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Directly assessing interpersonal RSA influences in the frequency domain: An illustration with generalized partial directed coherence

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Abstract

Despite recent research indicating that interpersonal linkage in physiology is a common phenomenon during social interactions, and the well-established role of respiratory sinus arrhythmia (RSA) in socially facilitative physiological regulation, little research has directly examined interpersonal influences in RSA, perhaps due to methodological challenges in analyzing multivariate RSA data. In this article, we aim to bridge this methodological gap by introducing a new method for quantifying interpersonal RSA influences. Specifically, we show that a frequency-domain statistic, generalized partial directed coherence (gPDC), can be used to capture lagged relations in RSA between social partners without first estimating RSA for each person. We illustrate its utility by examining the relation between gPDC and marital conflict in a sample of married couples. Finally, we discuss how gPDC complements existing methods in the time domain and provide guidelines for choosing among these different statistical techniques.

KEYWORDS

gPDC, Granger causality, interpersonal physiology, marital conflict, RSA

1 | INTRODUCTION

Although psychophysiology has been primarily studied as an intraindividual process, recent research suggests that interpersonal linkage in physiology is a common phenomenon during social interactions (Butler, 2011; Palumbo et al., 2016; Timmons, Margolin, & Saxbe, 2015). Social partners are found to synchronize or coregulate one another through various biological systems, and the characteristics of these processes are shown to have meaningful and important implications across various contexts, such as in parent-child interactions (Feldman, Magori-Cohen, Galili, Singer, & Louzoun, 2011; Field, Healy, Goldstein, & Guthertz, 1990; Ham & Tronick, 2009; Moore et al., 2009), romantic relationships (Ferrer & Helm, 2013; Helm, Sbarra, & Ferrer, 2012; Levenson & Gottman, 1983; Liu, Rovine, Klein, & Almeida, 2013; Saxbe & Repetti, 2010), between therapists and clients during psychotherapy (Marci, Ham, Moran, & Orr, 2007; Marci & Orr, 2006; Stratford, Lal, & Meara, 2012), among women discussing a film (Butler, Wilhelm, & Gross, 2006), and among teammates during collaborative tasks (Strang, Funke, Russell, Dukes, & Middendorf, 2014; Walker, Muth, Switzer, & Rosopa, 2013). This article focuses on interpersonal influences in respiratory sinus arrhythmia (RSA), a measure of parasympathetic control on heart rate. Although RSA is a well-documented indicator of socially facilitative physiological regulation (Porges, 1995, 2007), research on interpersonal RSA linkage is surprisingly rare. This lack of research may be partly due to the underdevelopment of statistical methods for properly quantifying associations between multivariate RSA data. The current study thus aims to bridge this methodological gap. In particular, we introduce a frequency-domain statistic—generalized partial directed coherence (gPDC)—for quantifying interpersonal RSA influences without first estimating RSA for each person. Originally developed for analyzing EEG data (Baccalá & de Medicina, 2007; Baccalá & Sameshima, 2001), gPDC is a validated measure for capturing lagged regression relations with multivariate time series data. In this article, we illustrate how gPDC can be adapted to measure interpersonal RSA influences using empirical data from a sample of married couples. We also discuss how gPDC complements existing methods in the time domain and provide guidelines for choosing among these different statistical techniques.

1.1 | Time domain methods for assessing RSA linkage

RSA refers to the variation in cardiac rhythms across the respiratory cycle. Conventionally, RSA is quantified by performing a Fourier transform on the interpolated interbeat intervals (IBI) series, which indicate the time between each R peak in the electrocardiogram (ECG). The power in the frequency range of respiration indicates the variance in IBI that is attributable to respiration, and is used as a measure of RSA. To ensure a sufficient number of data points to accurately estimate power, Fourier transform is typically conducted based on IBI series in 60- to 120-s epochs (Task Force, 1996). However, because most research on physiological linkage involves social interactions that last for only a few minutes, this conventional method typically does not yield enough RSA estimates for modeling dynamic processes at the level of the social unit (e.g., dyad).

