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Verbal information exchange enhances collective performance through increasing group identification

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ABSTRACT

Information exchange is a key factor in the attainment of collective outcomes and the navigation of social life. In the current study, we investigated whether and how information exchange enhanced collective performance by combining behavioral and neuroimaging approaches from the perspective of multiparticipant neuroscience. To evaluate collective performance, we measured the collaborative problem-solving abilities of triads working on a murder mystery case. We first found that verbal information exchange significantly enhanced collective performance compared to nonverbal exchange. Moreover, both group sharing and group discussion positively contributed to this effect, with group discussion being more essential. Importantly, group identification mediated the positive effect of verbal information exchange on collective performance. This mediation was supported by higher interactive frequency and enhanced within-group neural synchronization (GNS) in the dorsolateral prefrontal cortex (DLPFC). Taken together, we provided a multiparticipant theoretical model to explain how verbal information exchange enhanced collective performance. Our findings deepen the insight into the workings of group decision-making.

1. Introduction

Human beings are faced with making decisions in various aspects of their lives, ranging from minor choices to significant ones (Barton et al., 2014; Hamby et al., 2015; Helm et al., 2018). However, individual decision-making may have limitations, leading to the delegation of significant decisions to groups (Hofmann and Jones, 2005; Rowe et al., 2021). While the importance of information exchange during group decision-making is widely acknowledged in enabling this delegation, there are conflicting results regarding its exact impact on achieving collective performance. Some studies suggest that information exchange can enhance collective performance (e.g., De Wilde et al., 2017; Kerr and Tindale, 2003; Stasser and Abele, 2020), while others suggest that it can weaken collective performance (e.g., Lu et al., 2012; Stasser and Titus, 2003; Tong and Crosno, 2016). These conflicting results may be attributed to the various ways of information exchange, such as verbal and nonverbal exchanges. Therefore, the present study aims to investigate how different ways of information exchange affect group decision-making from both psychological and neural perspectives.

Information exchange is a critical aspect of group decision-making that involves the conversion of individual private information into shared information known to all (De Freitas et al., 2019; Tindale and Winget, 2019). Such information exchanges can take two primary forms: verbal and nonverbal. The key to verbal information exchange is verbal interaction that expands the scope of available information and constructively addresses doubts, criticisms, and competing scenarios (Park and DeShon, 2018; Larson et al., 1994; Lee Cunningham et al., 2021) and ultimately leads to a well-informed collective decision. Verbal information exchange is facilitated by two stages: group sharing and group discussion. Group sharing enables the collective generation of decisions by combining different information (Lee Cunningham et al., 2021; Metcalf et al., 2019), while group discussion facilitates open deliberation and exchange of opinions among members, leading to collective insights and understanding through verbal interactions (Jiang

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et al., 2015). In contrast, nonverbal information exchange requires texting to exchange information, thus lacking the direct and interactive nature of verbal interactions. This type of text-based information exchange may negatively impact collective performance (Mesmer-Magnus and Dechurch, 2009; Reinero et al., 2021; Sebeok, 2005). For example, Reinero et al. (2021) reported that nonverbal information exchange during a series of online problem-solving tasks using laptops had a detrimental effect on collective performance, as observed in the winter survival and tapping tasks. Therefore, based on the differences between verbal and nonverbal information exchange, we hypothesize that verbal information exchange is more effective than nonverbal information exchange in achieving collective performance, as both group sharing and group discussion positively contribute to this effect.

Group identification, which is the extent to which an individual perceives themselves as belonging to a group, is also recognized as a critical aspect of group decision-making, complementing the information exchange process. Social identity theory underscores the connection between information exchange and identification, suggesting that identification is a cognitive construct that links information exchange to collective performance (Bicchieri, 2002; Gundlach et al., 2006; Tajfel and Turner, 1979). Empirical studies provide consistent evidence that group identification is a strong predictor of collective performance (e.g., Pärnamets et al., 2020; Reinero et al., 2021; Számadó et al., 2021; Solansky, 2011). For example, Pärnamets et al. (2020) found that group identification positively predicted group decision-making accuracy. The task presented to the groups simulated a real-world problem, requiring collective input and collaboration. The accuracy of the group's decision-making was assessed using an objective standard connected to the problem. Reinero et al. (2021) showed a positive correlation between the strength of group identification and the effectiveness of team-based medical interventions. Moreover, evidence suggests that the pooling of information can strengthen group identification, leading to effective goal attainment in group decision-making (Brewer and Kramer, 1986; De Cremer and Van Vugt, 1999). Van Bavel and Cunningham (2012) suggested that the act of sharing information can foster a sense of shared identity with the group, which can lead to greater cooperation and better group outcomes. Given this empirical evidence, we hypothesize that group identification is the key factor in explaining the enhancement of collective performance through verbal information exchange.

The explanation of how group identification contributes to achieving collective performance is supported by evidence from both behavior and neuroscience. Previous studies have established that behaviors and communication are reliable indicators of group action, revealing a strong connection between interactive behaviors and successful problem-solving during dynamic multiparticipant interactions (Dikker et al., 2022; Hirsch et al., 2018; Jiang et al., 2015; Liu et al., 2021; Prochazkova et al., 2022). These studies also suggest that interactive frequency among group members, including smiling, eye contact, and communication, may be linked to greater group identification, which enhances the ability of the group to perform effectively (Dikker et al., 2022; Prochazkova et al., 2022). We hypothesize that, at the behavioral level, verbal information exchange will increase interactive frequency, leading to higher group identification and enhanced collective performance. To assess this relationship, we employed some behavioral indicators with distinct roles in understanding the dynamics within a group (i.e., collective performance, group identification, and interactive frequency). Collective performance was evaluated by analyzing the accuracy of the triad's responses to a murder mystery case, providing an assessment of the group's ability to collaboratively solve problems and make decisions effectively. Group identification was measured using a scale developed specifically for this purpose. Additionally, the interactive frequency was determined by quantifying the occurrence of three-person group interaction behaviors, such as smiling, eye contact, and communication.

Furthermore, utilizing fNIRS (Functional Near-Infrared Spectroscopy), we monitored neural activity in each individual within a group. We selected two brain regions of interest on the basis of earlier work related to group decision-making and discussion: the left temporoparietal junction (left TPJ) and dorsolateral prefrontal cortex (DLPFC). The DLPFC belongs to a group of brain regions involved in collective and strategic decision-making, and those with reduced prefrontal activity tend to display more out-group hostility and in-group bonding (Goupil et al., 2021; Jankovic, 2014; Yang et al., 2020). The left TPJ is linked to activities such as sharing and discussion, and achieving consensus decisions within a group (Miyata et al., 2021; Suzuki et al., 2015). It has also been suggested that the left TPJ processes social and emotional information, which helps to understand interpersonal interactions within the group (Jiang et al., 2015). Accordingly, we further hypothesize that verbal information exchange can lead to higher neural synchronization in the left TPJ and/or DLPFC, which in turn contributes to group identification and enhanced collective performance. Taken together, the integration of behavioral and neuroscientific evidence provides a comprehensive understanding of the potential pathways through which information exchange can alter group identification and ultimately impact collective performance.

To test our hypotheses, the effect of different information exchanges (verbal and nonverbal) on collective success was first investigated in a collaborative problem-solving task (Experiment 1). Subsequently, the mediating role of group identification in this effect was examined, in terms of behavior and brain activity (Experiment 2).

2. Materials and methods

2.1. Participants

G* Power 3.1 (Faul et al., 2007) indicates that for ANOVAs with a medium-to-large effect size ($f = 0.27$), an alpha level of 0.05 and a desired statistical power of 0.80 (Cohen, 1988), a sample size of at least 136 triads is needed for Experiment 1 and 110 triads for Experiment 2. In total, the data of 432 (216 females, 19.93 ± 1.82 years), and 360 (180 females, 20.33 ± 3.27 years) healthy college students were included in Experiment 1 (behavioral study) and Experiment 2 (functional near-infrared spectroscopy study), respectively. In addition, 3 participants (1 female, 21.33 ± 2.33 years) without knowledge of the experimental design details were recruited to rate the collective performance for Experiments 1 and 2, while another 3 participants (2 females, 23.0 ± 1.00 years) were recruited to rate the interactive frequency for Experiment 2. The study had full ethical approval by the University Committee on Human Research Protection (HR2-0036-2021), East China Normal University. Informed written consent was obtained from each participant before each experiment.

