Virtual (Zoom) Interactions Alter Behavioral Cooperation, Neural Activation, and Dyadic Neural Coherence

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ABSTRACT

A growing number of social interactions are taking place virtually on video conferencing platforms. Here, we explore potential effects of virtual interactions on observed behavior, subjective experience, and neural "single-brain" and "inter-brain" activity via functional near-infrared spectroscopy (fNIRS) neuroimaging. We scanned a total of 72 participants (36 dyads) who engaged with their partner in three naturalistic tasks (i.e., problem-solving, creative-innovation, socio-emotional task), in either an in-person or virtual (Zoom®) condition. We also coded cooperative behavior from audio recordings. We found increased and sustained prefrontal activation in the virtual condition, potentially providing a neural basis of "Zoom® fatigue". We also observed reduced behavioral cooperation (i.e., conversational turn-taking), and altered patterns of averaged and dynamic inter-brain coherence, in virtual interactions. Inter-brain coherence patterns that were characteristic of the virtual condition were associated with reduced behavioral cooperation. These insights can inform the design and engineering of the next generation of video conferencing technology.

Keywords: Functional near-infrared spectroscopy (fNIRS), hyperscanning, virtual interaction, social neuroscience, cooperation

1. Introduction

Video conferencing technology is an increasingly integral part of business[1], education[2], healthcare[3] and leisure activities[4], especially during the COVID-19 pandemic. Given the prevalence of video conferencing, a growing number of empirical studies have considered the potential effects of this technology on the quality and nature of social interaction across different contexts. Research in this area, however, has produced mixed findings as to whether video conferencing has negative, positive, or no impact on the quality of social interaction. Some studies have found that virtual interactions are no different from in-person interactions in terms of perceived effectiveness and performance in administering neuropsychological assessments[5], psychotherapy[6], educational activities[7,8], facilitating social connectedness[9], and participating in leisure activities such as yoga[4]. In contrast, other studies found that virtual interaction led to or was associated with a reduction in perceived therapeutic skills[10] and reduced memory function in health care workers[11], a decline in exam performance[12], and increased communication and management problems in the workplace[13]. Researchers have also examined potential impacts on multisensory perception that may arise from small, variable transmission delays during video conferencing[14]. While one study found no performance differences in a multisensory motion perception task when comparing a virtual with an in-person setting[15], another study demonstrated that transmission delays during video conferencing disrupt the natural rhythm of a conversation, leading to delays in turn initiation[16]. Potentially related, there is both anecdotal and empirical evidence that prolonged virtual interactions lead to feelings of exhaustion and irritation, a mental state commonly referred to as "Zoom® fatigue"[17–21]. Researchers demonstrated that frequency, duration, and time between video conferencing were associated with a higher level of fatigue. In turn, this fatigue was associated with negative attitudes towards the video conferencing[22]. The same researchers suggest that increased Zoom® fatigue could be caused by an increase in cognitive effort related to heightened self-focused attention, the experience of looking at a grid of staring faces with increased eye contact, inhibition of body movement, and production and interpretation of unnatural nonverbal cues in virtual interactions such as nodding in an exaggerated way to signal agreement[19]. Neuroimaging-based measures of cognitive effort may advance our understanding of the mechanistic effects of video conferencing technology on social interaction. Specifically, we propose that functional near-infrared spectroscopy (fNIRS) is a potentially informative tool to investigate neural and inter-brain differences between virtual and in-person interactions in a naturalistic setting[23].

Functional NIRS is an optical brain imaging modality that measures changes in cortical oxygenation which occur when regions of the cortex become active[24,25]. The major advantages of fNIRS over other neuroimaging technologies are its relative tolerance to movement and increased portability that enable the assessment of neural activity and behavior under naturalistic conditions[26]. Importantly, increased cortical oxygenation, especially in prefrontal areas, has been used as a neural measure of cognitive load and effort[27–29]. About a decade ago researchers extended fNIRS neuroimaging from assessing single-brain functioning to multi-brain "hyperscanning" experiments to gain novel insights into neural activity across interacting individuals[30,31]. Researchers have especially focused on studying when and how neural processes become synchronized, and how inter-brain coherence ("IBC", i.e., correlation of cortical activity between brains) relate to behavioral measures of interaction[23,32,33]. Prior studies have found that increased IBC is associated with synchronously executed activities such as joint limb movement[34–36], coordinated button presses[30,31,37], singing[38,39], drumming[40], and walking[41]. Beyond the mere engagement for the same activity, it appears that shared attention is important for the occurrence of IBC. Studies have found increased IBC when pairs completed a task together in contrast to completing the identical task (simultaneously) alone[42–47]. In addition to joint attention, research shows that joint goal-directed intention is related to IBC[48], and dyads demonstrate increased IBC when cooperating in contrast to

when competing with one another[31,49]. Increased IBC has also been observed in other prosocial interaction contexts such as in-group bonding[50], empathy[51], and after gift exchanges[52,53]. While earlier fNIRS hyperscanning studies primarily utilized computerized, experimental tasks to study IBC[e.g.,30,31], recent work has shifted towards studying IBC in more naturalistic contexts. For example, researchers have assessed the occurrence of IBC during unstructured collaborative conversation tasks focused on joint problem-solving[54], creative-innovation[55] or socio-emotional experiences during psychological counseling[56]. As highlighted in recent literature reviews[23,32,33,57], analytic approaches have most commonly utilized task-averaging to assess mean levels of IBC at the region specific level. We refer to these analytical approaches as "averaged" in this paper. One limitation of these approaches is that they do not consider changes in IBC that reflect the dynamic nature of social interaction. To overcome this methodological limitation, researchers have recently proposed a novel analytical approach that captures the dynamic modulation of the IBC pattern[58]. We utilize both averaged and dynamic IBC analytical approaches in this study to provide both standard and time-varying insights into social interaction.

This study explored the potential impacts of virtual interactions on observed behavior, subjective experience, and "single-brain" and "inter-brain" activity. Using a portable fNIRS neuroimaging system, we measured cortical activation from dyads who interacted within the context of either an **in-person or virtual condition**. Dyads performed three naturalistic paradigms including a **problem-solving task, a creative-innovation task, and a socio-emotional task**. We further observed behavior based on audio recordings (i.e., conversational turn-taking and observed performance) and measured participants' subjective experiences during the experiment (i.e., affective responses, subjective cooperation, subjective performance, and interpersonal closeness). Data analyses focused on: (1) elucidating differences between in-person and virtual interactions with respect to observed behavior, subjective experience, brain functioning, and (averaged and dynamic) inter-brain coherence; and (2) to exploring potential associations among these measures.

2. Materials and Methods

The experimental methodology was approved by Stanford's Institutional Review Board (IRB #18160) and followed COVID-19 regulations for human experimentation as defined by the Stanford University School of Medicine.

Participants

A total of 72 adults participated in the study (*N* = 36 female, *N* = 36 male, mean age: 27.11 ± 7.57 years). All participants were healthy, right-handed, and had normal or corrected to normal hearing and vision. The study followed a between-subject design and we randomly assigned dyads to either an in-person or virtual interaction condition. Participants of the same dyad were previously unacquainted. Both conditions included six female-female, six male-male, and six female-male dyads. We recruited participants through local advertisement on flyers, email lists, and social media. We obtained written consent and compensated participants with an Amazon gift card ($ 25 USD per hour). The experimental procedure lasted approximately three hours.

Experimental Procedure

In the in-person condition, dyad partners sat face-to-face at the opposite side of a squared table. In compliance with COVID-19 regulations, participants kept 9-feet distance and wore clear "anti-fog" face masks that were approved by the US Food and Drug Administration. In the virtual condition, dyad partners sat at desks in two separate and auditorily disconnected rooms and interacted over video conferencing using Zoom® (Zoom Video Communications, Inc.). To eliminate the potential confound of wearing a mask in only one condition, participants of the virtual condition also wore clear face masks throughout the experiment. We used two identical laptops for

the virtual interaction (Lenovo Yoga 730-730-15IKB, 15.6") and set Zoom® settings to full screen without self-view windows. We attached fNIRS caps while participants were in the same room or while the Zoom® connection was already established. We instructed participants to not talk to one another during that time. Before starting the experiment, participants had three minutes to introduce themselves to one another. Participants were alone in the room and received task instructions via audio prompts. Dyads completed three experimental tasks and filled out subjective experience questionnaires after each task. We collected video- and audio recordings of the participants. After the experiment, each participant completed additional assessments in separate rooms to assess personality traits, creative ability, and familiarity with virtual (Zoom®) interactions.