With increasing interest in modeling physiological processes in social interactions, recent research has aimed to measure RSA based on shorter IBI epochs, thus producing a larger number of RSA estimates per person given the same length of IBI series. For example, Gates, Gatzke-Kopp, Sandsten, and Blandon (2015) demonstrated that a multitapering algorithm called peak matched multiple windows (Hansson & Jönsson, 2006), applied before Fourier transform, could produce precise estimates of power at the respiratory frequency band. Hence, they were able to obtain accurate RSA measures with 32-s IBI segments. Using a moving window that shifts forward 1 s at a time, they obtained time series data containing hundreds of RSA values per person based on minutes of dyadic interactions, which allowed them to assess interpersonal synchrony in RSA with the within-dyad correlation. A similar approach was used in a study by Helm, Sbarra, and Ferrer (2014), who obtained RSA values based on Fourier transform of 30-s nonoverlapping IBI segments. With the short time series that data produced (∼28 observations), they were able to examine RSA coregulation using a multilevel cross-lagged regression model. In these and other similar studies (Creaven, Skowron, Hughes, Howard, & Loken, 2014; Elkins et al., 2009; Hill-Soderlund et al., 2008; Lunkenheimer et al., 2015; Walker et al., 2013), RSA was first estimated for each person over time and then analyzed with a statistical model involving time (e.g., a cross-lagged model) to capture the dynamic characteristics of interpersonal physiology. Hence, although the estimation of RSA involves frequency-domain techniques (i.e., Fourier transform), we refer to these methods as time domain methods for assessing RSA linkage.

1.2 | Assessing RSA linkage in the frequency domain

In this article, we introduce a frequency-domain approach for directly evaluating lagged relations in the respiratory frequency band, which provides an alternative method for assessing RSA linkage. Importantly, this method bypasses the estimation of RSA, and hence may be particularly suitable for studying social interactions that last for only a short period of time. Specifically, this approach utilizes gPDC, a measure originally developed by Baccalá and colleagues (Baccalá & de Medicina, 2007; Baccalá & Sameshima, 2001) to examine functional connectivity patterns in the brain with EEG data. EEG signals are known to be rhythmic, with different frequency bands corresponding to different "waves" that have distinct clinical implications. As such, they share common statistical properties with heart rate signals. The use of gPDC to assess RSA linkage is thus a natural extension of this technique. Because the reliability and validity of gPDC in representing frequency-domain lagged effects have been studied elsewhere (de Brito, Baccalá, Takahashi, & Sameshima, 2010; Van Wettere, Marinazzo, Lanquart, Linkowski, & Jurysta, 2013), we focus here on demonstrating its utility for studying RSA linkage. In the following, we first give a brief introduction to the estimation of gPDC at the respiratory frequency band with IBI data, and then present an empirical example in which these statistics are used to examine interpersonal RSA influences and their covariates in a sample of married couples.

1.2.1 | Estimating gPDC

The estimation of gPDC is conducted in the framework of the vector autoregressive (VAR) model, a commonly used statistical model for examining lagged relations with stationary multivariate time series data (i.e., time series whose statistical properties, such as mean and variance, are constant over time). A general form of a VAR model can be written as

$$\vec{Y}_t = A_1 \times \vec{Y}_{t-1} + A_2 \times \vec{Y}_{t-2} + \ldots + A_p \times \vec{Y}_{t-p} + \vec{U}_t \quad (1)$$

where $\vec{Y}_t$ is an $m \times 1$ vector of observed data at time t with mean zero, A_k are $m \times m$ matrices of regression coefficients at lag k up to a max lag of order p, and $\vec{U}_t$ represents an m-dimensional Gaussian residual process (Lütkepohl, 2006).