2.2. Tasks

2.2.1. Overview

We adopted a well-validated collaborative problem-solving task that incorporated the hidden profile task to solve a murder mystery case (De Wilde et al., 2017; Stasser and Stewart, 1992). The case description contained 24 relevant arguments that were either incriminating or exonerating for each suspect (Suspect A, B, and C). In total, each suspect had 6 incriminating arguments presented against them. Additionally, Suspects B and C each had three exonerating arguments to their defense, while Suspect A did not. Accordingly, when combining all 24 relevant arguments, suspect A was the real guilty suspect, while suspects B and C could be ruled out because of the exonerating clues. However, each group member was not privy to all of the relevant information. To uncover the truth, individuals had to exchange and combine their knowledge with the knowledge of their group members, as the common information incorrectly indicated that Suspects B or C were guilty.

2.2.2. Experiment 1

Experiment 1 aimed to examine the impact of three different types of information exchange (verbal information exchange, nonverbal information exchange, and control condition) on collective performance. Participants in Experiment 1 were randomly assigned to 144 groups, each consisting of 3 people of the same gender. The participants in each triad were unfamiliar with one another and had not previously participated in similar games. Studies have revealed that problem-solving performance may be associated with personality traits such as gender, age, agreeableness, reasoning ability, and emotions (Raven, 2003; Reinero et al., 2021). To exclude the potential influence of these traits, the participants completed various personal trait assessments, including the Raven's Standard Progressive Matrices (SPM) (Raven, 2003), the Chinese Big Five Personality Inventory (CBF–PI) (Wang et al., 2010), and the Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988). Each group member was given 18 common and 2 private pieces of information, which they read in 5 min (see Fig. 1(B)). After this, the 144 triads were randomly assigned to three conditions: verbal, nonverbal, and control (see Fig. 1(A)). In the verbal condition, the groups exchanged and discussed information by talking, in the nonverbal condition they exchanged and discussed information by texting on Tencent Meeting, and in the control condition they deduced the case independently without exchanging information (see Fig. 1(C)). Ultimately, participants in each group were asked to answer the following questions: (i) the probability of three suspects, 0–100% for each suspect; (ii) the motivation and tool of crime; and (iii) deduced the entire process of crime.

2.2.3. Experiment 2

In Experiment 2, 120 triads with the same gender were randomly organized. The participants in each triad were unfamiliar with one another and had not previously participated in similar games. Experiment 2 was different from Experiment 1 in that it only concentrated on verbal information exchange to observe how it impacted collective performance. An innovative task was developed based on a general paradigm of information exchange (De Wilde et al., 2017; Stasser and Stewart, 1992) and the definition of verbal information exchange (Asan et al., 2015; Hendron, 2015), which was divided into two stages: group sharing (Sharing private information vs. No Sharing private information) and group discussion (Discussing the information vs. No Discussing the information). This task enabled researchers to study the impact of specific components during information exchange on collective decisions. During the group sharing stage, each group used Tencent Meeting to text their private information to their group members for 5 min (see Fig. 2(B)). During the group discussion stage, each group discussed the information that had been disclosed orally for 20 min. To

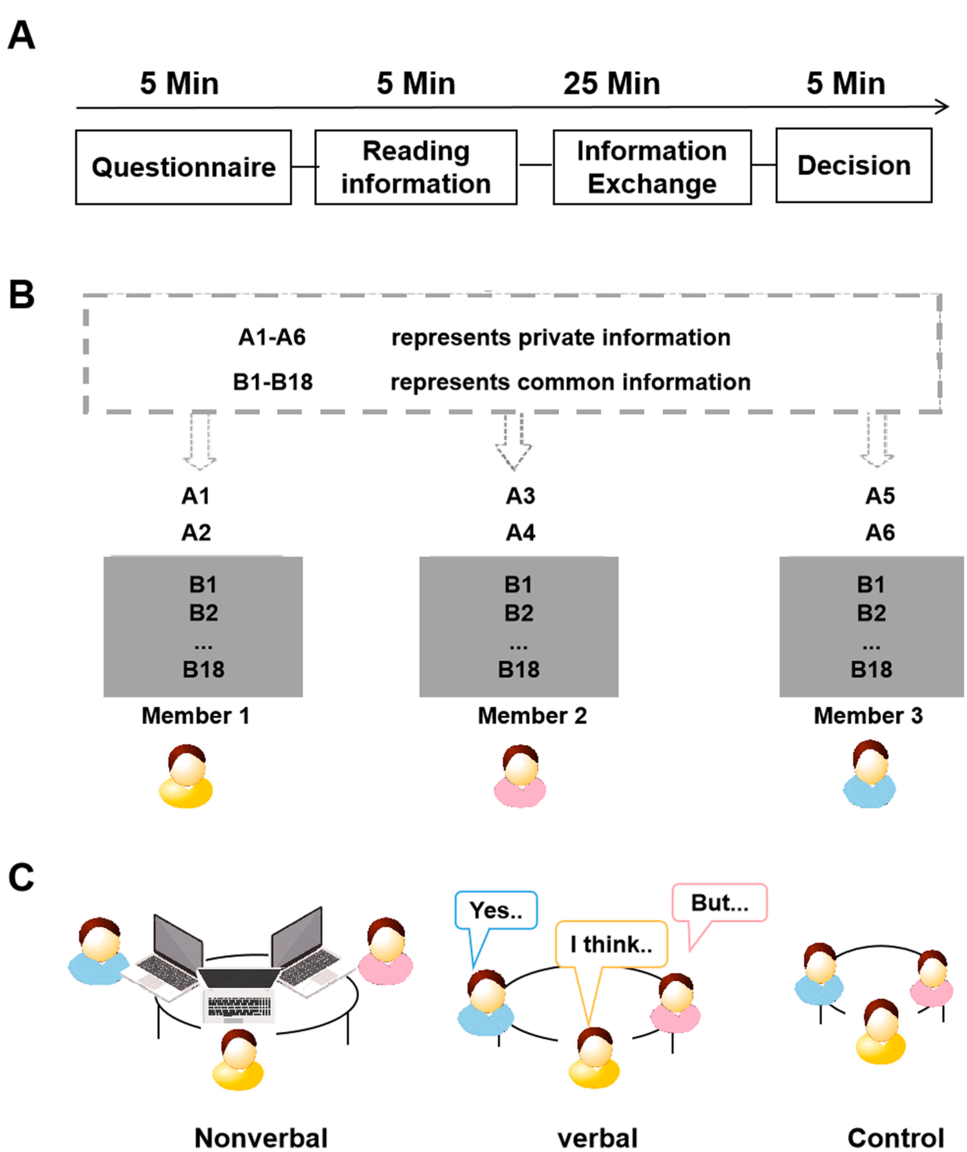

Fig. 1. Experimental procedure of Experiment 1. (A) The procedure of task. First, participants completed a series of individual difference questionnaires before the task. Then, each group member received 18 common information and 2 private information. They read their information within 5 min. After that, 144 triads were randomly assigned to three conditions to exchange information for 25 min (verbal condition, nonverbal condition, and control condition). Ultimately, participants in each group were asked to answer the following questions. (B) Each member of the group was given 18 common information and 2 private information (C) Three conditions to exchange information in Experiment 1. Groups under verbal conditions exchanged and discussed the information by talking, groups under nonverbal conditions exchanged and discussed by texting, and groups under control conditions deduced the case independently without information exchange.