Experimental Tasks

We designed the experiment to explore potential impacts of virtual interactions on observed behavior, subjective experience, and neural mechanisms across diverse interaction tasks intended to simulate collaborative activities that are important in workplace environments. Specifically, we selected three naturalistic collaboration tasks: (1) a problem-solving task, (2) a creative-innovation task, and (3) a socio-emotional task. Dyads collaborated on each task for eight minutes with no interventions. The task order was randomized across participants, and we separated tasks by a two-minute calming video of a beach to minimize carryover effects across tasks.

The *problem-solving task* resembled a naturalistic team discussion in industry that requires reasoning, rationalizing, and consensus decision-making. In this task, dyads were asked to solve problems related to traffic rules. One of the study inclusion criteria was therefore possession of a valid US driver's license. We asked participants to collaborate and identify the four most important traffic rules that enhance safety on US highways. To emphasize the importance of each rule, participants had to describe how a chosen rule enhances safety on US highways and why the rule was more important than other traffic rules. We instructed the dyads to write down their rules and safety justification after completion of the task. We administered a *creative-innovation task* influenced by Design Thinking practices[55]. The task resembled a creative brainstorming session in a Research and Development unit. We asked participants to collaborate and design a solution that could increase water conservation in the highest possible number of households in California. The solution could take any form (i.e., product, process, campaign, etc.). We instructed dyads to write down their solution after completion of the task. For the *socio-emotional task,* we asked participants to engage in a modified version of a Nonviolent Communication (NVC) exercise that is used to increase interpersonal closeness between individuals[59]. We provided participants with a NVC list of "Needs We All Have"[59] (i.e., we selected the 10 needs within the "connectedness" section) and asked participants to collaborate and identify four needs from the list that were most meaningful to them. To emphasize the importance of each need, participants had to describe a situation from their life when that need was not met and how it made them feel. We instructed the partner to actively listen, to acknowledge the feelings of the one who shared and to describe why the need was also meaningful to them. We instructed dyads that they would have to describe their list of needs to an experimenter after completion of the task.

Behavioral Assessments

We captured video and audio recording of participants during the experiment and derived two behavioral assessments based on audio recording, including conversational turn-taking and observed performance.

Conversational Turn-taking. From the audio recordings, we counted the number of turn-taking events between dyad partners for each task.

Observed Performance. For the problem-solving task, two researchers (author S.B. and trained research assistant) rated the level of obtained safety, individually for each of the four traffic rules on a five-point scale ranging from 1 ("very low") to 5 ("very high"). We averaged the scores across the four rules to generate the final problem-solving performance score. Inter-rater reliability index was good (interclass correlation coefficient [ICC] = 0.803). We repeated the procedure for the creative-innovation task and two researchers rated the level of creative-innovation as performance rating. Both raters had expertise in assessing creative-innovation according to the Stanford Design School principles (authors S.B. and G.H.). Specifically, we assessed the creative-innovation rating based on four subscales, including *fluency* (i.e., total number of solution elements), *originality* (i.e., statistical rarity of the response across answers in this study), *elaboration* (i.e., level of imagination and exposition of detail), and *accountability* (i.e., effectiveness of water conservation) as derived from[60]. We obtained the ratings on a five-point scale ranging from 1 ("very low") to 5 ("very high") and averaged the scores from these four subscales to get the final creative-innovation performance score. Inter-rater reliability index was good (ICC = 0.855). For the socio-emotional task, two researchers (author S.B. and trained research assistant) blindly rated the performance by listening to the conversations through recorded audio material. To blind the audio files, we first applied an audio effect filter to the recordings (i.e., https://voicechanger.io/; "old radio" filter; distortion = 55; effect = 1). We blindly rated performance based on (1) the level of vulnerability and openness and (2) level of emphatic response for each dyad partner from 1 ("very low") to 5 ("very high"). We calculated the average value across all four scores as final performance score. Inter-rater reliability index was good (ICC = 0.827).

Subjective Experience Assessments

Questionnaires captured the subjective experience of participants during the experiment, including affective responses, subjective cooperation index, subjective performance index, and interpersonal closeness index.

Affective Responses. Participants completed the Affect Grid Survey[61] to inquire about their level of arousal and level of valence on a 9-point Likert scale ranging from "sleepy" to "energized" and "unpleasant" to "pleasant" respectively. Self-reported levels of stress were obtained via the Perceived Stress Scale[62], using a 9-point Likert scale ranging from "low" to "high".

Subjective Cooperation Index. Participants rated the overall cooperation of the team on a 9-point Likert scale ranging from "not at all cooperative" to "extremely cooperative".

Subjective Performance Index. Participants also rated their subjective performance of the team for each task session on a 9-point Likert scale ranging from "not at all" to "extremely".

Interpersonal Closeness Index. Participants rated subjective sense of closeness towards their dyad partner (i.e., "Interpersonal Closeness"[63]) on five 7-point Likert sub scales, including questions about connectedness and trust[64], an adapted version of the inclusion of other in self scale[65], likeability[66] and similarity in personality[67]. The final score was produced by averaging the subscores.

Post Experimental Assessments

To assess the similarity of the two interaction conditions, we assessed participants' personality traits, creative ability, and prior Zoom® familiarity after the experiment in two separate rooms.

Personality Traits. Participants completed the NEO-FFI-3 survey[68], the Adult Attachment Scale Survey[69], and Wong and Law's Emotional Intelligence Survey[70] to capture personality traits. For the NEO-FFI-3 survey, we calculated T-scores for all five sub scales, including Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness. For the Adult Attachment Scale, we calculated Avoidant and Anxious subscales. For the

Emotional Intelligence score, we calculated the average of the four sub scores: self-emotional appraisal, other's emotion appraisal, use of emotion, and regulation of emotion.

Creative Ability. We further applied the Alternate Uses Task (AUT) to assess individual levels of divergent thinking and creativity[71]. We presented pictures of four common objects (i.e., a pillow, key, toothbrush, and ceramic plate) to the participants, that also displayed each object's name and most common everyday use case. Participants had to list as many alternative uses as possible for each object for a duration of eight minutes, while being as creative as possible. We presented participants with an example of alternate uses for a paper cup prior to the task. We only included responses that did not replicate the common uses of the objects. Scoring included *fluency* (number of responses) and *originality* (statistical rarity of the response across answers in this study) following procedures as described in [60], with final scores being the average score of all items.

Zoom® Video Conferencing Familiarity. Participants rated their prior experience and proficiency with Zoom® video conferencing on a 5-point Likert scale ranging from "not at all" to "extremely".

Functional NIRS Data Acquisition and Preprocessing

We recorded cortical hemodynamic activity of each participant using a continuous wave fNIRS system (NIRSport2 System, NIRX, Germany) with two wavelengths (760 and 850 mm) and a sampling frequency of 10.2 Hz. We divided a total of 128 optodes (64 sources x 64 detectors) between the two participants resulting in 100 measurement channels per participant that were placed over the entire cortex according to the international 10-20 EEG placement system (see **7a** in the Appendix). The system connected via network and allowed time synchronization between two spatially separated systems.

We analyzed the raw fNIRS data using the NIRS Brain AnalyzIR Toolbox[72] in Matlab version R2021a (MathWorks, Inc.). We assessed data quality via the scalp coupling index (SCI)[73]. Results showed that 74.13% of the data had a SCI of more than 0.8. We excluded the channels with excessive noise (i.e., SCI ≤ 0.8) from subsequent analyses and converted remaining raw data to optical density data. We then corrected for motion artifacts using a wavelet motion correction procedure[74] and transformed data into concentration changes of oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) according to the Modified Beer-Lambert Law[75]. Since HbO and HbR data are relative values, we converted resulting data to z-scores. We created 32 ROIs via source localization by averaging all channels that shared a common fNIRS source (see 7**b** in the Appendix). To derive the center location of each ROI, we averaged across the Montreal Neurological Institute "MNI" coordinates of each ROI's channels and projected all ROIs onto the cortical surface using an automatic anatomical labeling method[76,77] (see **Table 2** in the Appendix). Because HbO measures are known to be more robust and sensitive to task-associated changes compared to HbR measures [78,79], we only use HbO data for further analyses.