The parameters on the diagonal of A_k are the autoregressive coefficients, which represent the temporal dependency of a variable on itself, whereas the off-diagonal parameters are the cross-lagged regression coefficients, which represent the temporal dependency of a variable on another variable. Importantly, because the VAR model controls for the autoregressive relations, the cross-lagged coefficients can be interpreted as a special kind of causal lagged effect from one variable to another, which is known as Granger causality (Granger, 1969). For example, if $\vec{Y}_t$ is a bivariate time series (i.e., $m=2$) of a particular physiological measure from two partners in a heterosexual relationship, the VAR model would produce two sets of cross-lagged coefficients, one representing the so-called Granger causal effect from the male to the female, and the other representing the Granger causal effect from the female to the male. The magnitudes of these coefficients are commonly interpreted as the strengths of coregulatory effects in the dyadic system (Fisher, Reeves, & Chi, 2016; Gates & Liu, 2016; Helm et al., 2014). However, because of the possibility of omitted variables, Granger causality may not always represent truly causal relations. Hence, when interpreting these coefficients, researchers need to apply the same caution as when interpreting any regression coefficient, and consider alternative explanations that may give rise to interpersonal lagged relations, such as a shared social context.

Conceptually, gPDC is the counterpart of the cross-lagged coefficients in the frequency domain. It is computed by performing a discrete Fourier transform on A_k from Equation 1, which yields

$$A(f)=I-\sum_{k=1}^{p} A_k \cdot \exp\left(-i2\pi fk\right). \tag{2a}$$

where $i=\sqrt{-1}$. Here, k indicates the lag, and f represents the discrete frequency components:

$$f=\frac{n}{N},\ n=0,\ 1,\ \ldots,\ N-1. \tag{2b}$$

where N is the number of time points in the original time series. The zero frequency component ($n=0$) corresponds to the mean of the data, and hence will equal zero if data are centered. The nth component, where $0<n<\frac{N}{2}$, represents the discrete frequency with n cycles in N data points. The discrete frequency with $n=\frac{N}{2}$, also known as the Nyquist frequency, is the highest frequency that can be represented with the current sampling rate.[1] For example, consider a zero-mean (centered) time series measured every second over 60 s (Figure 1). Suppose this time series is best represented by a VAR model of Order 2, hence $p=2$. Based on Equation 2a and 2b, we can obtain a series of $A(f)$, where $f=\frac{0}{60}, \frac{1}{60}, \cdots, \frac{59}{60}$. The component $A\left(\frac{0}{60}\right)$ would equal zero because the data are centered. The component $A\left(\frac{1}{60}\right)$ represents the lagged influences between variables at the lowest discrete frequency for these data, namely, 1 cycle per 60 s (solid line). This matrix can be computed as

$$A\left(\frac{1}{60}\right)=I-\left[A_1\cdot\exp\left(-i2\pi*\left(\frac{1}{60}\right)*1\right)+A_2\cdot\exp\left(-i2\pi*\left(\frac{1}{60}\right)*2\right)\right], \tag{3}$$

where A_1 and A_2 are the matrices of regression coefficients in the estimated VAR model. Similar computation can be performed for other discrete frequency components. Lastly, $A\left(\frac{30}{60}\right)$ represents the lagged influences between variables at the highest discrete frequency component, namely, 30 cycles per 60 s, or 1 cycle per 2 s (Figure 1, dotted line). It can be computed as

$$A\left(\frac{30}{60}\right)=I-\left[A_1\cdot\exp\left(-i2\pi*\left(\frac{30}{60}\right)*1\right)+A_2\cdot\exp\left(-i2\pi*\left(\frac{30}{60}\right)*2\right)\right]. \tag{4}$$

The dimensions of $A(f)$ are the same as the dimensions of A_k. That is, if the time series is bivariate (i.e., $m=2$) and hence A_k are 2×2 matrices, $A(f)$ will also be 2×2 matrices. Because discrete Fourier transform is simply a mathematical transformation, no information is gained or lost. Hence, the resulting matrices $A(f)$ contain the same information as their time domain counterparts A_k about the temporal associations among variables. That is, the elements on the diagonal of $A(f)$ represent autoregressive effects, whereas the elements off-diagonal represent cross-lagged effects. However, unlike A_k, which are interdependent with each other and hence cannot be directly interpreted when the order of the VAR is larger than 1, $A(f)$ at different frequencies are orthogonal to each other. Therefore, each $A(f)$ matrix only includes information at the corresponding discrete frequency and can be interpreted accordingly.