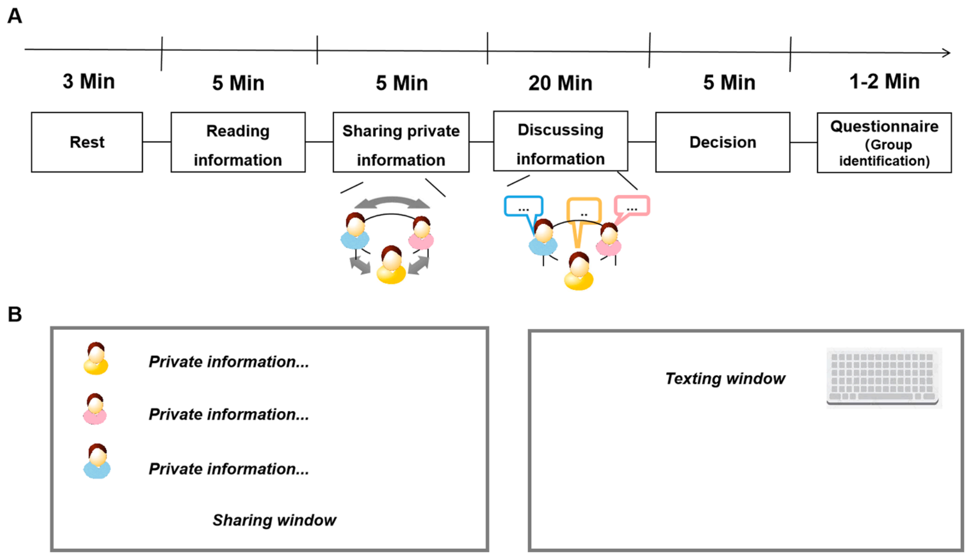

Fig. 2. Experimental procedure of Experiment 2. (A) The procedure of task in Experiment 2. Participants were given a 3-minute rest before the experiment began. Based on the definition of information exchange, we divided the process of information exchange into two separate components: group sharing (Sharing private information vs. No Sharing private information) and group discussion (Discussing the information vs. No Discussing the information). Each group member texted the private information to other members by Tencent Meeting during sharing stage for 5 min, and they discussed the information currently disclosed with others orally during the discussing stage for 20 min. After exchanging information, the groups had a period of 5 min to answer the questions. Ultimately, we measured participants' group identification using a 3-item measure. (B) A web-based system (Tencent Meeting) intended to enable the sharing of private information.

start the procedure, participants were given 3 min to rest. Each group member then received 18 common information and 2 private information and had five minutes to read their information. Then, the 120 triads were randomly assigned to four groups (Sharing-Discussion, No Sharing-Discussion, Sharing-No Discussing, and No Sharing-No Discussion groups) (see Fig. 2(A)). The participants in the Sharing groups were asked to text private information on Tencent Meeting during the group sharing, while the participants in the No Sharing groups were asked to read and deduce the case instead of texting private information on Tencent Meeting during the group sharing. The participants in the Discussion groups were asked to discuss the case during the group discussion, while the participants in the No Discussion group were asked to read and deduce the case instead of discussing it during the group discussion. The S-D group was allowed to share private information via text and discuss both common and private information orally. The NS-D group was not able to share private information, and only discussed the common information orally. Two experimenters would monitor and document the results of the group discussion to determine if the groups only discussed the common information orally, and the recordings would then be re-examined after the experiment had concluded. The S-ND group shared their private information via text, but were instructed to deduce the case without discussion. The NS-ND group was not allowed to share private information and was asked to deduce the case independently without discussion. After exchanging information, all groups were given 5 min to answer the following questions (i) the probability of three suspects, 0−100% for each suspect; (ii) the motivation and tool of crime; and (iii) deduced the entire process of crime. Ultimately, we evaluated the participants' group identification through a 3-item questionnaire (Van Bavel et al., 2012) with each item being rated on a 100-point scale ranging from 0 = strongly disagree to 100 = strongly agree. The reliability of this scale was confirmed to be high ($\alpha = 0.85$).

2.3. fNIRS data acquisition

In Experiment 2, the brain activities of participants in each group were simultaneously recorded with fNIRS using an ETG-7100 optical topography system (Hitachi Medical Corporation, Japan). The absorption of near-infrared light (two wavelengths: 695 and 830 nm) was measured with a sampling rate of 10 Hz. The oxyhemoglobin (HbO) and deoxyhemoglobin (HbR) were obtained under the modified Beer-Lambert law. We focused our analyses on the HbO signal for the following reasons: (i) HbO concentration is sensitive to changes in regional cerebral blood flow (Hoshi, 2003); (ii) the HbO signal was reported to have a higher signal-to-noise ratio than the HbR signal (Mahmoudzadeh et al., 2013); and (iii) an increasing number of studies have revealed neural synchronization based on the HbO signal (Yang et al., 2020).

Two optode probe sets were used to cover each participant's prefrontal and left TPJ regions (Fig. S1A), which have been previously reported to be associated with decision-making and information exchange (De Freitas et al., 2019; Tindale and Winget, 2019). For each participant, one 3 × 5 optode probe set (8 emitters and 7 detectors forming 22 measurement points with 3 cm optode separation, see Table S1 for detailed MNI coordinates) was placed over the prefrontal cortex (reference optode is placed at Fpz). The other 2 × 4 probe set (4 emitters and 4 detectors forming 10 measurement points with 3 cm optode separation) was placed over the left TPJ (reference optode is placed at T3, see Table S2 for detailed MNI coordinates). The probe sets were examined and adjusted to ensure consistency of the positions across the participants (Fig. S1B).

2.4. Analyses

2.4.1. Collective performance

The collective performance was evaluated based on the group's answers to the case, which included the probability of three suspects (0−100% for each suspect, the probability of each suspect was 2 points, total totaling 6 points), the motivation (1 point) and tool of crime (1 point), and the deduction of the entire process of crime (20 points). Three independent raters were then invited to assess the collective performance, with a Cronbach's alpha of 0.86 in Experiment 1 and 0.83 in Experiment 2. The scores of the three raters were then averaged to determine the collective performance. To examine the collective performance in the verbal, nonverbal, and control conditions, a one-way ANOVA on collective performance was conducted in Experiment 1. To examine if the results were associated with personal traits, a series of one-way ANOVAs on personal traits such as gender, age, agreeableness, reasoning ability, and emotions were conducted.

To examine the beneficial effect of verbal information exchange on collective performance by manipulating group sharing and group discussion, a univariate ANOVA was then performed on the collective performance of four groups (S-D, NS-D, S-ND, and NS-ND), with group sharing and group discussion as the fixed factors in Experiment 2. Furthermore, hierarchical multiple regression was conducted, using collective performance as the dependent variable, to determine the weight of group sharing, group discussion, and their interaction.

2.4.2. Group identification

We conducted a univariate ANOVA to assess the effect of verbal information exchange on group identification. Furthermore, hierarchical multiple regression was conducted, using group identification as the dependent variable, to determine the weight of group sharing, group discussion, and their interaction. Subsequently, the Pearson correlation was used to investigate the relationship between collective performance and group identification. Finally, PROCESS Model 4 with 5000 bootstraps resamples was used to determine if the effect of verbal information exchange on collective performance was mediated by group identification (Preacher and Hayes, 2008).

2.4.3. Interactive frequency

We sought to understand the behavioral mechanisms behind the information exchange induced group identification that occurred in Experiment 2. Three independent raters were invited to rate the interactive frequency of each group, with a Cronbach's alpha of 0.88. It is suggested to take into account the following items, including verbal interactive frequency (e.g., 'I agree with you', 'You're right', 'I know what you mean') and nonverbal interactive frequency (e.g., eye contact and smiling). The rating stage consisted of group sharing and discussion, where the raters rated according to the suggested items using one minute as the epoch. Then the scores for 25 epochs were aggregated. Furthermore, hierarchical multiple regression was conducted, using interactive frequency as the dependent variable, to determine the weight of group sharing, group discussion, and their interaction. In the end, the final interactive frequency of the group was calculated by averaging the scores of three raters for each group.