Averaged Inter-Brain Coherence Analysis

We used Wavelet Transform Coherence (WTC)[31] analysis to assess averaged inter-brain coherence (IBC), i.e., the similarity between NIRS signals of dyad partners. Specifically, we utilized the wavelet coherence function ('wcoherence') in Matlab 2021a (MathWorks, Inc.). We calculated wavelet coherence values between each ROI and the rest of ROIs on the converted HbO time series data (a total of 1024 combinations: 32 ROIs X 32 ROIs). We averaged the IBC between the same ROI pairs, resulting in 528 ROI pairs. Thereafter, we converted the averaged coherence values to Fisher z-statistics. Following recent approaches in the field[81,82], we derived specific frequency bands of interest that were specifically associated with condition (i.e., in-person vs. virtual) and/or task, instead of averaging across an entire predefined frequency band. For each ROI pair and each task separately, we ran a

series of independent t-tests between the conditions across all frequency increments within the range 0.01 - 0.2 Hz (i.e., 53 frequencies). We did not consider data above 0.2 Hz to avoid systemic noise such as heart rate (0.6 - 2 Hz) and respiration (0.2 - 0.3Hz), and further excluded data below 0.01 Hz to remove low frequency fluctuations[74]. Using FDR correction ($p < 0.05$), we corrected the resulting p values for each ROI pair across the 53 frequency increments. We used inter-brain coherence values of statistically significant frequency increments for further analyses. If an ROI pair had several significant frequency increments, we averaged IBC values across these increments. A total of 50 ROI pairs exhibited significant frequency increments. We only allowed ROI pairs with a minimum of 50% of data entries across participants for further statistical analyses. This reduced the eligible ROI pairs to a total of 20. Notably, almost half of ROI pairs that exhibited significant frequency increments included ROIs in occipital areas.

Dynamic Inter-Brain Coherence State Analysis

We adopted a dynamic functional connectivity approach[58] to characterize the dynamic inter-brain coherence (dIBC) states during each task. We conducted the analysis independently for each task, utilizing the data from the 20 eligible ROI pairs. The dIBC approach uses a sliding window to segment a WTC-computed IBC matrix across the entire task duration for each dyad. We set the window size to 30 seconds and shifted in an increment of 1 s along the task duration. We averaged all IBC matrices within each time window to obtain an averaged IBC matrix. We then segmented the 8-min measurement duration into a series of windowed IBC matrices (16 ROIs × 16 ROIs × 581 windows) for each dyad and used a k-means clustering approach to cluster the condition-concatenated, time-varying windowed IBC matrices into distinct dynamic IBC states across the task period. We determined the number of clusters using the elbow criterion of the cluster cost, computed as the ratio between within-cluster distance to between-cluster distance[83,84]. Following the previous approach[58], we characterized the properties of dIBC states by the occurrence rate of each dIBC state. Occurrence rate of a state is defined as the percentage of total duration a dIBC state occurs within the entire task period[83].

Statistical Analyses

Testing whether the two conditions were matched on individual difference variables. We ran a series of non-parametric Mann-Whitney U-tests to assess whether there were differences in *age*, *inter-dyad age differences*, personality traits (i.e., *NEO-FFI-3 T scores*, *Adult Attachment style*, emotion intelligence), creative ability (i.e., *AUT fluency*, *AUT originality*), and familiarity with Zoom® video conferencing (i.e., *experience* and *proficiency*) between the two conditions as summarized in **Table 1**.

Observed behavior and subjective experience analyses. We conducted a series of two-way repeated measures analyses of variance (ANOVAs) to determine the effect of condition (i.e., virtual/in-person interaction) and/or task (i.e., problem-solving/ creative-innovation/ socio-emotional task) on the observed behavior and subjective experience measures. For measures that showed significant effects, we conducted correlation analyses with all other observed behavior and subjective experience measures. We corrected the resulting p values for multiple analyses (i.e., seven correlation analyses per measure) using false discovery rate correction (FDR) ($p < 0.05$).

Single-brain analyses. We clustered ROIs into six cortical areas and used FDR correction for tests conducted on ROIs within each cortical area. Cortical areas comprised the prefrontal area (ten ROIs), premotor/supplementary motor area (four ROIs), primary motor area (two ROIs), temporal area (four ROIs), parietal area (six ROIs), and occipital area (six ROIs). For each of the cortical areas, we conducted two-way repeated measures multivariate analyses of variance (MANOVAs) to examine the effect of condition and/or task on the combined dependent

variables (i.e., cortical activation across the ROIs of the same cortical area). If we identified significant multivariate effects, we inspected follow-up two-way repeated measures ANOVAs while correcting resulting *p* values across the ROIs of the same cortical area using FDR correction ($p < 0.05$). For example, in case of the prefrontal area that contained ten ROIs, we FDR-corrected for ten analyses. For the eight ROIs that showed significant univariate effects, we conducted correlation analyses with each observed behavior and subjective experience measure and FDR-corrected the resulting *p* values for multiple analyses (i.e., eight correlation analyses per measure).

Assessment of time effects on single-brain data. We calculated the averaged cortical activity for Time 1 (i.e., first task for each dyad independent of the nature of the task), Time 2 (i.e., second task for each dyad independent of the nature of the task), and Time 3 (i.e., third task for each dyad independent of the nature of the task) across the eight significant prefrontal ROIs with weights for each ROI based on its number of channels. We also "time-clustered" all observed behavior and subjective experience measures. We conducted a two-way repeated measures ANOVA with condition as between-subjects factor and time as within-subject factor to determine the effect of condition (i.e., virtual/in-person interaction) and/or time (i.e., Time 1, Time 2, Time 3) on the observed behavior and subjective experience measures. We then executed correlation analyses between averaged cortical activity and all time-clustered observed behavior and subjective experience measures, and FDR-corrected the resulting *p* values for multiple analyses (i.e., eight correlation analyses).

Averaged inter-brain coherence analyses. We clustered the 20 ROI pairs into four groups for statistical testing. Each group comprised ROI pairs from the same cortical regions, including six *prefrontal-prefrontal* ROI pairs (group 1), four *prefrontal-premotor/primary motor* ROI pairs (group 2), five *prefrontal-temporal/parietal* ROI pairs (group 3), and five *temporal-primary motor/parietal* ROI pairs (group 4). For each of the four groups, we conducted two-way repeated measures MANOVAs with condition as between-subjects factor and task as within-subject factor to examine the effect of condition and/or task on the combined dependent variables (i.e., IBC across the ROI pairs of the same group). If we identified significant multivariate effects, we inspected follow-up two-way repeated measures ANOVAs while correcting resulting *p* values across the ROI pairs of the same group using FDR correction ($p < 0.05$). For the three ROI pairs that showed significant univariate effects, we conducted correlation analyses with each observed behavior and subjective experience measure and FDR-corrected the resulting *p* values for multiple analyses (i.e., three correlation analyses per measure).

Dynamic inter-brain coherence analyses. For each task, we conducted a series of independent t-test to assess whether there were different occurrence rates between the conditions across brain states. We only included states that had at least 50% of the data in the statistical analysis (i.e., we excluded state 4 of the problem-solving task, along with state 3 and 4 of the creative-innovation task). We FDR-corrected resulting *p* values for multiple

