H.S., L.M.T., L.T., S.M.B., E.B.F., D.I.T.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41467-024-51990-7.

Correspondence and requests for materials should be addressed to Sebastian P. H. Speer.

Peer review information *Nature Communications* thanks Takahiko Koike, and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. A peer review file is available.

Reprints and permissions information is available at http://www.nature.com/reprints