To examine whether interactive frequency significantly differed among four conditions during group sharing and group discussion, univariate ANOVA was conducted on interactive frequency, using group sharing and group discussion as the fixed factors. Subsequently, the Pearson correlation between group identification and interactive frequency was conducted. After that, PROCESS model 6 with 5000 bootstraps resamples was used to test how interactive frequency and group identification mediated the effect between information exchange and collective performance (Preacher and Hayes, 2008).

2.4.4. Within-group neural synchronization

We sought to understand the neural mechanisms behind the information exchange induced group identification that occurred in Experiment 2. Data were preprocessed using the Homer2 package in MATLAB 2020b (Mathworks Inc., Natick, MA, USA). First, motion artifacts were detected and corrected using a discrete wavelet transformation filter procedure. After that, the raw intensity data were converted to optical density (OD) changes. Then, kurtosis-based wavelet filtering (Wav Kurt) was applied to remove motion artifacts with a kurtosis threshold of 3.3 (Chiarelli et al., 2015). Based on a prior multi-brain study of social interactions (Cheng et al., 2022), the output was bandpass filtered using a Butterworth filter with order 5 and cut-offs at 0.01 and 0.5 Hz to remove longitudinal signal drift and instrument noise. Finally, OD data were converted to HbO concentrations.

After pre-processing, within-group neural synchronization (GNS) was used as the neural index (i.e., interpersonal brain activities that covary along the time course). Concerning GNS, and similar to previous studies (Yang et al., 2020), the wavelet transform coherence (WTC) (Eq. (1)) was used to assess the cross-correlation between two oxy-Hb time series of pairs of participants. Here, t denotes the time, s indicates the wavelet scale, $\langle\cdot\rangle$ represents a smoothing operation in time, and W is the continuous wavelet transform (Grinsted et al., 2004).

$$WTC(t,s) = \frac{|\langle s^{-1} w^{ij}(t,s)\rangle|^2}{|\langle s^{-1} w^{i}(t,s)\rangle|^2 |\langle s^{-1} w^{j}(t,s)\rangle|^2} \tag{1}$$

Within each triad (taking one triad with subject IDs of 1, 2, and 3 as an example), WTC was applied to generate the brain-to-brain coupling of each pair in each triad (Coherence1&2, Coherence 1&3, and Coherence 2&3). Then, three coherence values from three pairs were averaged as the GNS for each triad, that is, GNS = (Coherence 1&2 + Coherence 1&3 + Coherence 2&3) / 3. Regarding the first step, we estimated whether GNS was enhanced during the information exchange compared to the baseline. Time-averaged GNS (also averaged across channels in each group) was compared between the baseline session (i.e., the resting phase) and the task session (the whole verbal information exchange stage, that is, from the sharing stage to the discussing stage) using a series of one-sample t-tests. Here, p values were thresholded by controlling for FDR ($p < 0.05$; Benjamini and Hochberg, 1995). To compare the significantly changed GNS, we employed univariate ANOVA on GNS, with group sharing and group discussion as the fixed factors. Here, p values were thresholded by controlling for FDR ($p < 0.05$;). After that, the nonparametric permutation test was conducted on the observed interaction effects on GNS of the real group against the 1000 permutation samples. By pseudo-randomizing the data of all participants, a null distribution of 1000 pseudo-groups was generated (e.g., time series from member 1 in group 1 were grouped with member 2 in group 2 & member 3 in group 3) (Fig. 3). The GNS of 1000 reshuffled pseudo-groups was computed, and the GNS of the real groups was assessed by comparing it with the values generated by 1000 reshuffled pseudo-groups. To provide a complete picture of the underlying neural features, we also analyzed the GNS based on the HbR signal (see Supplementary Materials).

Second, the Pearson correlation between group identification and GNS was performed. It is plausible that neural synchronization is closely associated with information exchange, group identification, and collective performance, suggesting that it serves as a promising mechanism to explore how group identity influences collective outcomes. Moreover, previous research has established that neural synchronization facilitates the emergence of group identification, and the degree to which neural synchronization occurs among group members may shape how individuals identify with the group (Reinero et al., 2021). Therefore, PROCESS model 6 with 5000 bootstraps resamples was used to test how GNS and group identification mediated the effect between verbal information exchange and collective performance (Preacher and Hayes, 2008).

Third, to explore whether GNS could predict the scores of group identification a Support Vector Regression (SVR) analysis was conducted (Vapnik, 1995). Our SVR analysis consisted of the following steps. For our first step, the GNS of sharing stage and discussing stage from all channels were extracted as the features, and the response variable was the group identification of each group. Second, 80% of the response variable were then selected as a training dataset. The training dataset was trained by ε-support vector regression (ε-SVR) with the

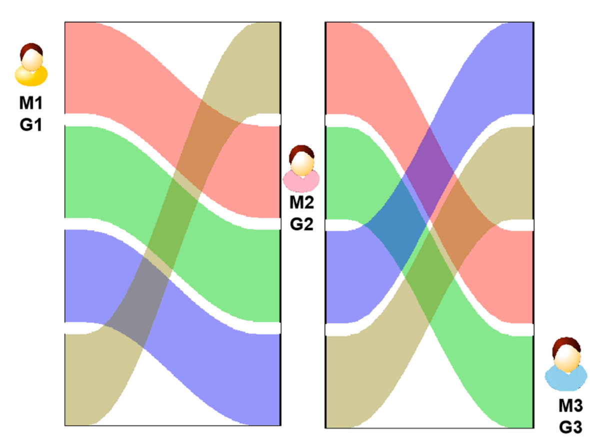

Fig. 3. Pseudo-groups. For example, time series from member 1 in group 1 were grouped with member 2 in group 2 & member 3 in group 3.

radial basis function (RBF). The ε-SVR algorithm is a generalization of the known support vector classification algorithm to the regression case (Yan et al., 2008). The parameter ε was set to 0.01. The other two parameters (C, γ) were used to adjust the efficiency of the algorithm. An auto-searching program named "grid regression" was adopted to search for the best parameters (C, γ) through a leave-one-out cross-validation (LOOCV) approach. Finally, the prediction accuracy of the model was expressed by the Pearson correlation coefficient between the actual and predicted values (Kosinski et al., 2013). A higher correlation coefficient indicates a better fit of the model.

Additionally, we aimed to gain a more comprehensive understanding of the GNS in the context of sharing and discussing stages. To this end, we used one minute as the epoch to extract the average GNS for both the sharing and discussing stages. Then, a paired-sample *t*-test was conducted to compare the two. Furthermore, the time course of the dynamic GNS during information exchange was plotted and a one-way ANOVA was conducted to identify when GNS significantly differed among the four conditions. To comprehend the interactive behavior that dynamic GNS elucidates, we fused correspondence between GNS in the time series and interactive behavior in the video recording. The time course of GNS was down-sampled to 1 Hz to obtain point-to-frame correspondence between the brain data sets and the video-recording data sets. Decoding was performed on a 1-min time scale, with a particular focus on the group members' interactive behaviors, such as smiling, eye contact, and verbal agreement.

3. Results

3.1. Group discussion is the key to improving collective performance

In Experiment 1, a one-way ANOVA on collective performance demonstrated that the collective performance varied among the information exchange conditions (verbal, nonverbal, and control conditions) ($F_{(2,\ 141)} = 65.12$, $p < 0.001$, $f = 0.96$; Fig. 4(A)). Further analyses showed that collective performance was significantly enhanced when exchanging information verbally ($t\ (94) = 10.01$, $p < 0.001$), while no significant enhancement in the nonverbal condition ($t\ (94) = -0.20$, $p = 0.842$). The verbal and nonverbal conditions were significantly distinct from each other, $t\ (94) = 10.34$, $p < 0.001$. These findings revealed that verbal information exchange was more effective than nonverbal information exchange to make collective decisions. This effect could not be associated with personality traits such as gender, age, agreeableness, reasoning ability, and emotions (see Table S3).

