

Group-level physiological synchrony and individual-level anxiety predict positive affective behaviors during a group decision-making task

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Abstract

Joint performance can lead to the synchronization of physiological processes among group members during a shared task. Recently, it has been shown that synchronization is indicative of subjective ratings of group processes and task performance. However, different methods have been used to quantify synchronization, and little is known about the effects of the choice of method and level of analysis (individuals, dyads, or triads) on the results. In this study, participants performed a decision-making task in groups of three while physiological signals (heart rate and electrodermal activity), positive affective behavior, and personality traits were measured. First, we investigated the effects of different levels of analysis of physiological synchrony on affective behavior. We computed synchrony measures as (a) individual contributions to group synchrony, (b) the average dyadic synchrony within a group, and (c) group-level synchrony. Second, we assessed the association between physiological synchrony and positive affective behavior. Third, we investigated the moderating effects of trait anxiety and social phobia on behavior. We discovered that the effects of physiological synchrony on positive affective behavior were particularly strong at the group level but nonsignificant at the individual and dyadic levels. Moreover, we found that heart rate and electrodermal synchronization showed opposite effects on group members' display of affective behavior. Finally, trait anxiety moderated the relationship between physiological synchrony and affective behavior, perhaps due to social uncertainty, while social phobia did not have a moderating effect. We discuss these results regarding the role of different physiological signals and task demands during joint action.

KEYWORDS

electrodermal activity, group interactions, heart rate, interpersonal synchrony, multidimensional recurrence quantification analysis, physiological synchrony

Ilanit Gordon and Sebastian Wallot contributed equally to writing this manuscript and share first authorship.

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1 | INTRODUCTION

Groups are critical units of our social world; they shape our identity, and through our membership in them (sometimes even via intra- or inter-group conflicts), we cooperate to achieve cultural, economic, and societal goals (Tajfel, 1982). Grouping is a universal, age-old phenomenon in social species (Gordon et al., 2014; Shamay-Tsoory et al., 2019) and thus is considered an innate element of our nature. As social beings, humans' tendencies to group drive unique human cognition and behaviors that have specific implications for the brain and biological functioning (Cacioppo et al., 2010; Shamay-Tsoory et al., 2019). One of the main consequences of human grouping is an emergent interpersonal synchrony between group members, not only in behaviors and attitudes (Gordon & Berson, 2018) but also in physiological processes (Gordon et al., 2020). The effects of physiological synchrony for prosocial behavior in groups are a major focus of the current research. Because groups are critical to our existence, it is important to understand what determines the success or failure of groups. A recent focus of research on groups has been the nesting of individuals in the group as a whole or in dyads that form parts of the whole group (e.g., Yammarino & Gooty, 2019). As such, group performance can be determined by individual-level effects, by the input of dyads, and/or by the actual product of the whole group (Drazin et al., 1999). Understanding the sources of variance, which were once treated as error, is now at the heart of theory and considered critical for the identification of the building blocks of group functioning (Paruchuri et al., 2018).

Despite the importance of multilevel considerations in the context of groups, most research has employed a “single level” approach as well as a focus on static rather than dynamic phenomena (Ballard et al., 2021). In this study, we focused on physiological interpersonal synchrony in groups, defined as the automatic, spontaneous temporal coordination of physiological processes between several individuals (Mayo & Gordon, 2020; Palumbo et al., 2017). Interpersonal synchronization is calculated from dynamic time-series that can reflect individual-, dyad-, and team-level processes (Gordon et al., 2014). Several studies have identified patterns of interpersonal interaction that predict group performance (Abney et al., 2015; Fusaroli & Tylén, 2016; Wallot, Roepstorff, et al., 2016), even though the role of these patterns can change in the context of particular task demands (Richardson et al., 2015; Wallot, Mitkidis, et al., 2016).

Indeed, despite the importance of groups to social identity and action (Gordon et al., 2014), we know very little about the underlying physiological indices in groups and group-level interpersonal synchrony processes (see Palumbo et al., 2017's review for an idea of the relatively scant amount of group studies). A study by Mønster and colleagues (2016) showed that during a shared group task in small groups of three, smiling synchrony (measured via electromyography) was positively related to

group cohesion, while synchrony in sympathetic arousal (measured via electrodermal activity: EDA) was positively related to group tensions. Recently, we showed (Gordon et al., 2020) that in triads, physiological synchrony in cardiac interbeat intervals (IBIs) emerged during a joint drumming task. In this drumming study, physiological synchrony in IBIs uniquely contributed to predicting individuals' sense of group cohesion (Gordon et al., 2020). It is important to note, that research has shown physiological synchrony to emerge not only in cooperation but also in competitive and conflictual experiences (Danyluck & Page-Gould, 2018, 2019; Levenson & Gottman, 1983). The type of physiological measure, the type of synchrony calculation, context and individual differences may all account for these apparently inconsistent effects (Mayo & Gordon, 2020). Palumbo and colleagues (2017), in their systemic review, showed that very little research has explored the consequences of physiological synchrony in groups or teams. In summary, further research is needed to elucidate the role of physiological synchrony in shared or cooperative experiences in groups.

One important marker of social engagement among group members is the display of smiles and positive affect between individuals in a shared setting (Gordon & Berson, 2018). This specific type of behavioral affective signaling is a key feature of early bond relationships (Gordon et al., 2010), as well as groups of adults working together toward a joint goal (Mønster et al., 2016). More positive affective displays among group members can indicate group bonding, for example, due to the influence of a charismatic leader (Gordon & Berson, 2018). Moreover, there is a biobehavioral basis for affective displays driven by the neurohormone oxytocin, known for its role in human affiliation, social motivation, and bonding (Gordon & Berson, 2018; Gordon et al., 2011). The importance of positive affective displays during social interactions is not limited to individuals within a bonded relationship or groups. For instance, between two strangers, smiling synchrony while watching a positive movie was positively related to cardiovascular synchrony and a reported convergence in their positive emotions (Golland et al., 2019). In total, positive affective displays in a social context contribute to social engagement and are relevant even for newly formed social systems, yet the relationship between this key social behavior and physiological synchrony among group members remains largely unknown.