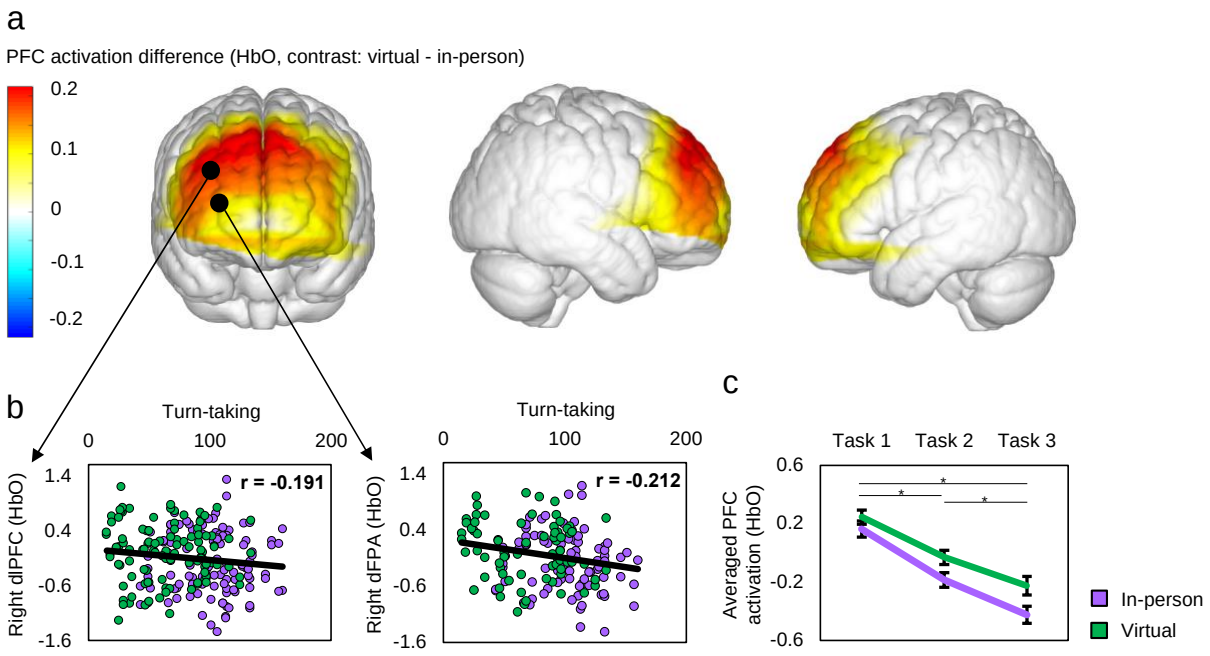

Fig. 1 | Overview of the single-brain results. (a) Compared to the in-person condition, the virtual condition was characterized by increased activation in the prefrontal cortex in all tasks. The prefrontal ROIs showing statistically significant condition effects (mean differences between virtual and in-person conditions) were: left dorsal frontopolar area (dFPA; $F(1,50) = 4.348$, $p = 0.042$, partial $\eta^2 = 0.080$, mean difference = 0.134 (95% CI, 0.005 to 0.263)), right dFPA ($F(1,50) = 10.480$, $p = 0.016$, partial $\eta^2 = 0.173$, mean difference = 0.207 (95% CI, 0.079 to 0.336)), frontal eye field (FEF; ($F(1,50) = 7.258$, $p = 0.020$, partial $\eta^2 = 0.127$, mean difference = 0.144 (95% CI, 0.037 to 0.251)), left dorsolateral prefrontal cortex (dlPFC; ($F(1,50) = 4.562$, $p = 0.038$, partial $\eta^2 = 0.084$, mean difference = 0.136 (95% CI, 0.008 to 0.264)), right dlPFC ($F(1,50) = 15.580$, $p < 0.001$, partial $\eta^2 = 0.238$, mean difference = 0.251 (95% CI, 0.123 to 0.379) location shown with arrow), left lateral frontopolar area (lFPA; ($F(1,50) = 7.220$, $p = 0.010$, partial $\eta^2 = 0.126$, mean difference = 0.180 (95% CI, 0.045 to 0.314) location shown with arrow), right lFPA ($F(1,50) = 13.45$, $p = 0.005$, partial $\eta^2 = 0.212$, mean difference = 0.228 (95% CI, 0.103 to 0.353)), and right posterior inferior frontal gyrus (pIFG; ($F(1,50) = 9.526$, $p = 0.003$, partial $\eta^2 = 0.160$, mean difference = 0.196 (95% CI, 0.069 to 0.324)). **(b)** Right dlPFC and right dFPA activation were negatively associated with conversational turn-taking. **(c)** Averaged prefrontal activation showed habituation effects over time regardless of condition; the virtual condition was associated with higher activation relative to the in-person condition regardless of time. Abbreviations: oxygenated hemoglobin (HbO), dorsolateral prefrontal cortex (dlPFC), dorsal frontopolar area (dFPA), prefrontal cortex (PFC), and correlation coefficient (r). Statistically significant differences at FDR-corrected $p < 0.05$ are indicated by *. Variance is illustrated as the standard error of the means.

analyses (i.e., thirteen analyses). For dIBC states that showed significant differences, we ran correlation analyses with all observed behavior and subjective experience measures while FDR-correcting resulting *p* values for multiple analyses (i.e., eight correlation analyses per dIBC state).

3. Results

Conditions were Matched on Individual Difference Variables

Subjects participating in the two conditions (virtual or in-person interaction) were matched on *age*, *inter-dyad age differences*, personality traits (i.e., *NEO-FFI-3 T scores*, *Adult Attachment style*, *emotional intelligence*), creative ability (i.e., Alternate Uses Task *AUT fluency*, *AUT originality*), and familiarity with Zoom® video conferencing (i.e., *experience* and *proficiency*). As shown in **Table 1** in the Appendix, subject groups participating in the in-person and virtual conditions were not significantly different from one another for any of the measured variables.

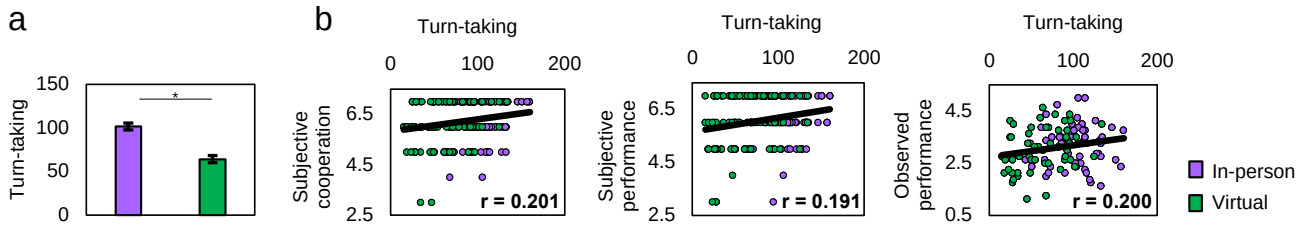

Fig. 2 | Overview of the observed behavior results. (a) Virtual interaction decreased conversational turn-taking. **(b)** Conversational turn-taking was positively associated with pro-social subjective experience measures (i.e., subjective cooperation, subjective performance) and observed performance. Abbreviation: correlation coefficient (r). Statistically significant differences at FDR-corrected p < 0.05 are indicated by *. Variance is illustrated as the standard error of the means.

Virtual Interaction Leads to Higher Prefrontal Activation in Single-Brain Analyses

We assessed whether condition affected brain functioning across 32 cortical ROIs clustered into six cortical areas for statistical analyses. Results showed a multivariate main effect of condition on the combined ROIs of the prefrontal area ($F(10, 41) = 2.252$, $p = 0.033$, Wilks' $\Lambda = 0.645$, partial $\eta^2 = 0.355$). Tests for the other cortical areas did not reveal significant activation differences between the conditions. Follow-up analyses showed a univariate main effect of condition on eight of the ten prefrontal ROIs, with consistently higher cortical activation in the virtual condition (see **Figure 1a**). The two remaining prefrontal ROIs that did not exhibit activation differences for condition were the anterior frontopolar area (aFPA) and left posterior inferior frontal gyrus (pIFG). Subsequent correlation analyses showed a significant negative correlation between turn-taking and activation in the right dlPFC ($r = -0.191$, $p = 0.044$) and the right dFPA ($r = -0.212$, $p = 0.030$; **Figure 1b**). All remaining six ROIs were negatively correlated with turn-taking as well, ranging between $r = -0.142$ to $r = -0.197$, but did not pass our statistical significance threshold after FDR correction for multiple comparisons (all uncorrected $p < 0.072$). There were no significant correlations with any other observed behavior or subjective experience measure.

Prefrontal Habituation Effects in Virtual and In-person Condition

As a follow-up analysis, we assessed whether condition differentially affected prefrontal activation. Results revealed only a main effect of time ($F(1.655,115.880) = 46.525$, $p < 0.001$, partial $\eta^2 = 0.399$) (**Figure 1c**). Post-hoc analysis with FDR correction indicated decreased prefrontal activation over time across both conditions, with activation decreasing significantly from Task 1 to Task 2 (mean difference = 0.313 (95% CI, 0.192 to 0.435), $p < 0.001$, Cohen's d = 1.012) and from Task 2 to Task 3 (mean difference = 0.217(95% CI, 0.100 to 0.333), $p < 0.001$, Cohen's d = 0.635). Tests of within-subjects contrasts showed that this decrease followed a linear trajectory ($F(1,70) = 63.261$, $p < 0.001$, partial $\eta^2 = 0.475$). There were no statistically significant correlations between prefrontal activation and measures of observed behavior or subjective experience (all $p > 0.180$).