In Experiment 2, we investigated the effect of group sharing and group discussion on collective performance. The univariate ANOVA on the collective performance revealed a significant interaction between group sharing and group discussion ($F_{(1,\ 116)} = 7.92$, $p = 0.006$, $\eta_p^2 = 0.06$; Fig. 4(B)). Moreover, in the Discussing condition (i.e., S-D vs. NS-D), groups performed better when they shared private information with members (Sharing) than when they did not share private information with members (No sharing) ($t\ (118) = 6.70$, $p < 0.001$). However, this sharing effect was decreased in the No discussing condition (i.e., S-ND vs. NS-ND) ($t\ (118) = 3.24$, $p = 0.002$). Furthermore, we sought to address the weight of group sharing, group discussion, and the interaction of these two factors on collective performance. Results from the hierarchical multiple regression revealed that the model which included group discussion ($R^2 = 0.29$, $SE = 3.90$) was more successful in predicting collective performance than the model which included group sharing ($R^2 = 0.18$, $SE = 6.52$). These results pointed out that informational discussion should be more essential for superior collective performance than only sharing private information.

All of the above findings suggest that verbal information exchange could enhance collective performance; more importantly, engaging in deeper exchange (such as group discussion) was essential for a better collective decision.

3.2. Group identification mediates the enhancement of collective performance

In Experiment 2, the univariate ANOVA on group identification revealed a significant interaction between group sharing and group discussion ($F_{(1,\ 116)} = 5.94$, $p = 0.016$, $\eta_p^2 = 0.05$; Fig. 5(A)). Moreover, in the Discussing condition (i.e., S-D vs. NS-D), groups reported higher group identification when they shared private information with members (Sharing) than when they did not share private information (No Sharing) ($t\ (118) = 4.29$, $p < 0.001$). However, this Sharing effect was decreased in the No discussing condition (i.e., S-ND vs. NS-ND) ($t\ (118) = 3.93$, $p = 0.002$). Results from the hierarchical multiple regression revealed that the model which included group discussion ($R^2 = 0.32$, $SE = 4.02$) was more successful in predicting group identification than the model which included group sharing ($R^2 = 0.14$, $SE = 4.72$).

The Pearson correlation analysis revealed that greater group identification was associated with enhanced collective performance ($r = 0.44$, $p < 0.001$) (Fig. 5(B)). The mediation model demonstrated a satisfactory fit (CFI = 0.94, TLI = 0.91, RMSEA = 0.04), suggesting that our manipulation of group sharing and group discussion affected group identification, which consequently resulted in variations of collective performance ($\beta_a = 0.56$, $SE = 0.27$, $t = 9.08$, $p < 0.001$; $\beta_b = 0.31$, $SE = 0.06$, $t = 5.58$, $p < 0.001$; $\beta_c = 0.40$, $SE = 0.03$, $t = 6.06$, $p < 0.001$; Fig. 5 (C)). These results showed that group identification mediated the effect of verbal information exchange on collective performance.

3.3. Interactive frequency correlates to the mediation effect

The univariate ANOVA analysis showed a significant interaction between group sharing and group discussion ($F_{(1,\ 116)} = 14.25$, $p <$

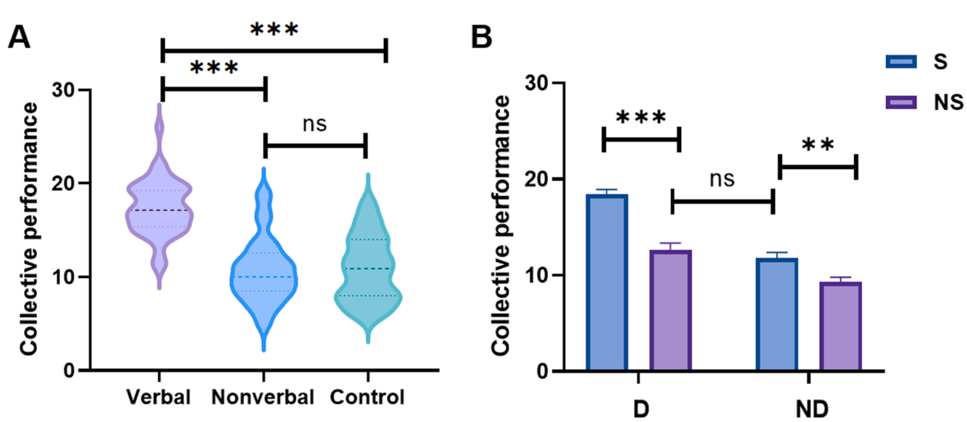

Fig. 4. Verbal information exchange enhanced collective performance. (A) In Experiment 1, information exchange influenced collective performance in the manipulation of exchanging information in various ways (verbal, nonverbal, and control conditions). (B) In Experiment 2, information exchange influenced collective performance in the manipulation of sharing and discussing stages. S was Sharing private information, NS was No-Sharing private information, D was Discussing information, and ND was No-Discussing information. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, *ns* is non-significant. Error bars reflected 1 SEM.

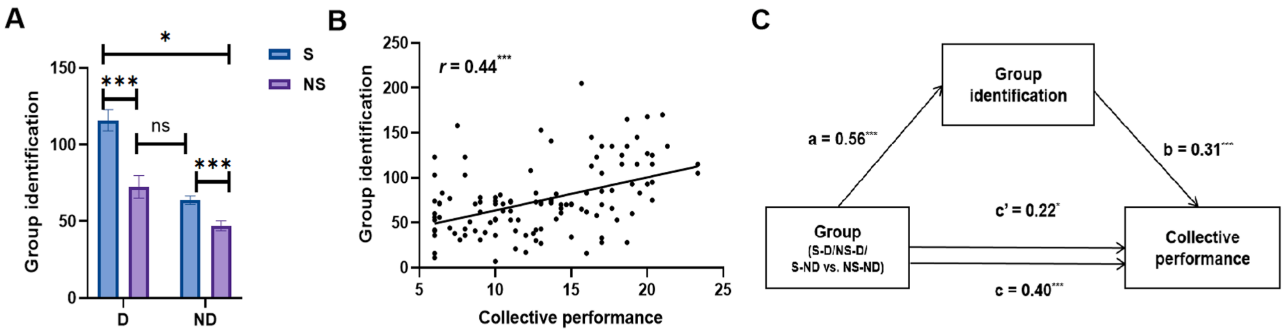

Fig. 5. Group identification mediated the effect of verbal information exchange on collective performance enhancement. (A) Experiment 2 revealed that group identification had a psychological influence on the enhancement of collective performance. (B) In Experiment 2, group identification was positively correlated with better collective performance. (C) A mediation analysis suggested that group identification mediated the relationship between the manipulation of verbal information exchange and collective performance. S was Sharing private information, NS was No-Sharing private information, D was Discussing information, and ND was No-Discussing information. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, *ns* is non-significant.

0.001, $\eta_p^2 = 0.11$; Fig. 6(A)). Moreover, in the Discussing condition (i.e., S-D vs. NS-D), groups showed more frequent interactions between members when they shared private information with members (Sharing) than when they did not share private information (No Sharing) with members (t (118) = 4.80, $p < 0.001$). However, this Sharing effect was not significant in the No discussing condition (i.e., S-ND vs. NS-ND) (t (118) = 1.95, p = 0.056). Results from the hierarchical multiple regression revealed that the model which included group discussion (R^2 = 0.26, SE = 0.42) was more successful in predicting interactive frequency than the model which included group sharing ($R^2 = 0.17$, SE = 1.33). These results indicated that interactive frequency was a behavioral indicator that could indicate the level of interaction between the groups.