Beyond the general question of the relationship between physiological synchrony and group outcomes during joint action, there are two other related important research questions regarding the level at which group activity happens and, accordingly, the level at which it should be analyzed and how individual differences between group members influence group dynamics. In the study by Mønster and colleagues (2016), in which groups of 3 participants were asked to build origami boats together in a competitive task, effects of physiological synchrony were found in subjective but not objective performance measures (i.e., the number of boats built). Physiological

synchrony was calculated as the average of dyadic synchrony between all possible pairs of group members. And yet, it is established that behavior in a triad is more complex than the average behavior of all three dyadic synchronies constituting the group (Riley et al., 2011). As such, a measure that does not assess participants' simultaneous interactions beyond the dyadic level to include potential higher-level interactions in the group cannot fully capture some aspects of group outcomes.

To resolve this issue, the method of multidimensional recurrence quantification analysis (MdrQA) (Wallot, Roepstorff, et al., 2016) was developed. MdrQA allows the analysis of joint dynamics of any group size. A reanalysis of the EDA data from the Mønster et al. (2016) study revealed that group-level joint dynamics reliably predicted boat-building performance, while the dyadic aggregated measures did not. Alternatively, it is plausible that not all participants engaged in the group to the same degree; accordingly, individual participants' behaviors may then be a function of the degree of individual contribution to joint action. Therefore, we propose a measure of individual group members' participation during joint action, namely, averaged individual dyadic synchrony, which can also be computed within the framework of MdrQA (for further details, see the Calculation of Physiological Synchrony section and Wallot, Roepstorff, et al., 2016). Accordingly, in the current study, we aimed to test at which level—or levels—physiological group dynamics are informative about group members' behavior because the failure to detect such relationships in previous research might have been due to the measurement of physiological synchrony strictly at the dyadic level, which can obscure existing relationships (i.e., Wallot, Mitkidis, et al., 2016).

The second pertinent question, regarding interindividual differences, may likewise factor into the relations between physiological synchrony and behaviors made by group members. Individual variables such as trait anxiety and social phobia have not been investigated to a great extent in joint action research (Mein et al., 2016). However, it is known that such traits strongly influence a person's behavior in a group (Jonas et al., 2014; Walters & Inderbitzen, 1998). Accordingly, we chose to investigate the roles of trait individual-level anxiety and social phobia as potential moderators of the relationship between physiological synchrony and behavioral displays of positive affect as proxies of engagement with the group and its members. The overarching aim of the current study was to test the association between HR and EDA synchrony among group members and positive affective behaviors during a shared group task. More specifically, we wanted to investigate whether such associations occurred at different group levels and whether such associations were moderated by interindividual differences in reported levels of trait anxiety and social phobia.

We collected data from 20 three-person groups participating in a joint decision-making task. The task was videotaped for later microanalysis of positive affective behaviors,

and all group members' electrocardiograms (ECG)—to allow later derivation of heart rates (HR)—and EDA were recorded throughout the task. HR represents the (average) number of heart beats per minute and is dually innervated by both the sympathetic and the parasympathetic branches of the autonomic nervous system (in a dynamic manner that does not allow to determine the exact contribution of either branch). EDA represents the level of skin conductance and is thought to reflect sympathetic influences, which may be associated with a challenge or stress (Dawson et al., 2017).

In terms of relational correlates of HR synchrony in groups (such as commitment, cohesion, satisfaction, togetherness, and comprehension)—previous studies have mostly reported positive associations (Gordon et al., 2020; Järvelä et al., 2016; Jun et al., 2019; Mitkidis et al., 2015; Noy et al., 2015). Only one previous study, to our knowledge, found a negative association between HR synchrony and trust in groups (Strang et al., 2014). As such, we expected synchrony in heart beats per minute (BPM synchrony) to have a positive association with group members' positive affective displays.

As for EDA synchrony, previous results regarding the associations with relational outcomes in groups are far less consistent. Several studies found positive correlations with group satisfaction, collaboration, and affective valence (Gashi et al., 2018; Jun et al., 2019; Schneider et al., 2020). Others reported negative associations with group tensions and interpersonal liking (Kaplan et al., 1963; Mønster et al., 2016). Since the results are mixed, we follow the direction of previous results from Mønster et al., 2016, which examined EDA synchrony in groups during a cooperative task via the same type of data analysis we perform in the current study. Thus, we expected EDA synchrony to have a negative association with positive affective behaviors made by group members (smiling and laughing). Finally, we expected individual-level anxiety and social phobia to moderate the associations between physiological synchrony and individuals' behaviors.

2 | METHOD

2.1 | Participants

Sixty individuals (16 men) nested in 20 three-person groups participated in the study. The average age of the participants was 22.96 years ($SD = 2.43$ years, Range: 20–33 years). Education level was high (Range: 12–17 years) Participants were all undergraduate students in the Department of Psychology at Bar-Ilan University. Triads were either all women or mixed, as we had no a priori hypotheses regarding gender composition, and we did not control for gender or gender composition in the current study. Individuals who reported any heart conditions were excluded from participation. The current study was the first to use group-level measures

such as MdRQA in combination with a desert survival task, and so a priori sample size power calculations were not appropriate, as the respective effect sizes were unknown. The selected sample size was guided by our intuitions of what may constitute a reasonable sample size in this context.