Based on $A(f)$, $gPDC$ at a particular discrete frequency f can be estimated as

$$gPDC_{ij}(f)=\left|\frac{\frac{1}{\sigma_i}A_{ij}(f)}{\sqrt{\sum_{i=1}^{m}\frac{1}{\sigma_i^2}\left|A_{ij}(f)\right|^2}}\right|^2. \tag{5}$$

Here, $A_{ij}(f)$ is the element in the ith row, jth column in $A(f)$, where i and j range from 1 to m, and σ_i^2 is the residual variance of variable i. In other words, $gPDC_{ij}$ represents the ratio between the effects from variable j to i in respect to the sum of effects that j has on all variables (including itself), weighted by the standard deviation of the residuals to make it scale invariant. It has been shown that this index is a valid representation of Granger causality, and hence a measure of the direct lagged effect of variable j on variable i, at a particular frequency f, controlling for all variables included in the

[1]Discrete frequencies with $\frac{N}{2}<n<N$ correspond to the frequency band between the negative Nyquist frequency and zero.

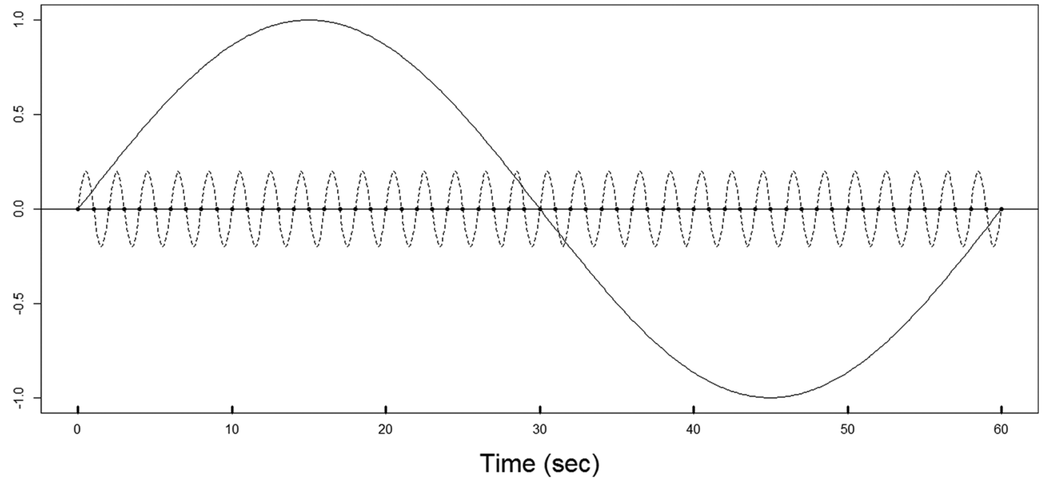

FIGURE 1 Transformation from time domain to frequency domain. Each dot represents one data point. Solid line represents the lowest discrete frequency component that can be captured by these data. Dotted line represents the highest discrete frequency component that can be captured by these data. The power of these two components are represented by the magnitudes of the waves, which are arbitrarily selected here for ease of display

model (Baccalá & Sameshima, 2001; Schlögl, 2007; Schlögl & Supp, 2006). As a ratio, it is bounded between 0 and 1. In general, higher values of *gPDC* indicate larger effects. However, when evaluating effect sizes, it is also important to take into account the number of variables in the data. For example, for bivariate data, a *gPDC* of 0.1 may be considered small because only 10% of the total effects from a given variable are cross-lagged effects, and the remaining 90% are autoregressive effects. However, if there are a large number of variables in the data (such as in EEG brain imaging), a *gPDC* of 0.1 may be considered a large effect.