We then tested whether interactive frequency affected group identification. Results showed that higher interactive frequency was associated with higher group identification ($r = 0.53$, $p < 0.001$; Fig. 6(B)). Then, we tested whether interactive frequency induced changed group identification, thereby enhancing collective performance. The serial mediation model demonstrated a satisfactory fit (CFI = 0.88, TLI = 0.86, RMSEA = 0.03), suggesting that our manipulations of information exchange generated an interactive frequency which then caused a significant alteration in group identification, and ultimately related to the collective performance ($\beta_{a1} = 0.17$, $SE = 0.03$, $t = 2.81$, $p = 0.026$; $\beta_{a3} = 0.24$, $SE = 0.03$, $t = 4.08$, $p = 0.009$; $\beta_{b2} = 0.18$, $SE = 0.04$, $t = 3.36$, $p = 0.017$; Fig. 6(C)). Our findings revealed that interactive frequency was a reliable marker of behavior that was associated with the impact of group identification.

3.4. Neural synchronization correlates to the mediation effect

We sought to test whether interactive frequency affected group identification. First, by performing one-sample t-tests for GNS, we observed a significantly increased GNS in the DLPFC (CH3, t (119) = 5.85, $p < 0.001$, FDR corrected) and the OFC (CH20, t (119) = 3.01, p = 0.030, FDR corrected). We then conducted the univariate ANOVA on GNS in CH3 and CH20, indicating a significant interaction between group sharing and group discussion in the DLPFC (CH3, $F_{(1, 116)} = 4.87$, $p = 0.041$, FDR corrected, $\eta_p^2 = 0.04$) (Fig. 7(A)). A permutation test confirmed that the observed interactive effects on GNS in real groups were outside the 95% CI of a null distribution comprising 1000 pseudo groups (Fig. S2). Therefore, the neural synchronization was only found in the 'real' groups who were interacting in the task. These results indicated that GNS was a neural indicator that could indicate the level of interaction between the group. The pattern of associated results was similar to that of HbO when the analyses of HbR were conducted (See the Supplementary Materials).

To establish how group identification mediated the effect of verbal information exchange on collective performance on the neural level, we first tested whether GNS in the right DLPFC affected group identification. Results showed that greater GNS in the right DLPFC (CH3) was associated with higher interactive frequency ($r = 0.35$, $p < 0.001$; Fig. 7(B)). The serial mediation model demonstrated a satisfactory fit (CFI = 0.88, TLI = 0.86, RMSEA = 0.03), suggesting that GNS in the DLPFC which was relevant to our manipulations of information exchange caused reliable changes in group identification, and ultimately changed the corresponding collective performance ($\beta_{a1} = 0.22$, $SE = 0.93$, t =

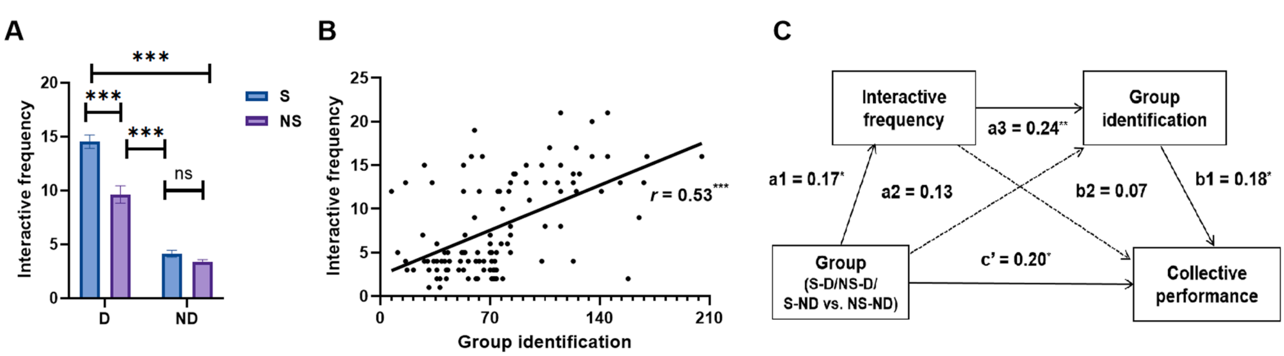

Fig. 6. Interactive frequency correlates to the mediation effect. (A) A significant interaction between group sharing and group discussion on interactive frequency was observed during the information exchange stage. (B) Higher interactive frequency was associated with higher group identification. (C) A serial mediation model suggested that interactive frequency and group identification mediated the relationship between information exchange and collective performance. S was Sharing private information, NS was No-Sharing private information, D was Discussing information, and ND was No-Discussing information. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, *ns* is non-significant.

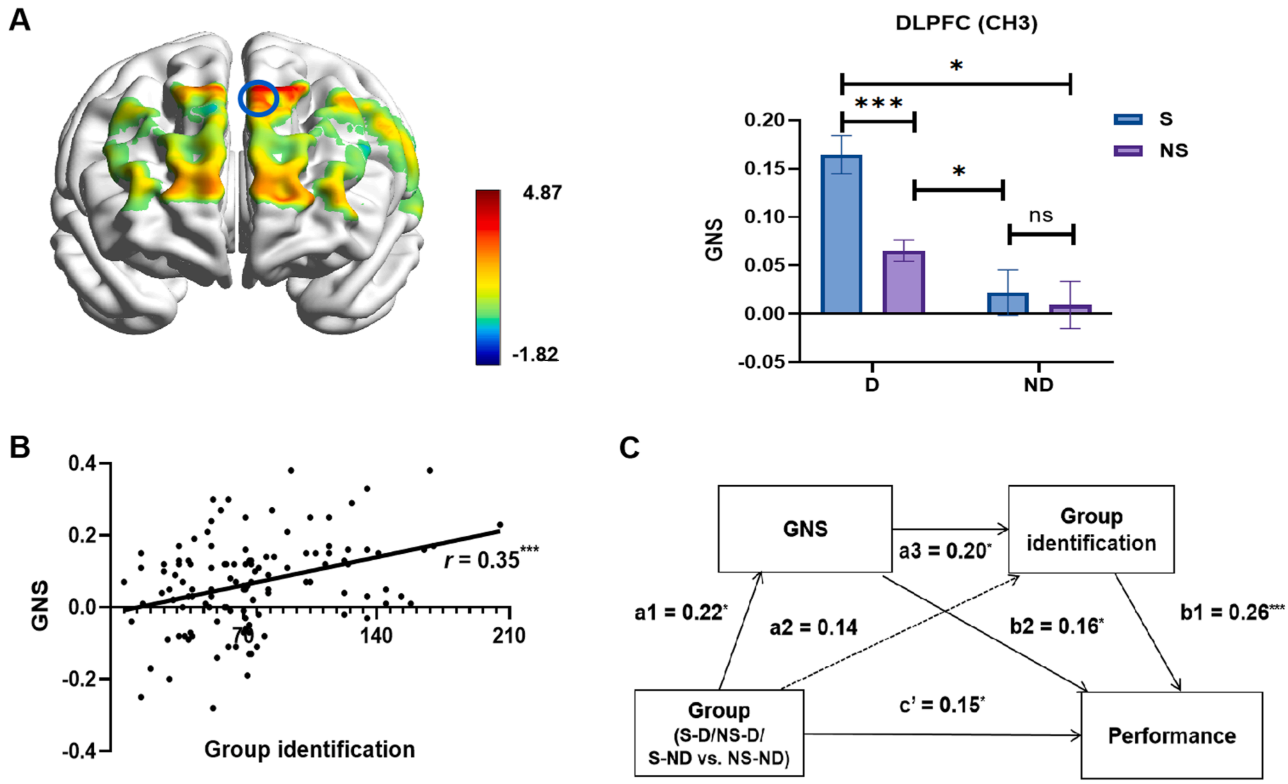

Fig. 7. Neural synchronization correlates to the mediation effect. (A) A significant interaction between group sharing and group discussion on GNS in the DLPFC (CH3) was observed during the information exchange stage (*p*-value, FDR corrected). (B) Greater GNS in the right DLPFC (CH3) was associated with higher group identification. (C) A serial mediation model suggested that GNS and group identification mediated the relationship between information exchange and collective performance.