2.2 | Procedure

The study was approved by the Institutional Review Board of the Department of Psychology at Bar-Ilan University and was performed strictly according to their ethical approval. Prior to data collection, participants were contacted via email by the experimenter and asked to arrive at the study well hydrated and to avoid caffeinated drinks as well as nicotine for at least two hours prior to data collection. The lab visit duration was approximately 2 hr. Upon arrival at the lab, the research assistants (RAs) in charge of the study welcomed participants and explained the task. Participants were told that they would be a part of a joint decision-making task. Participants were connected to electrodes to collect physiological data (ECG and EDA data). The RAs explained that the data acquisition would be neither invasive nor dangerous or painful. In addition, they explained that the entire procedure would be videotaped and that the videos would be used for data analysis only by the research team. Participants provided informed written consent and were then individually connected to MindWare mobile recorders (MindWare Technologies, Gahanna, OH). Participants were asked to limit the movement of their nondominant arm where the electrodes for the collection of EDA data were placed (this was done to avoid motion artifacts in EDA data, although there are methods to detect and remove such artifacts in the preprocessing stages). Before the task began, we performed a 5-min baseline recording of physiological measures during which participants were asked to simply sit together and relax and not to move or talk. Then, the group task began. The collection of the ECG and EDA data from all group members was conducted simultaneously and in synchrony with video recording during the baseline phase and the task.

2.3 | Group task

Group members were instructed to complete the desert survival task (DST), which has been extensively used in research to examine group dynamics (Lafferty & Pond, 1974). We chose this task because it enabled us to carefully and continuously monitor group members' interaction as it occurred using different modalities (video, audio, and physiological arousal measures) and allowed us to later analyze and identify individual behaviors and physiological synchrony between group members (Gordon & Berson, 2018). The group members were asked to rank order 15 items (e.g., water, map,

compass), first individually and later within a group discussion, based on the items' perceived importance for survival in a desert. Participants were asked by the experimenter to imagine that they had survived an airplane crash and to individually rank order items regarding their value for survival. Later, participants were told that they needed to reach a consensus among group members on the ranking of the items. The DST facilitates group discussion and face-to-face interaction. In addition, the shared discussions and need to reach an agreement also tend to increase member interdependence, as these aspects increase the importance of belonging to group.

2.4 | Physiological measures

2.4.1 | Physiological data collection

An electrocardiogram (ECG) was obtained for every participant using a modified lead II configuration. The impedance cardiogram, which provides respiratory data for the analysis of IBI, was obtained using the standard tetrapolar electrode system (Sherwood et al., 1990). Electrodermal activity (measured in microsiemens [μS]) was collected via two disposable Ag-AgCl electrodes, both placed on the palm of the participant's nondominant hand. EDA values were outputted from the MindWare EDA analysis software as the mean skin conductance level recorded at 2 Hz. All recorders for the physiological signals are transmitted synchronously and wirelessly to a laptop computer in the control room adjacent to the lab room, with a sampling rate of 500 Hz.

2.4.2 | Preprocessing

For preprocessing of physiological data acquired, we used standard procedures outlined in the MindWare technologies manuals for their analysis applications (<https://support.mindwaretech.com/training/guides/>).

ECG

Each participant's ECG signal was visually examined and analyzed in the MindWare Technologies HRV application software (v3.1.4). Visual inspection and manual editing of the data were completed by trained graduate students to ensure the proper removal of artifacts and ectopic beats (Nabil & Reguig, 2015; Peltola, 2012). The signal was amplified by a gain of 1,000 and filtered with a Hamming windowing function. IBIs were extracted from the ECG recording. As IBI data usually differ in terms of number of data points between participants due to differences in the frequency of heart beats, they were transformed to BPM signals to obtain time series of equal rate for each participant. BPM series were oversampled to retain the full variability of the dynamics of the IBIs to increase the sensitivity of

recurrence analysis (Wallot et al., 2013). The resulting physiological time series used for the following analyses are for epochs of 500 milliseconds.

EDA

Each participant's EDA signal was again examined visually and analyzed in the MindWare Technologies EDA application software (v3.1.4). When unusual peaks or sudden, unreasonable drops in the data were found, linear spline interpolation was used to replace the corrupted portions of the signal, limited to a maximum of 5% of each individual's data. We used a rolling filter set for a block size of 500 milliseconds. In the cases in which the editor identified an unusual peak or a drop for more than 5% of the data or in the case of a complete loss or flat line of the data, the participant's EDA signal was not used in the final analysis. The outputted physiological time series for following analyses were for epochs of 500 milliseconds.

2.4.3 | Calculation of physiological synchrony

We used MdrQA (Wallot, Roepstorff, et al., 2016) to calculate the different synchrony measures for the EDA and BPM data. MdrQA was particularly suited for the analysis of the coupling of physiological time series in the present study for two reasons. First, recurrence-based analyses are extremely robust to outliers, heterogeneous variance over time, and nonstationarity (Marwan et al., 2007), which are common features of extended physiological recordings. Second, MdrQA provides a coherent analysis framework analyzing multivariate signals of different dimensionality, particularly the simultaneous coupling of more than two time series (Wallot, Roepstorff, et al., 2016).

The basic concept of MdrQA is the repetition of the same or similar values between time series. This is achieved by calculating the distances between all coordinate pairs of data points in a multidimensional time series. Then, recurrences are determined by thresholding this distance matrix, where distances below the threshold are treated as recurrent, and distances exceeding the threshold are treated as nonrecurrent. This yields a square matrix R_{ij} with thresholded values, coded as 1 or 0, of the i th and j th values of the time series:

$$R_{ij} = \Theta \left(r - \|X_i - X_j\| \right), i, j = 1, \dots, N, \quad (1)$$

where R is the thresholded distance matrix; \sum is the threshold parameter; $\Theta(\cdot)$ is the Heaviside step function (where $\Theta(x) = 0$, if $x < 0$, and $\Theta(x) = 1$ otherwise); X is a variable containing the time-series data; $\|\dots\|$ is a distance norm, typically the Euclidean norm; N is the number of data points of X ; and r is some threshold value. In MdrQA, X is not a unidimensional time series but a multidimensional coordinate vector.