Virtual Interaction Reduces Behavioral Cooperation (i.e., Conversational Turn-taking)

We assessed whether there were main effects of condition (i.e., in-person and virtual) or interaction effects of condition and task (i.e., problem-solving, creative-innovation, socio-emotional task) on any of the observed behavior and subjective experience measures. We identified main effects of condition on conversational *turn-taking* ($F(1,70) = 39.790$, $p < 0.001$, partial $\eta^2 = 0.362$, **Figure 2a**). Regardless of the task, we observed less turn-taking (mean difference = -37.574 (95% CI, -49.454 to -25.694)) in the virtual condition compared to the in-person

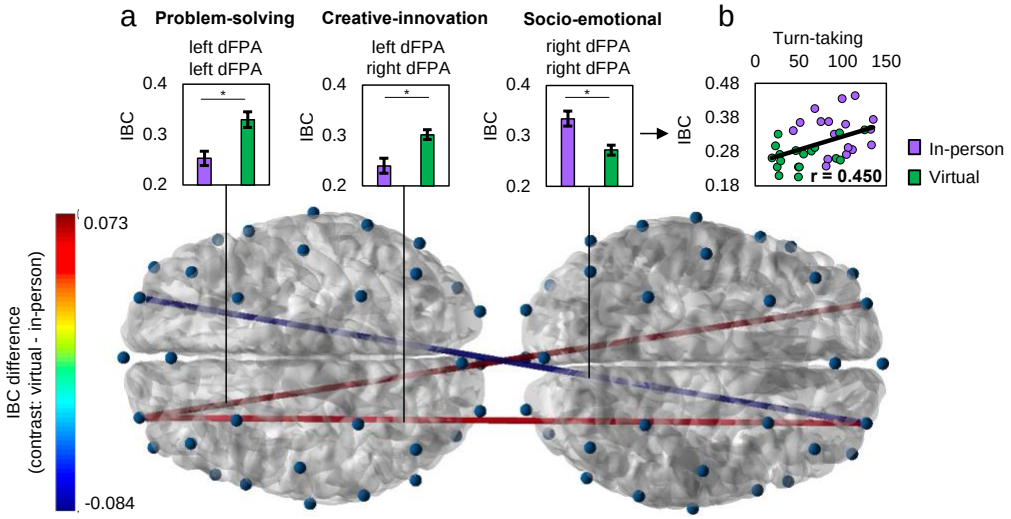

Fig. 3 | Overview of the averaged inter-brain coherence results. (a) ROI pairs that showed significant differences between the conditions in the problem-solving task, creative-innovation task, and socio-emotional task. **(b)** Scatterplot depicts significant correlation between averaged IBC in the right dFPA-right dFPA ROI pair and turn-taking in the socio-emotional task. Abbreviations: dorsal frontopolar area (dFPA), averaged inter-brain coherence (IBC), and correlation coefficient (r). Statistically significant differences at FDR-corrected p < 0.05 are indicated by *. Variance is illustrated as the standard error of the means.

condition. In contrast, there were no significant interaction or main effects of condition for *observed performance* nor any of the subjective experience measures (i.e., *arousal*, *valence*, *stress*, *subjective cooperation*, *subjective performance*, and *interpersonal closeness*). Subsequent correlation analyses revealed that turn-taking was positively correlated with subjective cooperation (r = 0.201, p = 0.021), subjective performance (r = 0.200, p = 0.011), and observed performance (r = 0.192, p = 0.010). Scatterplots of these associations are presented in **Figure 2b.** We further identified main effects of task on conversational turn-taking, with highest values for the problem-solving task and lowest values for the socio-emotional task (see results in the Appendix, **Figure 5**).

Virtual Interaction Affects Averaged Inter-Brain Coherence (IBC) Between Dyad Partners

We assessed whether condition affected averaged IBC across 20 ROI pairs clustered into four groups for statistical analyses. Each group comprised ROI pairs from the same cortical regions (e.g., group 1 comprised six *prefrontal-prefrontal* ROI pairs). We observed a statistically significant multivariate interaction effect between condition and task on the combined ROI pairs for group 1 (F(12, 15) = 2.781, p = .032, Wilks' Λ = 0.310, partial η^2 = 0.690), but not for any other group. Follow-up analyses with FDR correction for multiple comparisons showed a univariate interaction effect between condition and task for the *left dFPA-left dFPA* ROI pair (F(2, 52) = 7.553, p = 0.001, partial η^2 = 0.225), the *right dFPA-left dFPA* ROI pair (F(2, 52) = 6.815, p = 0.002, partial η^2 = 0.208), and the *right dFPA-right dFPA* ROI *pair* (F(2, 52) = 7.273, p = 0.002, partial η^2 = 0.219). We used post-hoc analyses with FDR correction to understand the nature of the significant interaction between condition and task for these three ROI pairs. We found higher averaged IBC in the virtual condition compared to the in-person condition during the problem-solving task for the *left dFPA-left dFPA* ROI pair (mean difference = 0.073 (95% CI, 0.027 to 0.118, p = 0.009, Cohen's d = 1.330)); and during the creative-innovation task for the *right dFPA-left dFPA* ROI pair (mean

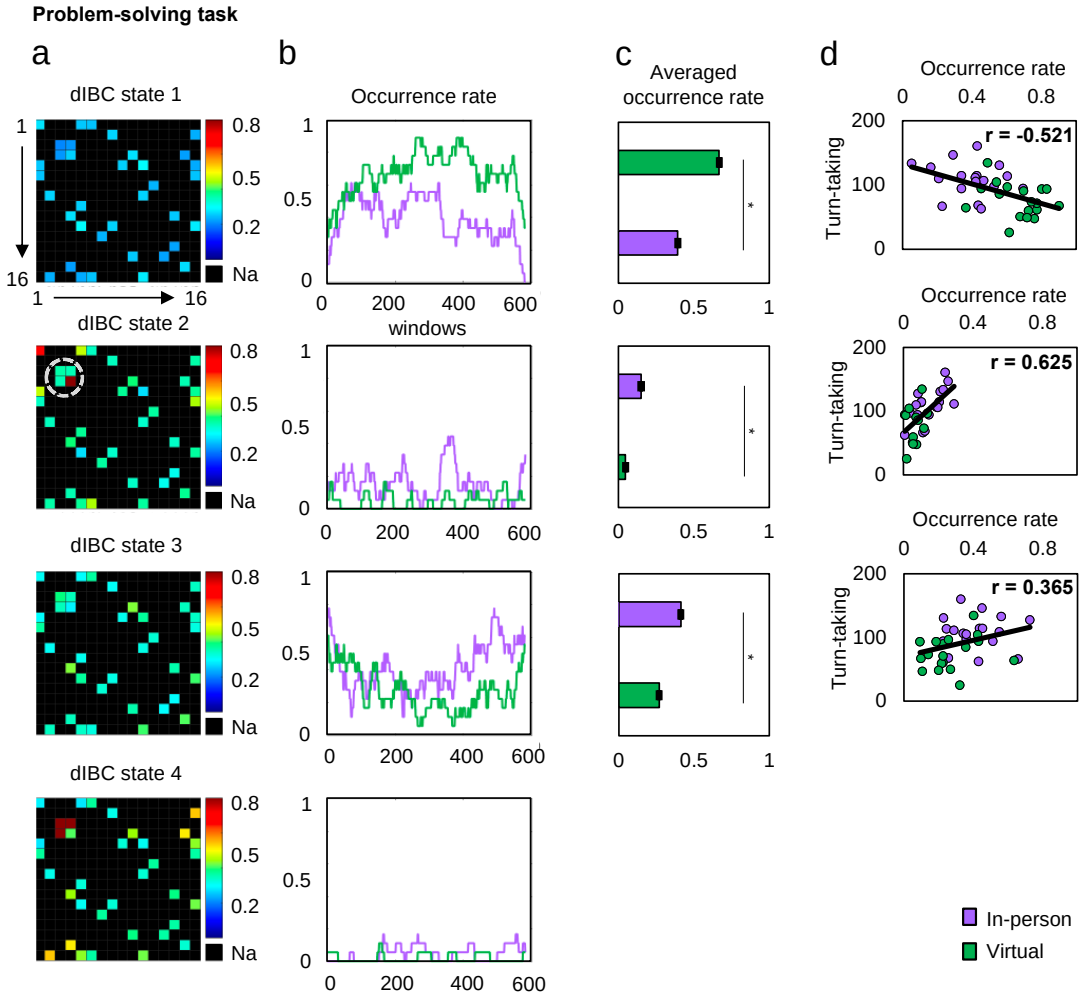

Fig. 4 | Overview of the dynamic inter-brain coherence (dIBC) state results for the problem-solving task. (a) We identified four distinct dIBC states for the problem-solving task. Each dIBC state is characterized by a "heatmap" of IBC values across a 16 x 16 ROI pair matrix. Because dIBC states were derived through an averaging approach across all dyads, dIBC states are inter-brain states that dyads from both conditions have in common. The dIBC state analyses assessed whether there were differences in the occurrence rate of dIBC states. The 16 x 16 ROI pair matrix included the following ROI positions across the x and y axes: 1 - anterior frontopolar area, 2 - left lateral frontopolar area, 3 - left dorsal frontopolar area, 4 - right dorsal frontopolar area, 5 - right lateral frontopolar area, 6 - right dorsolateral prefrontal cortex, 7 - right posterior inferior frontal gyrus, 8 - right supplementary motor area, 9 - right pre-motor cortex, 10 - right primary motor cortex, 11 - right middle temporal gyrus , 12 - right supramarginal gyrus, 13 - right somatosensory association cortex, 14 - left middle temporal gyrus, 15 - left primary motor cortex, and 16 - left somatosensory association cortex. The grey circle in dIBC state 2 highlights the ROI pairs that showed significant results in the averaged IBC analyses. **(b)** Occurrence rates for each dIBC state are shown across the 581 windows derived from sliding window time segmentation. **(c)** Results showed significant differences between conditions in the average occurrence rates of dIBC states 1,2, and 3. **(d)** We identified significant associations between dIBC states and behavioral cooperation (i.e., conversational turn-taking) for dIBC state 1, 2, and 3. Abbreviations: correlation coefficient (r) and not applicable (Na). Statistically significant differences at FDR-corrected $p < 0.05$ are indicated by *. Variance is illustrated as the standard error of the means.

difference = 0.063 (95% CI, 0.027 to 0.099, p = 0.003, Cohen's d = 1.350; **Figure 3a**)). In contrast, we identified lower averaged IBC for the virtual condition compared to the in-person interactions during the socio-emotional task for the *right dFPA-right dFPA* ROI pair (mean difference = -0.084 (95% CI, -0.123 to -0.045, $p < 0.001$, Cohen's

d = 1.178)). Subsequent correlation analyses revealed statistically significant associations between averaged IBC in the *right dFPA-right dFPA* ROI pair and turn-taking (r = 0.450, p = 0.021; **Figure 3b**). The associations between turn-taking and averaged IBC in the *left dFPA-left dFPA* ROI pair (r = -0.330, uncorrected p = 0.067) did not pass the statistical significance threshold.