Because RSA is the variance in IBI at the respiratory frequency band, interpersonal influences in RSA can be directly assessed by examining the lagged effects (i.e., gPDC) at the same frequency band obtained from interpersonal IBI series. For example, imagine that we have bivariate IBI series interpolated at 4 Hz from two social partners who had a conversation for 60 s, hence $N = 240$ IBI values per person. A VAR model (Equation 1) can be fit to the data, producing a series of *gPDC* values at 240 discrete frequencies (Equation 2, 5). In the range of $0<n<\frac{N}{2}$, the nth discrete frequency corresponds to the cyclical pattern with n period(s) in 60 s (i.e., n/60 Hz). Therefore, the adult respiratory frequency band, 0.12–0.40 Hz, is represented by discrete frequencies in the range between $n = 7$ (7/60 $\approx$ 0.12 Hz) and $n = 24$ (24/60 = 0.40). The average gPDC across these frequencies thus represents the lagged effects between the two partners' RSA, which can be used in further analyses to examine covariates of interpersonal RSA influences.

In the following, we demonstrate this approach with an empirical example of marital conflict. There is some evidence that physiological linkage is associated with marital quality. For example, Levenson and Gottman (1983) found that married couples with lower marital satisfaction on average have greater physiological concordance in their heart rate and skin conductance levels when discussing problems in their marriage. They argued that, in the context most likely infused with negative affect, physiological linkages reflect the scenario where both partners are "locked into" the interaction and unable to "step back." Similarly, stronger synchrony in cortisol, a biomarker of stress reactivity, has been found to be related to lower marital satisfaction and higher marital strain (Liu et al., 2013; Saxbe & Repetti, 2010), suggesting that the insusceptibility to stress of the spouse may be beneficial for relationship quality. However, research examining RSA linkage in marital relationships is rare. To our knowledge, only two studies directly addressed this research question, and their findings were mixed. Helm et al. (2014) found that higher lagged influences between romantic partners during a series of conversation tasks is associated with higher relationship satisfaction. In contrast, a previous study using the current data set found a positive relation between marital conflict and concurrent synchrony in RSA between spouses during family free play with their children (Gates et al., 2015). Because physiological linkage was operationalized differently in these two studies (lagged influence vs. concurrent association), it is unclear whether the mixed findings may be partly due to the methodological differences. Hence, in this study, we extend the previous work by examining whether lagged influences of RSA between spouses, as quantified by gPDC, are related to marital conflict. Based on past research with the same data and existing literature on linkage of other physiological signals, we hypothesize a positive relation between the strength of influences and conflict for both partners.

2 | METHOD

2.1 | Participants

Families were recruited through newspaper birth announcements, flyers posted at day cares, and a database of local families interested in participating in research as part of a larger study on parenting practices. To participate, couples had to be married or cohabitating and have two biological children between the ages of 2 and 5 years. A total of 70 families were recruited for the larger study; only 49 couples provided usable data for the present study (see Gates et al., 2015, for full description of data). Wives in the present study were, on average, 33 years old ($SD = 4.07$) and 49% were employed. Husbands were, on average, 35 years old ($SD = 4.78$) and 94% were employed. The median family income was \$70,000 (range \$10,000 to \$250,000). The sample was predominantly White (wives: 89% White, 8% Hispanic/Latino, 2% other; husbands: 92% White, 6% Hispanic/Latino, 2% other). Couples were married for an average of 9 years ($SD = 2.59$).

2.2 | Procedure

Families participated in a 2 1/2 hr laboratory visit, including procedures not described here, as part of a larger study. After obtaining informed consent, electrodes for recording cardiac data were attached to each family member. Families then participated in several interaction tasks. For the current study, cardiac data were collected during a tetradic family free-play (10-min) session where parents were instructed to play with their children as they would at home.

Parents were asked to complete a series of questionnaires. The present study utilizes wife and husband responses on the conflict subscale of the Intimate Relations Questionnaire (Braiker & Kelley, 1979), which is comprised of five questions concerning argument frequency, desire to change spouse, anger/resentment, problem severity, and negativity. Items were rated on a 9-point Likert scale (1 = *not at all* to 9 = *very much*) and averaged to create a composite score. Husbands and wives did not differ in level of reported conflict (paired $t = .97$, $p = .33$). Reliability for the present sample was good: Cronbach's alpha was .74 for wives and .77 for husbands.