To capture the proper dynamics of (multivariate) time series using MdrQA, one needs to estimate a delay parameter d , an embedding parameter m , and the threshold parameter r . We used multivariate parameter estimation methods (Wallot & Mønster, 2018), where tau is estimated as the first local minimum of the average mutual information function of the time series, m is estimated as the first local minimum of the multidimensional false-nearest-neighbor function, and r is chosen to yield an average percentage of recurrence points of approximately 5%–10% (Wallot & Leonardi, 2018). In practice, these functions sometimes level off instead of showing a clear local minimum, and then a point of minimal or no change is chosen instead. The parameters used for the present analysis were $d = 3$, $m = 5$, and $r = .55$ with Euclidean normalization. Notably, all time series were z -transformed before being subjected to MdrQA because we were interested in the similarities or differences between time series based on their sequential properties, not in differences based on the variance or level (Shockley, 2005).

For a thorough introduction to multivariate recurrence-based analysis in general, see Wallot and Leonardi (Wallot & Leonardi, 2018), and for a specific introduction to MdrQA, see Wallot et al. (Wallot, Roepstorff, et al., 2016). Using MdrQA, we calculated three kinds of synchrony measures: (1) averaged individual dyadic synchrony, (2) averaged group-level dyadic synchrony, and (3) group-level triadic synchrony. Notably, however, the calculation of recurrence measures this way involves the use of information from lags across the whole time series. While this approach yields a proper measure of synchrony in that all time series enter the analysis aligned at lag0, groups of time series that show more consistent dynamics are quantified as displaying higher levels of synchrony.

The averaged group-level dyadic synchrony (2nd synchrony measure) is the most common kind of measure used to aggregate synchrony measures for groups with $n > 2$ (Fusaroli & Tylén, 2016; Gordon et al., 2020; Mønster et al., 2016; Müller & Lindenberger, 2011). Synchrony measures are computed for each dyad within a group and are averaged at the group level so that each group's synchrony is effectively the average synchrony of all dyads within the group. MdrQA is conducted for each of the three possible dyads within a group, and the MdrQA outcome variables are averaged for each group. In addition to the averaged group-level dyadic synchrony, MdrQA specifically allows the computation of group-level triadic—or even higher-level—synchrony (3rd synchrony measure), where all three component signals for BPM or EDA are entered into the analysis simultaneously.

Moreover, we introduced a new calculation of synchrony within a group aimed at capturing specific individual participation in synchronous activity within a group, which we call the averaged individual dyadic synchrony (1st synchrony measure). We first proceeded with the 2nd synchrony measure by calculating all synchrony measures for all possible

dyads in a group. However, instead of averaging at the group level, we averaged synchrony measures at the dyadic level. Therefore, for a group of three with members A, B, and C, the first member was assigned the average dyadic synchrony he or she showed with each of the other two members. For a group of three people, this measure is calculated as follows (Equation 2):

$$\begin{aligned}
 A_{\text{indi-synch}} &= \frac{\text{synch}(A, B) + \text{synch}(A, C)}{2} \\
 B_{\text{indi-synch}} &= \frac{\text{synch}(B, A) + \text{synch}(B, C)}{2} \\
 C_{\text{indi-synch}} &= \frac{\text{synch}(C, A) + \text{synch}(C, B)}{2}
 \end{aligned}
 \quad (2)$$

Here, A , B , and C are data from three participants, and $\text{synch}()$ is some measure of synchrony between two time series, such as a recurrence measure. Then, each participant was assigned his or her individual synchronization value, indicating the strength of this participant's coupling with the other members in the group.

Like all recurrence-based analyses, MdrQA yields multiple outcome measures that capture different information about the coupling dynamics of time series. However, for data with a strong stochastic component, such as EDA recordings and BPM, these different measures are usually highly correlated and do not offer differential information about the time series under consideration. Hence, we chose to average the outcome measures into a single synchrony score. For such data, vertical line measures are more appropriate to capture the time-series dynamics (Marwan et al., 2007). Accordingly, in addition to the standard measure of the percentage of recurrent points (%Rec), we computed the vertical line measures of the percentage of laminarity (%Lam), average vertical line length (AVL), and maximum vertical line length (MVL)—all of which capture aspects of coupling strength, with high values indicating strong coupling and low values indicating weaker coupling. These four measures were z -transformed and then averaged into a single synchrony measure for the EDA data and for the BPM data. Note that the MdrQA outcome variables reflect synchrony in terms of absolute values, where high values imply high synchrony, be it positive or negative, in-phase or anti-phase-type patterns, while low synchrony values imply low synchrony, that is independence or near-independence of time series.

Tables 1 and 2 present the intercorrelations among these measures for individual-, dyadic- and group-level computations. These measures were highly correlated, justifying their averaging into a single synchrony score. This is also corroborated by the consistently high McDonald's ω values, all of which were $>.92$, indicating high internal consistency (Dunn et al., 2014). Each of the three different calculations of group synchrony was used as predictors of the effect of physiological synchrony on affective behavior.

TABLE 1 Correlations and consistency of the recurrence measures for BPM data

	%Rec	%Lam	AVL	MVL	ω
<i>Averaged individual dyadic synchrony</i>					
%Rec	–				
%Lam	.75	–			
AVL	.90	.85	–		
MVL	.60	.60	.72	–	$\omega_{\text{BPM}} = .94$
<i>Averaged group-level dyadic synchrony</i>					
%Rec	–				
%Lam	.70	–			
AVL	.88	.81	–		
MVL	.56	.54	.69	–	$\omega_{\text{BPM}} = .93$
<i>Group-level synchrony</i>					
%Rec	–				
%Lam	.74	–			
AVL	.87	.85	–		
MVL	.52	.52	.70	–	$\omega_{\text{BPM}} = .95$

TABLE 2 Correlations and consistency of the recurrence measures for EDA data

	%Rec	%Lam	AVL	MVL	ω
<i>Averaged individual dyadic synchrony</i>					
%Rec	–				
%Lam	.92	–			
AVL	.95	.89	–		
MVL	.97	.90	.97	–	$\omega_{\text{EDA}} = .95$
<i>Averaged group-level dyadic synchrony</i>					
%Rec	–				
%Lam	.42	–			
AVL	.69	.66	–		
MVL	.90	.54	.79	–	$\omega_{\text{EDA}} = .94$
<i>Group-level synchrony</i>					
%Rec	–				
%Lam	.37	–			
AVL	.61	.69	–		
MVL	.86	.40	.66	–	$\omega_{\text{EDA}} = .93$