Virtual Interaction Affects Dynamic Inter-Brain Coherence (dIBC) States Between Dyad Partners

Lastly, we assessed the potential impact of condition on dynamic inter-brain coherence (dIBC) states. The analyses identified four dIBC states for each task along with their corresponding occurrence rates across time. We assessed whether there were different occurrence rates of dIBC states between the conditions. We observed differences by condition for the problem-solving task (**Figure 4**, but not for the creative-innovation and socio-emotional task (**Figure 6**, Appendix). Specifically, the virtual condition was characterized by higher rates of dIBC state 1 (t(70) = -7.796, p < 0.001 (mean difference = -0.275 (95% CI, -0.346 to -0.205)) and lower rates of dIBC state 2 (t(60) = 5.037, p < 0.001 (mean difference = 0.086 (95% CI, 0.052 to 0.120)) and dIBC state 3 (t(70) = 4.309, p < 0.001 (mean difference = 0.033 (95% CI, 0.077 to 0.211)). Subsequent correlation analyses revealed significant associations between occurrence rate and turn-taking for dIBC state 1 (r = -0.521, p < .001), state 2 (r = 0.625, p < .0005), and dIBC state 3 (r = 0.365, p = 0.003).

4. Discussion

This study explored potential effects of virtual interactions on observed behavior, subjective experience, and neural "single-brain" and "inter-brain" activity. We measured cortical activation in dyads during social interactions that took place either in-person or virtually using video conferencing technology (Zoom®). All dyads performed three naturalistic conversation tasks, including a problem-solving task, a creative-innovation task, and a socio-emotional task. We coded cooperative behaviors from audio recordings and captured a variety of subjective experience measures using questionnaires. We found increased recruitment of prefrontal resources in the virtual condition across all tasks, providing a potential neural correlate of "Zoom® fatigue". Virtual interactions were also characterized by reduced behavioral cooperation (i.e., conversational turn-taking) and altered patterns of averaged and dynamic IBC. Further, patterns of IBC that were typical in the virtual condition were negatively associated with conversational turn-taking. These findings suggest that virtual interactions may promote patterns of IBC that constrain behavioral cooperation.

Across tasks, we found increased activation in 80% of the prefrontal ROIs in the virtual condition compared to the in-person condition. Affected ROIs comprised cortical areas that are implicated in a variety of processes that are important for effective communication, social understanding, attentional maintenance, decision-making, and problem solving[85–93]. Our findings suggest that virtual interactions may require more neural resources, or cognitive effort[27–29], to maintain and navigate effective social interaction. Interestingly, although prefrontal activation decreased over time, suggesting habituation to the experiment[94,95], prefrontal activation was always higher in the virtual condition. Studies have demonstrated that prolonged cognitive effort, which is rooted in prefrontal activation, can lead to cognitive and general fatigue[96–98]. In this context, our findings point to the possibility that increased and sustained recruitment of neural resources during virtual interactions may be a neural basis of "Zoom® fatigue". This interpretation aligns with recent theory that "Zoom® fatigue" is caused, in part, by increased cognitive effort[19]. Future neuroimaging research could study fatigue over the course of several hours[99,100] and apply novel questionnaires such as the 'Zoom Exhaustion & Fatigue Scale'[22] to systematically assess "Zoom® fatigue" and its components (i.e., general fatigue, visual fatigue, and social fatigue).

Our findings raise the question, what is it about virtual interactions that require or elicit increased recruitment of neural resources? One potential explanation is that individuals in the virtual condition had less access to non-verbal cues such as micro-expressions[101–104]. Micro-expressions are fast (i.e., 1/25-1/5 of a second[105,106]) and subtle facial movements (e.g., mouth motion, head pose, eye sight direction and blinking interval[107]), and have been identified as important for effective and cooperative communication[108,109]. Structural and functional MRI studies have implicated prefrontal regions in cognitive evaluation of micro-expressions[110,111]. In our study, reduced access to these subtle cues in the virtual condition may have required increased cognitive effort for visuo-spatial attention, response inhibition, and perspective-taking. Future research, however, is necessary to directly test this hypothesis and elucidate the specific features of virtual interactions that lead to heightened prefrontal activation.

In addition to affecting brain functioning, we found that virtual interaction impacted behavioral cooperation. Specifically, conversational turn-taking was reduced in the virtual condition across all tasks. It is worth noting that activation in specific right prefrontal regions, which was greater in the virtual condition, was linked to reduced turn-taking. Given that lower levels of turn-taking were associated with less positive subjective and behavioral aspects of social interaction (i.e., lower subjective cooperation and lower subjective and observed performance), decreased turn-taking likely reflects an adverse effect of virtual interaction. Our findings align with previous research that demonstrated adverse effects of virtual interactions on conversational behavior, such as delays in conversational turn initiation[16]. Although conversational turn-taking was associated with positive measures of social interaction, it is important to note that we did not identify differences in observed performance and subjective experience measures between the conditions for any of the three tasks. These results are similar to those of prior studies that found no differences in perceived effectiveness and performance in association with virtual interaction[4–9]. Thus, our findings that video conferencing affects social interaction at the behavioral level, but not subjective or performance level, may help to clarify some of the inconsistent findings in the literature. Alternatively, studies with larger samples may be necessary to detect the effects of virtual interaction on these outcomes.

We found that virtual interaction affected averaged inter-brain coherence (IBC) and dynamic inter-brain coherence (dIBC) states. The socio-emotional task elicited higher averaged IBC in the in-person condition in the *right dFPA-right dFPA* ROI pair, which was positively associated with behavioral cooperation (i.e., number of turn-taking). Our findings suggest that discussing socio-emotional content in-person elicits averaged IBC that is more conducive to prosocial interaction. These findings are consistent with prior studies that have found increased averaged IBC, particularly in right prefrontal ROI pairs, to be positively associated with prosocial behavior[31,43,49,112–115]. A potential reason for increased averaged IBC in the in-person condition could be access to more micro-expression which, in turn, may have facilitated behavioral cooperation. In contrast, the problem-solving and creative-innovation task elicited higher averaged IBC in the virtual condition in the *left dFPA-left dFPA* and *left dFPA-right dFPA* ROI pairs, and these patterns were associated with reduced behavioral cooperation. Increased averaged IBC in the left dFPA may be involved in or reflect increased effort for dyadic coordination[45,116]. We also found evidence that virtual interaction affected the dynamic nature of inter-brain coherence. Specifically, the virtual and in-person conditions were characterized by higher occurrence rates (i.e., greater frequency) of different kinds of dIBC states in the problem-solving task. Dynamic IBC state 1 was more frequent in the virtual condition, whereas dIBC states 2 and 3 were more frequent in the in-person condition. Dyads who spent more time engaged in dIBC state 1 demonstrated less behavioral cooperation, whereas dyads who spent more time engaged in dIBC states 2 and 3 demonstrated more behavioral cooperation. Notably, dIBC state 2 was characterized by increased IBC in the *right FPA-right FPA* ROI pair (see grey circle in **Figure 4a**). These findings,

combined with the averaged IBC findings, point to the possibility that inter-brain coherence in the right FPA plays an important role in pro-social interaction. In contrast, dIBC state 1 was characterized by lower IBC across all ROI pairs compared to dIBC states 2 and 3. Interestingly, prior work suggests that non-cooperative tasks elicit decreased IBC across brain regions compared to cooperative tasks[115]. Thus, one interpretation of the current findings is that virtual interactions constrain dyadic coherence across brain regions, and that this has negative implications for behavioral cooperation. It is worth highlighting that we found conditional differences using the dynamic IBC measure for the problem-solving task only. The problem-solving task was characterized by greater conversational turn-taking than the other two tasks. Dynamic IBC may therefore provide a meaningful lens when considering tasks that elicit more back and forth discussion between partners. Future studies should consider multiple task contexts and multiple IBC analytical approaches to further test this hypothesis.