2.3 | Physiological assessment

Cardiac data were assessed via three electrodes placed on the torso of the husband and wife in a Lead II configuration. An additional four electrodes were used to assess impedance, which was not examined in the current study. Ambulatory ECGs (MindWare Ambulatory Impedance Cardiograph Model 1000a) using the Mindware WiFi ACQ software, Version 3.0.1 (Mindware Technologies, Ltd., Westerville, OH) were used to collect the data. The ECG signal was sampled at a rate of 500 Hz and band-pass filtered at 40 to 200 Hz. Data from both participants were recorded simultaneously and time-locked to one another. The MindWare editing program (HRV v. 3.0.17) was used to identify IBIs and detect physiologically improbable intervals based on the overall distribution using a validated algorithm (Berntson, Quigley, Jang, & Boysen, 1990). Trained research assistants manually edited the data as appropriate, or determined it to be of insufficient quality.

Of the 70 couples who participated, 21 dyads were removed from the present analysis because equipment failure occurred for one ($n = 11$) or both ($n = 10$) of the individuals. No differences were observed in reported marital conflict between participants who did and did not have cardiac data for wives ($t = 2.09$, $p = .95$) or husbands ($t = 2.02$, $p = .94$). The data are thus taken as missing at random.

2.4 | Assessment of interpersonal RSA influences

The point-process IBI series was interpolated at 4 Hz using a cubic spline to arrive at equidistant data points (De Boor, 1978), then differenced and centered to remove trends. These decisions follow those that are often used when developing methods for arriving at RSA estimates (Hansson & Jönsson, 2006; Hansson-Sandsten & Jönsson, 2007) as well as within popularly used proprietary software (e.g., Mindware; Berntson et al., 1997). Augmented Dickey-Fuller tests (Dickey & Fuller, 1979) were performed to detect trends in the resulting time series, and none of the time series had a significant trend. Hence, each couple's data were fitted with a VAR model using the *ar* function in R (R Core Team, 2015), and the number of lags needed was determined by the Akaike Information Criterion (AIC; Akaike, 1974). The estimated VAR model was then Fourier transformed to produce gPDC estimates at various discrete frequencies. The mean of gPDC at the respiratory frequency band (0.12–0.40 Hz) from the wife to the husband was used to quantify RSA influence from the wife to the husband, and denoted as gPDC_{hw}. Similarly, RSA influence from the husband to the wife was estimated and denoted as gPDC_{wh}. R code for computing gPDC for one of the dyads can be found in the online supporting information.

3 | RESULTS

We found a large amount of variability in the form of the estimated VAR models. In particular, the order of the VAR models ranged from 8 to 28, with a median of 16. The variability in the estimated VAR models, however, does not affect the comparison of gPDC across dyads, which highlights one of the advantages of directly assessing RSA influences in the frequency domain.

The mean gPDC of the sample was 0.12 ($SD = 0.07$), and the mean gPDC was 0.11 ($SD = 0.06$). Both variables were highly positively skewed. An examination of the

TABLE 1 Descriptive statistics of $gPDC_{hw}$ (wife-to-husband influence) and $gPDC_{wh}$ (husband-to-wife influence)

Variable	*N*	Mean	*SD*	Min	Max	Skewness	Kurtosis
$gPDC_{hw}$	48	0.11	0.05	0.04	0.25	1.04	1.26
$gPDC_{wh}$	48	0.10	0.05	0.04	0.26	1.30	1.24

distributions revealed that the skewness was caused by an outlier whose values were more than 4 standard deviations above the mean in both variables. Hence, we removed this outlier from further analyses. Descriptive statistics for the remaining 48 couples are summarized in Table 1. It can be seen that the two variables had very similar statistical properties. Overall, interpersonal RSA influences in this sample of couples were not strong, but there was some variability across couples in these measures. Importantly, the correlation between $gPDC_{hw}$ and $gPDC_{wh}$ was very small and not significant ($r = 0.04$, $p = .82$), indicating that the two measures were capturing different aspects of the dyadic processes.