2.5 | Behavioral microanalysis and calculation of positive affective behavior

All group interactions were videotaped with two video cameras in angles that allowed us to capture all group members' faces. Videos were later microanalyzed by trained psychology students on a specialized computerized system (Noldus; The Vaggenigen, Netherlands), consistent with previous research on group interactions (Gordon & Berson, 2018). After

at least 85% interrater reliability was reached for all coders in 3 videos of the 20 collected, coders began performing microanalysis independently. Coders annotated each time a group member started displaying positive affect (smiling or laughing) and when these behaviors stopped. Consequently, we determined the durations of all points at which group members displayed positive affect.

2.6 | The state trait anxiety inventory

The state trait anxiety inventory (STAI) (Spielberger et al., 1970) is a well-validated 40-item scale consisting of two scales (20 items each) to measure individual differences in trait anxiety levels as well as state or current anxiety levels. Higher scores on the STAI subscales denote a higher level of reported anxiety by participants. In the current study, we used the trait anxiety level to assess the more stable context-independent effects of individuals' anxiety on group interactions.

2.7 | Missing data

Some data were missing from the 60 participants who performed the DST in groups of 3. Table 3 summarizes the missing data points by variable. The reasons for missing data were as follows: (1) technical issues with the video recording in one group, (2) a large % of motion artifacts for EDA for 10 participants that could not be corrected and an issue with EDA recording in one group, and (3) incomplete self-report measures for 6 participants.

2.8 | Inferential statistics

Inferential statistics were performed using multilevel modeling with the “lme4” package in R, version 1.1-23 (Bates et al., 2015). Effect size measures were estimated using the “effectsize” package in R, version 0.4.1. The dependent variable was entered into the models at the individual level (the percentage of time a group member was displaying positive

affect—smiling or laughing—during the interaction), while predictor variables were entered into the models either at the individual level (i.e., the individual synchrony index) or at the group level (i.e., averaged dyadic synchrony for each group and group-level synchrony). STAI and Social Phobia Inventory [SPIN] values were treated as moderators in the models and entered at the individual level and Random intercepts were added for groups. The model equations are reported with the results below.

3 | RESULTS

3.1 | Group-level analyses

3.2 | Research questions and modeling approach

To test for the effects of physiological synchrony, captured by measures of BPM and skin conductance, on participants' smiling and laughing behaviors during the interaction, we ran multilevel models using recurrence measures of both BPM and EDA as predictors and smiling and laughing behaviors during the joint task as the dependent variable, with the group added as a random factor.

Moreover, as we were interested in determining the level at which joint physiological activity was related to positive affective behaviors (smiling and laughing), we ran three models with different compositions of predictors. The “individual” model used dyadic recurrence measures averaged at the individual level, thus capturing the participation of each individual group member in the physiological synchrony dynamics (Equation 3):

$$y_{ij} = \gamma_{00} + \gamma_{10} \text{BPM}_i + \gamma_{20} \text{EDA}_i + \gamma_{30} \text{BPM}_i \text{EDA}_i + u_{0j} + e_{ij}, u_{0j} \sim N(0, \sigma^2) \quad (3)$$

where i is the index for individuals, j is the index for groups, BPM is the dyadic BPM synchrony dynamics averaged at the individual level, and EDA is the dyadic skin conductance synchrony dynamics averaged at the individual level.

The “dyadic” model used dyadic recurrence measures averaged at the group level, thus composing the group dynamics as the average dyadic physiological dynamics. Finally, the “group” model used group-level recurrence measures to capture the physiological synchrony dynamics of all three group members simultaneously (Equation 4):

$$y_{ij} = \gamma_{00} + \gamma_{01} \text{BPM}_j + \gamma_{02} \text{EDA}_j + \gamma_{03} \text{BPM}_j \text{EDA}_j + u_{0j} + e_{ij}, u_{0j} \sim N(0, \sigma^2) \quad (4)$$

where, again, i is the index for individuals, and j is the index for groups. For the “dyadic” model, BPM is the average dyadic

TABLE 3 Overview of missing data

Variable	# of Observations missing	% missing
BPM	0 out of 60	0.0%
EDA	13 out of 60	21.6%
Smiling behavior	3 out of 60	5.0%
SPIN	6 out of 60	10.0%
STAI	6 out of 60	10.0%

heart rate dynamics at the group level, and EDA is the average dyadic skin conductance dynamics at the group level. For the “group” model, BPM is the group-level BPM synchrony dynamics, and EDA is the group-level skin conductance synchrony dynamics.

3.2.1 | Effects of BPM and EDA on the display of positive affective behaviors as a function of group level

As can be seen in Tables 4–6, neither the individual model (Table 4) nor the “dyadic” model (Table 5) predictors yielded significant effects on the behavioral measure. However, the “group-level” model did (Table 6). Specifically, the duration of group members' positive affective behaviors during the interaction was positively related to BPM synchrony dynamics and negatively related to skin conductance synchrony

TABLE 4 Individual model

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>d</i>
(Intercept)	9.12	1.37	6.66	<.001	1.24
BPM	.15	1.44	.10	.918	.02
EDA	−1.35	1.41	−.96	.339	−.18
BPM:EDA	1.83	1.57	1.17	.241	.25

Note: *b* are the model coefficients, *SE* are the coefficients' standard errors, *t* and *p* are the associated values of a *t*-test, testing the coefficient, and the effect size *d* (see Brysbaert & Stevens, 2018).

TABLE 5 Dyadic model

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>d</i>
(Intercept)	7.83	1.21	6.46	<.001	1.22
BPM	.27	1.33	.21	.837	.04
EDA	−1.47	1.47	−.99	.319	−.23
BPM:EDA	−.86	1.32	−.65	.518	−.13

Note: *b* are the model coefficients, *SE* are the coefficients' standard errors, *t* and *p* are the associated values of a *t*-test, testing the coefficient, and the effect size *d*.