We note four limitations of this study. First, due to regulations related to COVID-19, participants in the in-person condition wore facemasks during the experiment. Participants in the virtual condition also wore face masks to avoid confounding the effect of video conferencing technology versus in-person interaction. Although we used clear, anti-fog face masks, they still might have obstructed some facial features and impacted our results. Future research should aim to replicate our findings without using face masks. Second, we used a between-subject design with respect to condition. Exposing the same participants to both virtual and in-person conditions, and examining within-person differences across conditions, would be a strong replication and extension of our findings. Third, a larger sample size may have been needed to detect statistically significant differences between conditions on some of our measures (e.g., subjective experience measures). Lastly, we explored the effects of virtual interactions on neural activation and inter-brain coherence across the (fNIRS-detectable) cortex. Achieving high signal to noise ratio in all measurement channels across the high-density/whole brain configuration is difficult. Although a scalp coupling index (SCI) of 74.13% suggested an overall good signal to noise ratio, occipital channels had overall poorer signal to noise ratio and were thus excluded from our inter-brain coherence analyses. Future studies should explore differences between virtual and in-person interactions in ROI pairs that include occipital regions if possible.

5. Conclusion

In conclusion, the current study provides evidence that virtual interactions affect specific aspects of behavior, neural activation, and inter-brain coherence across different social interaction contexts. At the neural level, virtual interactions were characterized by higher levels of prefrontal activation than in-person interactions, pointing to a potential neural explanation for "Zoom® fatigue". At the behavioral level, virtual interaction was associated with decreased behavioral cooperation (i.e., conversational turn-taking). Both averaged and dynamic inter-brain coherence in predominantly prefrontal areas were associated with behavioral cooperation. Our findings show that both adverse effects of video conferencing (i.e., increased cognitive effort and decreased behavioral cooperation) are linked to single-brain and inter-brain coherence in prefrontal areas. Reduced access to micro-expressions could be an underlying mechanism that explains both effects, but this interpretation is speculative and should be directly tested in future research. Taken together, our study serves as a call to action for more research on the effects of video conferencing technology on social interactions. This area of research will be crucial for advancing our understanding and improving our use of a technology that is increasingly integral to daily living.

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Author contributions statement

S.B.: Conceptualization, Methodology, Data Acquisition, Formal Analysis, Writing - Original Draft, Visualization; J.G.M. Conceptualization, Writing - Original Draft, Visualization; R.L. Partial Formal Analysis; G.H., Partial Formal Analysis; A.L.R.: Conceptualization, Funding Acquisition, Resources, Supervision, Writing - Original Draft, Visualization.

Data and code availability statement

Data and code will be made publicly available upon acceptance of the manuscript.

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Appendix

Table 1 | Description of the participant cohorts of both interaction conditions.

	In-person condition	Virtual condition	Mann-Whitney U-test
Number of participants	36	36	
Sex	18 females, 18 males	18 females, 18 males	
Age (*M*±*SD*)	27.83 ± 7.81 years	26.38 ± 7.36 years	p = .422
Inter-dyad age difference (*M*±*SD*)	7.00 ± 6.12 years	6.55 ± 6.17 years	p = .830
Race			
African American/Black	-	2	
Asian/ Pacific Islander	9	8	
Biracial/Multiracial	2	2	
Hispanic/Latino	4	7	
Middle Eastern	3	1	
South Asian	8	8	
Caucasian/White	10	8	
NEO-FFI Neurocism T score (*M*±*SD*)	48.98 ± 9.82	51.02 ± 10.2	p = .667
NEO-FFI Extraversion T score (*M*±*SD*)	48.24 ± 11.0	51.76 ± 8.64	p = .121
NEO-FFI Openness T score (*M*±*SD*)	47.98 ± 11.0	52.02 ± 8.54	p = .150
NEO-FFI Agreeableness T score (*M*±*SD*)	48.68 ± 11.1	51.31 ± 8.73	p = .347
NEO-FFI Conscientiousness T score (*M*±*SD*)	47.58 ± 10.4	52.42 ± 9.04	p = .073
Adult Attachment Scale Avoidant (*M*±*SD*)	33.39 ± 8.19	36.56 ± 8.38	p = .078
Adult Attachment Scale Anxious (*M*±*SD*)	12.72 ± 5.57	13.67 ± 4.44	p = .190
Emotional Intelligence (*M*±*SD*)	15.36 ± 2.36	15.29 ± 1.98	p = .889
AUT fluency (*M*±*SD*)	4.13 ± 1.57	4.28 ± 1.25	p = .390
AUT originality (*M*±*SD*)	0.80 ± 0.49	0.82 ± 0.48	p = .660
Zoom video conferencing experience (*M*±*SD*)	3.53 ± 1.18	3.89 ± 1.06	p = .180
Zoom video conferencing proficiency (*M*±*SD*)	3.58 ± 1.25	3.81 ± 1.09	p = .509

We used following abbreviations: mean (M), and standard variation (SD).

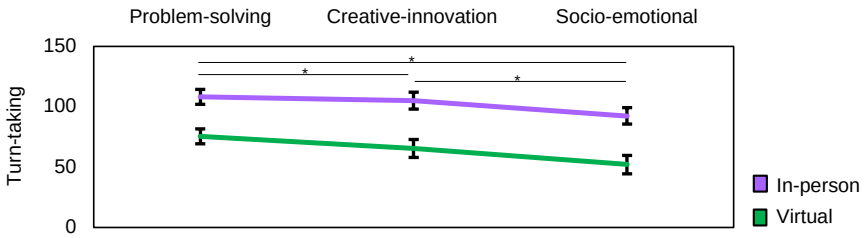

Fig. 5 | Main effects of task on conversational turn-taking. Two-way repeated measures ANOVA showed a main effect of task on conversational turn-taking ($F(1,70) = 39.790$, $p < 0.001$, partial $\eta^2 = 0.362$). Post-hoc analysis with FDR correction showed that the number of conversational turn-taking events was higher in the problem-solving task compared to the creative-innovation task (mean difference = 6.583 (95% CI, 1.248 to 11.919), p = 0.016, Cohen's d = 0.198) and socio-emotional task (mean difference = 19.583(95% CI, 14.061 to 25.105), p < 0.001, Cohen's d = 0.588). The number of conversational turn-taking events was further higher in the creative-innovation task compared to the socio-emotional task (mean difference = 13.000 (95% CI, 7.611 to 18.389), p < 0.0005, Cohen's d = 0.198). Statistically significant differences at FDR-corrected p < 0.05 are indicated by *.