4.18, $p = 0.001$; $\beta_{a3} = 0.20$, $SE = 0.04$, $t = 4.03$, $p = 0.003$; $\beta_{b2} = 0.26$, $SE = 3.14$, $t = 4.67$, $p < 0.001$; Fig. 7(C)). Our findings revealed that GNS was a reliable neuromarker that was associated with the impact of group identification.

Moreover, to answer the question of whether it is possible to infer group identification based on the GNS. The results of the SVR analysis revealed a significant Pearson correlation ($r = 0.58$, $p < 0.001$) between the actual and predicted group identification of the testing dataset based on the GNS during the discussion stage. However, concordant analyses based on the GNS during the sharing stage did not yield a significant correlation ($r = 0.32$, $p = 0.145$). These findings suggest that engaging in deeper exchange (such as information discussion) was a reliable predictor of group identification.

In order to gain a better comprehension of GNS, we decided to assess the dynamic GNS throughout the entire information exchange phase. The average GNS for the sharing stage was compared to the average GNS for the discussing stage using a paired-sample *t*-test. The findings revealed that the level of GNS was significantly higher when discussing than when sharing information (t (119) $= 2.70$, $p = 0.008$; Fig. 8(A)). The results of the one-way ANOVA test showed that GNS varied significantly among the four conditions ($F_{(3,\ 476)} = 8.47$, $p < 0.001$, $f = 0.09$; Fig. 8(B)). Specifically, the S-D group had a more pronounced GNS compared to the remaining three groups, which became visible approximately 6 min into the time course (i.e., the discussing stage). To comprehend the interactive behavior that dynamic GNS elucidates, we amalgamated video-recording and brain data sets. Results demonstrated that the higher GNS was associated with increased interactions among members, including eye contact, verbal agreement, and smiling, while the lower GNS was observed when few interactions occurred (see Fig. 8 (C) and (D) for an example).

3.5. *The theoretical model*

Building on the results of our study, we proposed a theoretical model that explains how to enhance collective performance through verbal information exchange (as shown in Fig. 9). Our findings suggest that engaging in verbal information exchange, such as group sharing and discussion, increases the interactive frequency and enhances within-group neural synchronization (GNS) in the dorsolateral prefrontal cortex (DLPFC). We found that these corresponding increases in interactive frequency and GNS in the DLPFC led to more relevant identification with groups. Ultimately, this better group identification resulted in enhanced collective performance.

4. Discussion

This study aimed to investigate whether and how verbal information exchange promoted collective performance within triads engaged in collaborative problem-solving tasks. We combined behavioral measurements and neuroimaging approaches to address this question and proposed a theoretical model to explain how verbal information exchange enhanced collective performance. In contrast to prior research that has treated information exchange as a singular construct (e.g., De Wilde et al., 2017; Larson et al., 1994), our study provided novel insights into the importance of group discussion in enhancing collective performance by distinguishing between group sharing and group discussion. Our findings also provided empirical support for the Social Identity Theory from a multiparticipant perspective by revealing that group identification mediated the positive effect on collective performance. This mediation was further supported by the observed higher interactive frequency and enhanced GNS in the DLPFC. Overall, our study provides a deeper understanding of group decision-making and highlights the importance of verbal information exchange, particularly group

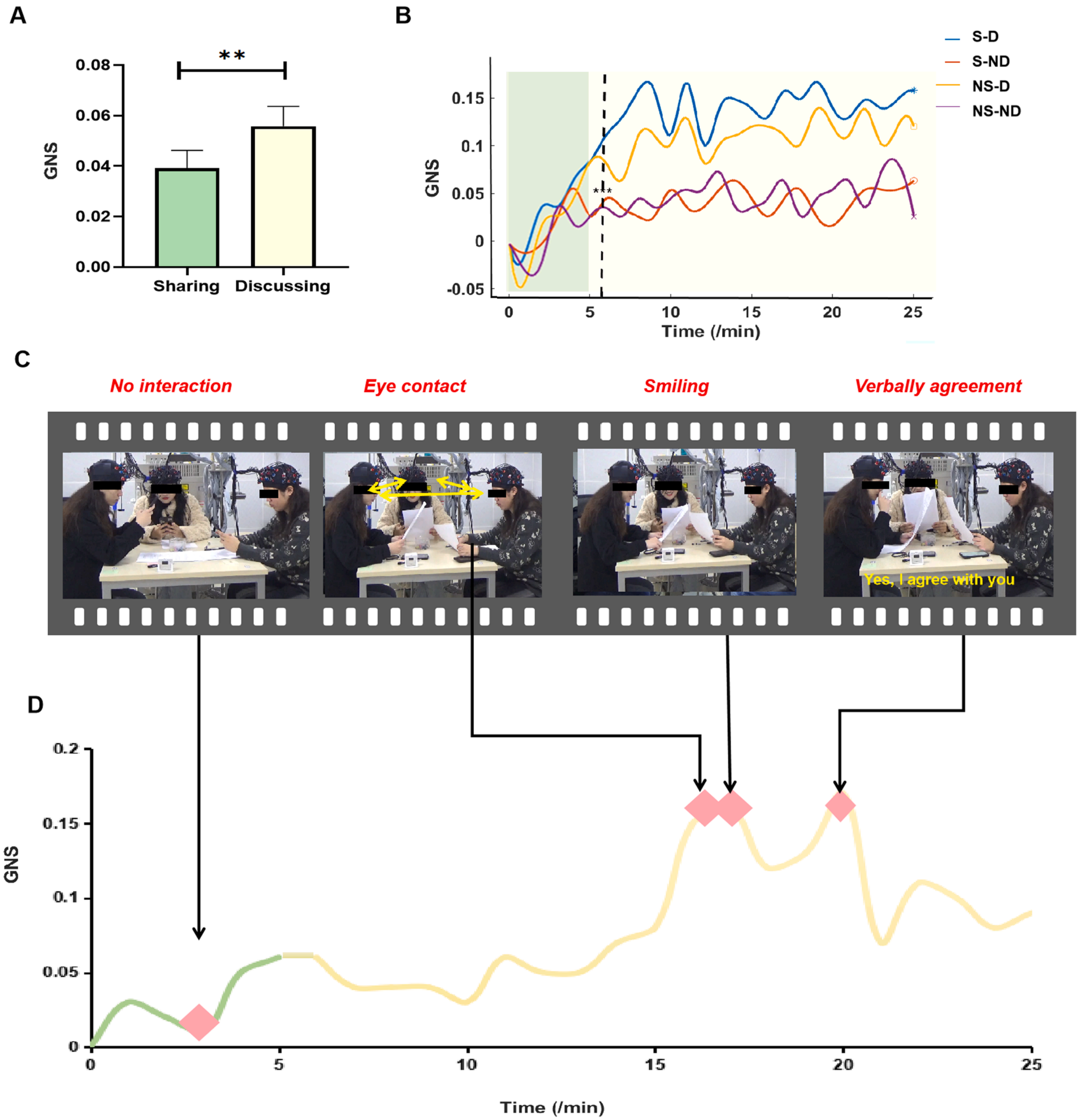

Fig. 8. The dynamic GNS during verbal information exchange. (A) The GNS for the group discussion stage was significantly higher than that in the sharing stage. The green shade stage was the sharing stage and the off-white shade was the discussing stage. (B) The time course of the averaged GNS indicated that GNS significantly differed among the four conditions 1 min after the group members entered the group discussion stage. (C) Example of the temporal evolution of GNS during information exchange. (D) Example video frames coding interactive behaviors. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$, *ns* is non-significant. Error bars reflected 1 SEM. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

discussion, in small groups.