TABLE 6 Group model

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>d</i>
(Intercept)	9.58	1.06	9.02	<.000	1.66
BPM	2.72	1.17	2.32	.020	−.67
EDA	−3.88	1.32	−2.93	.003	.47
BPM:EDA	−1.26	1.09	−1.16	.246	−.22

Note: *b* are the model coefficients, *SE* are the coefficients' standard errors, *t* and *p* are the associated values of a *t*-test, testing the coefficient, and the effect size *d*.

dynamics. There were, however, no significant interactions between the predictor variables within any of the three models.

3.3 | Trait anxiety and social phobia as person-specific moderators

3.3.1 | Research questions and modeling approach

Furthermore, we were interested in how individual trait characteristics, specifically social phobia and anxiety, moderated joint physiological effects on group members' displays of positive affect during the interaction. Therefore, we added the STAI (“group-level:STAI”) and SPIN values (“group-level:SPIN”) to the model as the individual-level predictor (Equation 5):

$$y_{ij} = \gamma_{00} + \gamma_{01} \text{BPM}_j + \gamma_{02} \text{EDA}_j + \gamma_{03} \text{TRAIT}_i + \gamma_{04} \text{BPM}_j \text{EDA}_j + \gamma_{05} \text{BPM}_j \text{TRAIT}_i + \gamma_{06} \text{EDA}_j \text{TRAIT}_i + \gamma_{06} \text{BPM}_j \text{EDA}_j \text{TRAIT}_i + u_{0j} + e_{ij}, u_{0j} \sim N(0, \sigma^2) \quad (5)$$

where *i* is the index for individuals, *j* is the index for groups, BPM is the group-level BPM synchrony dynamics, EDA is the group-level skin conductance synchrony dynamics, and TRAIT is the person-specific STAI value in the “group-level:STAI” model or the person-specific SPIN value in the “group-level:SPIN” model. As expected, STAI and SPIN values were positively correlated with $r = .62$.

3.3.2 | Effects of SPIN and STAI on the relation of BPM and EDA synchrony on display of positive affect

Table 7 presents the “group-level:STAI” model. Introducing the STAI value into the “group-level” model rendered the main effects of BPM and EDA nonsignificant. By itself, a higher STAI value led to increased smiling behavior. Moreover, we observed a significant three-way interaction between BPM, EDA, and STAI value. The interaction is graphed in Figure 1. As seen, the STAI value had a positive effect on smiling behavior, but this effect depended on both the BPM and EDA values. In particular, if there were strong BPM synchrony dynamics and/or strong EDA synchrony dynamics in the group, the effect of the STAI value on smiling disappeared, while low levels of both BPM synchrony and EDA synchrony resulted in a positive effect of the STAI value on smiling. SPIN values did not result in significant moderation effects to this “group-level” model (Table 8).

4 | DISCUSSION

The current study was concerned with the effects of physiological synchrony—in heart rate and skin conductance—on positive affective behavior in a joint task. It utilized a novel computational method to address a classic problem in group research—the extent to which interpersonal processes in groups, which evolve over time, reflect individual-, dyadic-, or group-level factors. Specifically, we investigated three research questions: (1) What are the associations between physiological synchrony and positive affective behaviors displayed by group members (2) At which level, i.e., the individual, dyadic, or group level, are the effects of synchrony best captured? (3) How do individual predispositions, such as social phobia and trait anxiety, moderate the effects of physiological synchrony on positive affective behavior? When we addressed the first

question, we found that group-level EDA synchrony (negatively) and BPM synchrony (positively) both predicted positive affective displays made by group members. It is important to restate here that physiological synchrony calculated by MdrQA denotes synchrony in terms of absolute values, where high values imply high synchrony, be it positive or negative, in-phase or anti-phasic, while low synchrony implies independence or near-independence of time series. In a similar fashion, low synchrony in the current analysis does not imply a compensatory coregulatory interpersonal dynamic—where one individual's signal goes up and another person's signal goes down. When interpreting these results, we can most accurately note that when there is high coupling in BPM between group members and low coupling in EDA between group members, we will observe more positive affective displays made by group members during the DST.

TABLE 7 Group-level: STAI model

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>d</i>
(Intercept)	3.05	2.70	1.13	.259	.61
BPM	5.29	2.74	1.93	.053	1.07
EDA	4.02	2.93	1.37	.170	.81
STAI	1.56	.67	2.34	.019	.32
BPM:EDA	−5.09	2.49	−2.04	.041	−1.03
BPM:STAI	−1.27	.67	−1.89	.058	−.26
EDA:STAI	−2.05	.66	−3.10	.002	−.41
BPM:EDA:STAI	1.79	.64	2.82	.005	.36

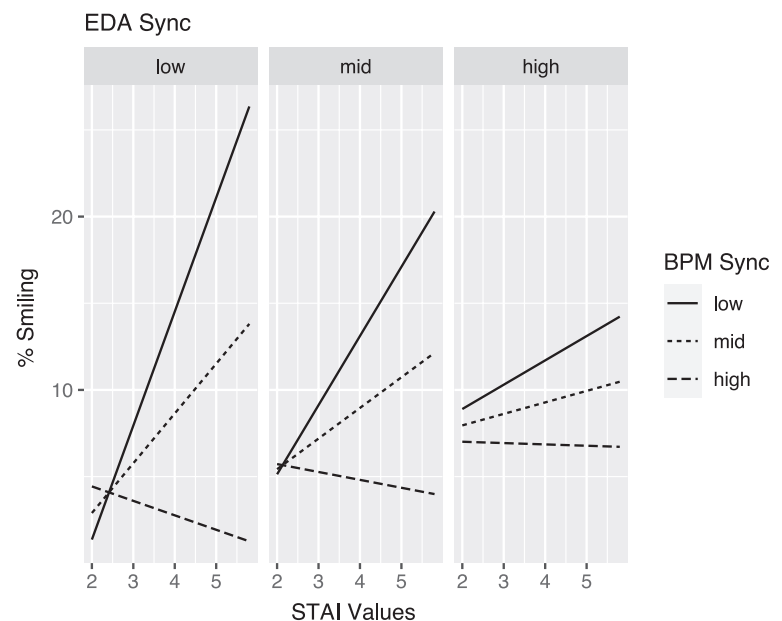
Note: *b* are the model coefficients, *SE* are the coefficients' standard errors, *t* and *p* are the associated values of a *t*-test, testing the coefficient, and the effect size *d*.