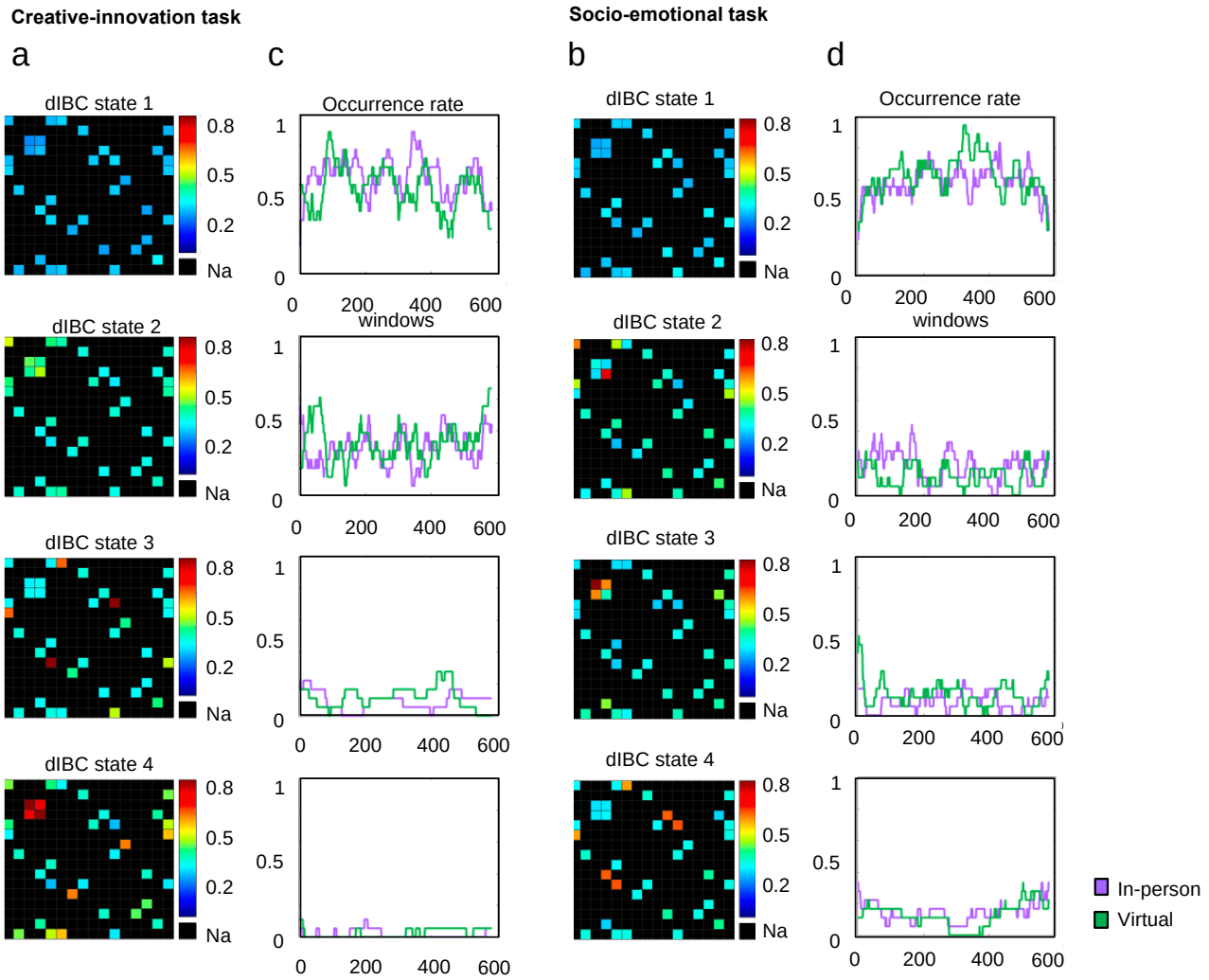

Fig. 6 | Overview of the dynamic inter-brain coherence (dIBC) state results for the creative-innovation and socio-emotional tasks. (a,b) For each task, we identified four distinct dIBC states that dyads exhibited and transitioned between during the social interaction. Each dIBC state is characterized by a "heatmap" of IBC values across a 16 x 16 ROI pair matrix. Because dIBC states were derived through an averaging approach across all dyads, dIBC states are inter-brain states that dyads from both conditions have in common. The dIBC state analyses assessed whether there were differences in the occurrence rate of dIBC states. The 16 x 16 ROI pair matrix included the following ROI positions across the x and y axes: 1 - anterior frontopolar area, 2 - left lateral frontopolar area, 3 - left dorsal frontopolar area, 4 - right dorsal frontopolar area, 5 - right lateral frontopolar area, 6 - right dorsolateral prefrontal cortex, 7 - right posterior inferior frontal gyrus, 8 - right supplementary motor area, 9 - right pre-motor cortex, 10 - right primary motor cortex, 11 - right middle temporal gyrus , 12 - right supramarginal gyrus, 13 - right somatosensory association cortex, 14 - left middle temporal gyrus, 15 - left primary motor cortex, 16 - left somatosensory association cortex. **(c,d)** Occurrence rates for each dIBC state are shown across the 581 windows derived from sliding window time segmentation. Abbreviations: correlation coefficient (r) and not applicable (Na). Statistically significant differences at FDR-corrected $p < 0.05$ are indicated by *.

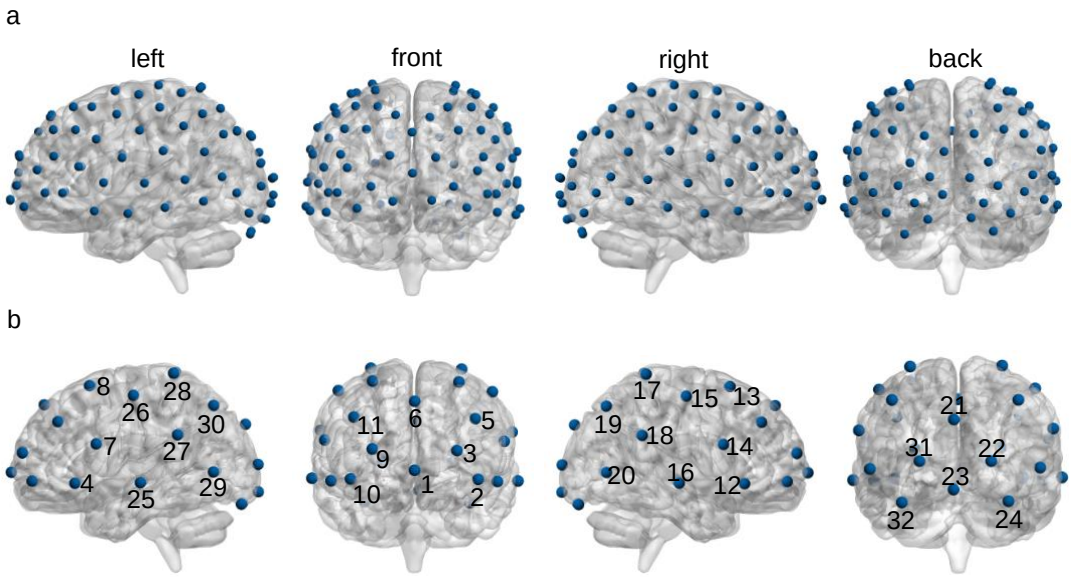

Fig. 7 | Positions of fNIRS measurement channels and ROIs. We clustered 100 measurement channels (**a**) into 32 ROIs (**b**) through source localization. We utilized BrainNet Viewer in Matlab for visualization[117].

Table 2 | Description of regions of interest (ROI) with Talairach Atlas labels.

ROI	Name	MNI coordinates x	y	z	Number of channels	Cortical area
1	Anterior frontopolar area	1.44	71.11	2.22	3	Prefrontal area
2	Left lateral frontopolar area	-42.17	56.50	-4.00	2	Prefrontal area
3	Left dorsal frontopolar area	-27.67	63.33	15.78	3	Prefrontal area
4	Left inferior frontal gyrus	-55.33	26.50	-5.50	2	Prefrontal area
5	Left dorsolateral prefrontal cortex	-40.22	38.44	37.67	3	Prefrontal area
6	Frontal eye field	1.33	48.00	49.56	3	Prefrontal area
7	Left pre-motor cortex	-60.00	11.67	22.08	4	Premotor and supplementary motor area
8	Left supplementary motor area	-29.00	16.22	62.89	3	Premotor and supplementary motor area
9	Right dorsal frontopolar area	30.44	63.22	16.89	3	Prefrontal area
10	Right lateral frontopolar area	45.33	56.17	-3.67	2	Prefrontal area
11	Right dorsolateral prefrontal cortex	43.00	38.00	38.78	3	Prefrontal area
12	Right inferior frontal gyrus (IFG)	58.67	25.17	-5.00	2	Prefrontal area
13	Right supplementary motor area	30.22	15.44	63.44	3	Premotor and supplementary motor area
14	Right pre-motor cortex	62.92	10.25	23.00	4	Premotor and supplementary motor area

15	Right primary motor cortex	53.58	-16.25	56.92	4	Primary motor area
16	Right middle temporal gyrus	71.78	-21.11	-3.22	3	Temporal area
17	Right somatosensory association cortex	31.33	-44.33	72.33	3	Parietal area
18	Right supramarginal gyrus	65.83	-47.33	29.75	4	Parietal area
19	Right somatosensory association cortex	42.25	-71.08	49.17	4	Parietal area
20	Right visual association cortex	57.00	-72.67	3.33	3	Temporal area
21	Visual association cortex (V3)	-1.33	-93.33	35.89	3	Occipital area
22	Right visual association cortex	23.92	-102.08	7.75	4	Occipital area
23	Visual association cortex	-1.56	-102.33	-11.44	3	Occipital area
24	Right visual association cortex	35.50	-91.17	-19.33	2	Occipital area
25	Left middle temporal gyrus	-69.44	-19.56	-5.11	3	Temporal area
26	Left primary motor cortex	-51.92	-14.67	56.08	4	Primary motor area
27	Left supramarginal gyrus	-65.50	-45.67	28.50	4	Parietal area
28	Left somatosensory association cortex	-30.89	-42.89	71.67	3	Parietal area
29	Left visual association cortex	-58.11	-70.78	2.44	3	Temporal area
30	Left somatosensory association cortex	-43.17	-70.92	49.08	4	Parietal area
31	Left visual association cortex	-24.58	-102.17	7.75	4	Occipital area
32	Left visual association cortex	-36.50	-90.50	-20.17	2	Occipital area