First, the current study provided novel insights into the role of information exchange, resolving the debate concerns that whether information exchange enhances or weakens collective performance. Our findings indicated that verbal information exchange was beneficial for enhancing collective performance, whereas nonverbal information exchange did not produce the same beneficial effect. This is because verbal communication allows for a clearer expression of information and intention than nonverbal communication (Duncan, 1969; Key, 2011). For example, verbal communication is effective in providing information and achieving consensus, resulting in higher achievement in cooperative tasks (Yager et al., 1985), learning tasks (Bevilacqua et al., 2019), and deserted island tasks (Jiang et al., 2015). Conversely, texting or symbols can lead to misunderstandings and misinterpretations if the receiver does not understand the message (Chen et al., 2022; Duncan, 1969; Stolk et al., 2016).

To gain a deeper understanding of the advantages of verbal information exchange, Experiment 2 focused on the two stages of verbal information exchange: group sharing and group discussion. Group sharing among group members was an advantage of the group decision-making process that enabled the production of group decisions of higher quality than any individual could have achieved with limited information (De

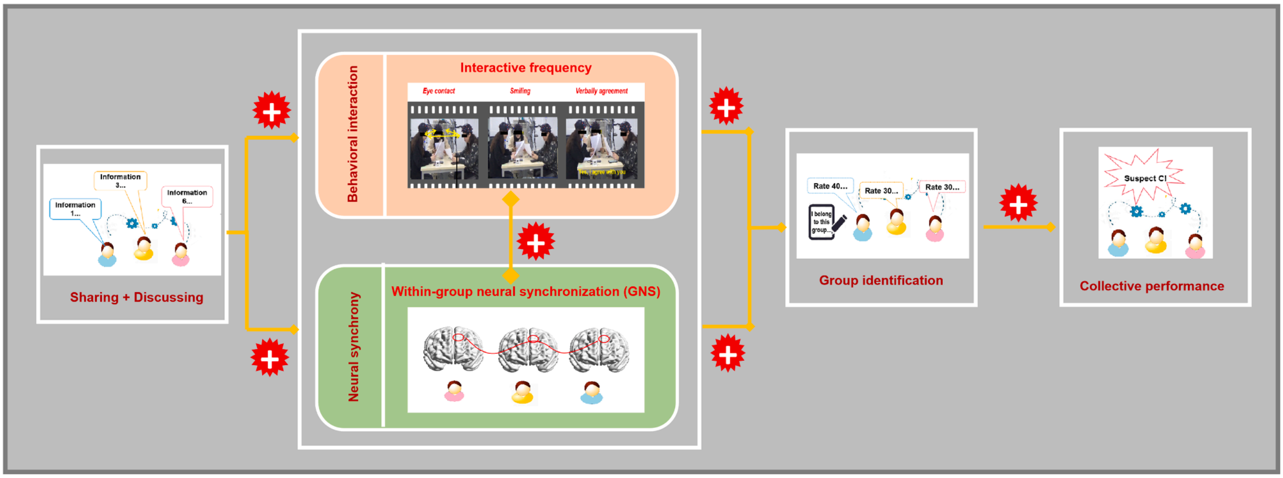

Fig. 9. The theoretical scheme of enhanced collective performance by verbal information exchange. Our evidence suggests that verbal information exchange enhanced collective performance through increasing group identification, the interactive frequency supported this process behaviorally, and the GNS in the DLPFC supported it neurally. Ultimately, groups exerted better collective performance.

Wilde, et al., 2017; Gigone, and Hastie, 1993; Lee Cunningham et al., 2021; Metcalf et al., 2019). Moreover, the major advantage of group decision-making was the “Wisdom of Crowds”, was often generated from the oral discussion, allowing for the expression, clarification, and understanding of information and thoughts (Kameda et al., 2022; Surowiecki, 2005; Savage, 2012). Consistent with these studies, our findings suggested both group sharing and group discussion significantly contributed to this positive outcome. While previous studies have been unable to isolate the stages of information exchange due to the simultaneous variation of both factors (e.g., De Wilde et al., 2017; Larson et al., 1994), it is important to understand the independent role of information exchange in collective performance. Our study broadens the scope of existing research, shedding light on the fact that group discussion is more significant in improving collective performance compared to group sharing. This finding adds to our understanding of the mechanisms by which verbal information exchange impacts group decision-making, and could inform future research on developing tools and techniques that maximize group discussion to attain optimal collective performance.

Third, a notable contribution of our work revealed the potential psychological-neural mechanism of verbal information exchange impacting performance. Our findings suggested that verbal information exchange enhanced performance through the mediating role of group identification. Group identification is proven to be crucial in affecting the relationship between information exchange and collective performance (Kim, 2018). This study opens up avenues for further inquiry into the precise role of group identification in influencing the association between information exchange and collective performance. By combining the tools and techniques from neuroscience and video analysis, this study provided an initial step towards a possible mechanistic understanding of how group identification mediates the effect of verbal information exchange improving performance. Behaviorally, this study has demonstrated that increased interaction between group members when exchanging information had a positive impact, and it strengthened their relationship, promoting collective performance. Our analysis is further validated by video recordings that highlight the contributions of information exchange to increasing interactive frequency. Previous research has explored nonverbal and physiological signals used to gage interaction between strangers (Palumbo et al., 2017; Reed et al., 2013). Our findings added to this conclusion by identifying verbal and nonverbal interactive signals that can quantify the degree of group identification and collective performance. Neurally, our research has demonstrated that neural synchronization was enhanced when exchanging information with group members, promoting the relations among them and thus improving collective performance. This is supported by previous research indicating the involvement of increased neural synchronization in the prefrontal area in collective performance (Liu et al., 2021; Wang et al., 2019; Yang et al., 2020). More broadly, our findings have gone further to show that neural synchrony can be used as a neuromarker to determine the degree of group identification through correlation analyses. Notably, we observed that the level of GNS was particularly elevated during group discussion, rather than nonverbal group sharing. This is in line with prior studies (Jiang et al., 2015; Stolk et al., 2016) which highlighted the importance of verbal communication in influencing group identification and collective performance. To sum up, our study has identified that interactive frequency and GNS generated by verbal information exchange have an impact on group identification, promoting collective performance. These findings have implications for future research aimed at improving our understanding of the psychological and neural mechanisms that underly group decision-making.

Our study has raised several interesting issues for further investigation. To begin with, future studies should consider using a trial-by-trial problem-solving task instead of subjective assessments, enabling the analysis of collective performance as a continuous variable rather than depending on ratings from raters. Second, our measure of group identification revealed that it mediated the effect of information exchange on collective performance. To further strengthen this effect, it would be beneficial to create tasks that can manipulate group identification beyond self-report measures. Third, the definition of nonverbal information exchange in the design differs from that of interactive frequency coding, such as eye contact and smiling, and thus requires more thorough consideration to be included in more suitable analyses. Lastly, it would be valuable to explore the potential implications of changing GNS in the DLPFC. Our theoretical framework suggests that information exchange enhanced collective performance, which was mediated by group identification and linked to GNS in the DLPFC. Therefore, to validate this result, future studies could combine our framework with brain stimulation techniques.

In summary, our work develops a systematic theoretical model that highlights the role of verbal information exchange in enhancing collective performance, with group identification as a significant psychological construct driving this positive effect. Our findings and theoretical model offer valuable insight into the decision-making process, which can ultimately lead to higher-quality decisions. Moreover, the implications of our work apply to a range of social contexts, including psychology, neuroscience, economics, and sociology. By shedding light on the factors that contribute to effective group decision-making, our study provides a foundation for future research aimed at improving collective outcomes in a variety of domains.

Data and code availability statement

Data and code of this project were obtained from the GitHub repository (available at https://github.com/xehui/group-deicison-making.git). The code is only to be made available via a request to the Authors, which requires a formal data sharing agreement.

CRediT authorship contribution statement

Enhui Xie: Conceptualization, Formal analysis, Methodology, Writing – original draft. **Keshuang Li:** Writing – review & editing. **Ruolei Gu:** Writing – review & editing. **Dandan Zhang:** Writing – review & editing. **Xianchun Li:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link to my data and code.

Acknowledgments

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.neuroimage.2023.120339.

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