TABLE 8 Group-level: SPIN model

	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	<i>d</i>
(Intercept)	12.05	2.59	4.65	<.001	−2.03
EDA	−5.54	3.14	−1.77	.077	−.93
BPM	2.45	2.90	.84	.400	.41
SPIN	−1.59	1.48	−1.08	.281	−.27
BPM:EDA	−4.86	2.71	−1.79	.073	−.82
EDA:SPIN	.51	2.01	.25	.802	.09
BPM:SPIN	−.31	1.79	−.17	.863	−.05
EDA:BPM:SPIN	3.06	2.10	1.45	.146	.52

Note: *b* are the model coefficients, *SE* are the coefficients' standard errors, *t* and *p* are the associated values of a *t*-test, testing the coefficient, and the effect size *d*.

FIGURE 1 Three-way interaction plot of the relation of the STAI value to smiling behavior as a function of group-level joint BPM and joint EDA. STAI exerted an increasingly positive effect on smiling when both joint BPM and joint EDA dynamics were weak



4.1 | At what level of synchrony can we capture the effects of physiological synchrony in the group task?

To answer the second question, we used three different measures to capture physiological synchrony in groups of $n = 3$: individual dyadic synchrony, averaged dyadic synchrony, and group-level synchrony. The results clearly show that for the current task, the measure of group-level synchrony was most sensitive. In fact, the other two measures did not reveal any significant effects of physiological synchrony on affective behavior, a finding in line with prior research investigating different levels of group dynamics (Wallot, Roepstorff, et al., 2016). One possible explanation for this finding is that the behaviors of smiling and displaying positive affect in a group, which are behaviors that are transmitted to the entire group at once, may be indicative of social engagement with the group (Gordon & Berson, 2018). As such, group-level, rather than dyadic- or individual-level, indices of physiological synchrony might be more predictive of outcomes.

However, we do not claim that group-level dynamics, as quantified here, are always the most appropriate measures to capture group dynamics. In the current task, participants were free to interact and to influence each other simultaneously. Additionally, the task did not demand that specific sets of actions be jointly performed by group members. For example, in a different situation where three participants stand at an assembly line that synchronizes their actions and where each member only interacts with one of the other members next to him or her at a time, a group of three could be better described as a composition of dyads, and dyadic measures of interaction might be better suited for modeling. Notwithstanding this argument, in the present task, group-level measures that took into account simultaneous interactions among all group members were more sensitive. Hence, an important implication here might be that the proper quantification of interpersonal synchrony demands prior analysis of task demands, followed by an appropriate choice of methodology.

We found that group-level EDA synchrony was a negative predictor of affective synchrony, whereas group-level BPM synchrony was a positive predictor of affective behavior. This pattern of results is in line with several previous studies (Elkins et al., 2009; Gordon et al., 2020; Henning et al., 2001; Mønster et al., 2016) that showed BPM or IBI synchrony to predict positive group outcomes and prosocial attitudes. BPM activity, influenced dynamically by both the sympathetic and parasympathetic branches of the ANS, represents to some level (albeit its extent is unknown for this measure) the regulation of the social engagement system (Porges, 2011); hence it is possible that interpersonal concordance in the activity of the social engagement system was a contributing factor to BPM synchrony, which was positively associated with smiling in group members

during the present social interaction. Since the BPM measure is not a “pure” parasympathetic measure, future studies may consider assessing measures like Respiratory Sinus Arrhythmia to assess this suggestion.

Interestingly, prior studies relating EDA synchrony to group outcomes have shown rather mixed results. Several studies found EDA synchrony to positively predict prosocial attitudes or performance outcomes, such as similarity ratings (Henning et al., 2001; Montague et al., 2014), group satisfaction (Chikersal et al., 2017) and cooperation (Behrens et al., 2019). Conversely, other studies showed that EDA synchrony was strongest during couple conflict (Coutinho et al., 2019) and predicted group tension (Mønster et al., 2016). EDA activity represents, to an extent, the output of the sympathetic branch of the ANS, and physiological synchrony in other measures of the sympathetic nervous system, such as the cardiac pre-ejection period, have previously been operationalized as stress contagion (Waters et al., 2014). In our study, the negative association of EDA synchrony with positive affective displays may suggest that EDA synchrony captured some aspects of the dynamics of stress in group members. Future studies that incorporate measures that are strictly related to sympathetic activity and assess lag relationships could establish whether stress contagion is indeed the synchronous factor contributing to reduced positive affective displays between group members.

4.2 | How do individual predispositions influence the effects of synchrony measures?

To answer the third research question regarding the impact of individual predispositions on positive affective displays, we added individual trait expressions of social phobia and trait anxiety to the regression models predicting affective behavior from group-level synchrony. While SPIN values did not show any significant effects (in fact, adding the SPIN value as a predictor variable eliminated the effects of heart rate and skin conductance synchrony), STAI values interacted in a complicated manner with physiological synchrony. In particular, high STAI values were associated with a greater display of smiling behavior when physiological synchrony, as captured by both BPM and EDA measures, was low.

If we interpret high levels of physiological synchrony to be markers of strong (positive or negative) engagement among group members, this pattern might suggest that smiling and positive affective behavior displayed by individuals with high levels of trait anxiety are not necessarily indicators of a positive emotional state per se but instead a coping mechanism under social uncertainty (Jonas et al., 2014). Specifically, participants perhaps displayed smiles and laughter to affiliate and bond with other people, a method known to alleviate anxiety. This approach or motivational behavioral mechanism

(Byrne et al., 1963; McGregor et al., 2010), which has been shown to help members connect with the group (Hogg et al., 2007), may also help reduce uncertainty and enhance feelings of control, all of which help reduce anxiety (Fritsche et al., 2013).

One explanation for the lack of effects of social phobia might be that in general, social phobia does not lead to displays of affective behavior toward others in group settings, but rather to avoidance or withdrawal (Moukheiber et al., 2010). That is, people who score high on SPIN might not modulate their smiling behavior as a function of group interaction, but rather generally refrain from displaying such behavior. This is because a social phobia is particular to social situations and usually leads to avoidance or withdrawal, while anxiety does not necessarily target social situations per se, but is often rather general insecurity, which might elicit smiling behavior as a way of coping with this insecurity or affiliating to reduce stress. Another explanation for the absence of SPIN effects could have to do with the composition of the sample: The expression of trait anxiety in our sample showed greater variance, and the maximum STAI value was higher than the maximum SPIN value. This might suggest that we see effects of trait anxiety in the present sample because the range of its values is less restricted and at the same time incorporates relatively higher values compared to social phobia, raising the effective effect size. In any case, our data clearly show a prominent role of individual predispositions and personality traits, which have not received much attention in joint action research to date. Future research should target anxiety and explore our findings further to achieve a full understanding of the interactions of anxiety and other relevant demographic or personality traits, such as extraversion or neuroticism and gender, with physiological coupling in predicting social engagement behaviors.

4.3 | Comparison of MdrQA to Guastello's and Peressini's measure S_E

Most joint action measures applied to group behavior are applications of dyadic measures in groups with $n > 2$. As described above, MdrQA allows estimation of group-level dynamics for groups of arbitrary size that are not a composition of dyadic interactions, but also capture higher-order (nonlinear) dependencies among them (Wallot, Mitkidis, et al., 2016). Moreover, in this paper, we have used MdrQA to calculate a person-level measure of synchrony that captures the degree to which an individual participates in group dynamics (see Equation 2). Guastello and Peressini (2017) also describe a method to calculate the strength of individual participation in a group activity, as well as a group-level synchrony measure, S_E . Guastello's and Peressini's (2017) individual level measure of synchrony relates to our

proposed measure in that both effectively describe the average bi-variate correlation between measures of one person with all the other persons in the group. However, while our recurrence-based measure is symmetric (no direction of influence between people is assumed) and model-free (no function is fit to the data), Guastello and Peressini (2017) first assess to what extent each participant's behavior is predicted or predicts other participants' behavior, and use a linear model to evaluate the magnitude of these influences. Guastello's and Peressini's (2017) model hence allows one to assess directional influences between participants, which our measures in their current form do not.

The group-level measure, S_E , proposed by Guastello and Peressini (2017) is, as with most other approaches, based on an average of bi-variate correlations within a group. More specifically, S_E characterizes the strongest effect of bi-variate influences. Hence, the measure is not quantifying group-level synchrony per se, but rather the strongest synchrony effect that can be observed between a single individual, the driver, and every other group member, while MdrQA (computed at the group-level) conceives of the group as a system that is not entirely reduced to its dyadic interactions.

4.4 | Limitations

One major limitation of the current study is that results are based on groups of people who did not know each other well. As such, the results are primarily relevant for nonrecurrent or newly formed groups. It is unclear whether the observed effects would hold for groups with greater familiarity among members and recurrent interactions, which is often the case in real-life group work. Therefore, one critical future direction of our work is to test whether the presented results generalize to such settings. Additionally, the DST group decision-making paradigm was relatively easy, as there are no agreed-upon performance measures, and it was mostly intended to promote group interaction. Task difficulty can affect whether motor synchrony is beneficial (Wallot, Mitkidis, et al., 2016), and stronger behavioral or physiological coupling is not always beneficial (Abney et al., 2015; Mayo & Gordon, 2020). Therefore, it is crucial for future research to examine whether task difficulty predicts the magnitude or quality of physiological synchrony in groups. Further research is also needed to understand the contexts in which physiological synchrony can hinder group performance or harm relationships.

5 | CONCLUSION

To conclude, we believe the results of the current study provide a basis for a more detailed understanding of the

physiological dimensions of interpersonal synchrony at the group level and the complex way these dimensions contribute to observed affective behaviors that may represent group bonding. Our study's results emphasize the fact that synchronous dynamics in groups are not always well-captured in terms of dyadic interactions, but that such dynamics can reside at higher group-level representations. We show that MdrQA (Wallot, Mitkidis, et al., 2016) is well-suited to capture synchrony dynamics. However, we still do not know which characteristics of a joint task may promote or hinder the emergence of synchronous dynamics or modulate its relationship to social outcomes. Synchrony in the current study emerged in BPM and EDA, but given that they are differentially related to smiling and laughing, physiological synchrony likely reflects different functions depending on the bodily system it is measured in. Although synchrony is not a mechanism for positive group interactions per se, it might have an augmenting influence. Insofar as certain physiological measures may reflect stress, arousal, positive or negative emotions, it could be that shared experience of these affective states enhances these experience—be they positive or negative. Our results are in line with such an interpretation and highlight the fact that prospective studies need to be conducted to clarify the complex role of synchrony in joint action. Finally, investigations of “trait” individual differences between group members are critical to figure out further influencing factors on joint action and synchronization. Such investigations will allow us to gain an understanding of the role of such traits for group joint action.

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CONFLICT OF INTEREST

Authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ilanit Gordon: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Supervision; Writing-original draft; Writing-review & editing. **Sebastian Wallot:** Conceptualization; Formal analysis; Methodology; Visualization; Writing-original draft; Writing-review & editing. **Yair Berson:** Conceptualization; Resources; Supervision; Writing-original draft.

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