Associations between strengths of partner influences and marital conflict were tested using an actor-partner interdependence model (APIM; Kenny, Kashy, & Cook, 2006). APIM is a dyadic model that takes into account the interdependence between social partners by simultaneously estimating actor effects (i.e., the effects of oneself) and partner effects (i.e., the effects of a partner). Here, we consider the effect of $gPDC_{hw}$ on wife's perceived marital conflict as an actor effect, and vice versa for the husband.[2] Similarly, we consider the effect of $gPDC_{wh}$ on wife's perceived marital conflict as a partner effect, and vice versa for the husband. The model was estimated in LISREL 9.2 using the full-information maximum likelihood method to handle missing data (Jöreskog & Sörbom, 2015), and the standardized coefficients are shown in Figure 2. There was a positive actor effect for wives, such that higher $gPDC_{hw}$ was associated with higher marital conflict reported by the wife ($r = 0.33$, $p < .05$). However, no actor effect was found for the husband. In addition, neither of the partner effects was significantly different from zero.

To examine whether gPDC truly reflects characteristics of the dyadic processes, we further conducted a permutation test by estimating gPDC for randomly paired couples. Whereas the means of the gPDC estimates from these randomly paired couples were similar to the matched couples ($gPDC_{hw} = 0.11$; $gPDC_{wh} = 0.12$), they were not associated with the marital conflict variables. Hence, although we cannot rule out the possibility that influences between partners may be partly due to the shared context, these results suggest that gPDC indeed captures the unique patterns of dynamic interactions for matched dyads.

In sum, our results indicate that characteristics of RSA linkage during marital interactions do reflect marital quality. The direction of effect we found is consistent with the majority of research on couple physiological linkage, which generally shows a negative association between strength of linkage and marital quality. However, our study also reveals substantial variability in the results when taking into account gender and the direction of physiological influences. Specifically, the relation between physiological linkage and marital conflict was only present for the wife, and when wife-to-husband influence in RSA was the predictor. Assuming that higher wife-to-husband influence in RSA reflects higher degree of wife's control over the interaction, this finding suggests that wives (but not husbands) who perceive themselves to be in high-conflict marriages may have husbands whose RSA values are greatly influenced by their partners when interacting with their spouses, even in a nonconflict situation.

4 | DISCUSSION

The current work contributes to the literature on interpersonal physiology by introducing a new method for directly assessing interpersonal RSA influences in the frequency domain. Our empirical example reveals a negative association between the strengths of physiological influences and an aspect of marital quality. However, given the mixed findings in other similar research on RSA specifically (Helm et al., 2014), it is too early to draw a decisive conclusion regarding the association between RSA linkage and marital relationship. Nonetheless, our results are consistent with previous research based on different psychophysiological measures that found higher levels of linkage related to lower marital satisfaction (Levenson & Gottman, 1983; Liu et al., 2013; Saxbe & Repetti, 2010). In addition, we find intriguing variability in the results across gender and direction of influences, highlighting the importance of considering these nuances when studying social interactions.

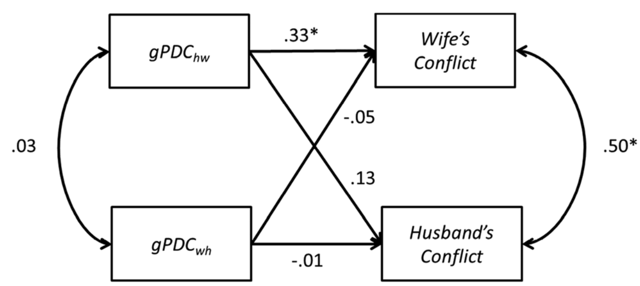

FIGURE 2 Standardized coefficients for the actor-partner interdependence model

[2]The definitions of actor and partner effects in our model are somewhat arbitrary because our predictor variables, $gPDC_{hw}$ and $gPDC_{wh}$, already involve both partners. However, we think that the definition used here is more intuitive because $gPDC_{hw}$ represents the influence from the wife to the husband.

The current method complements existing time domain methods for assessing RSA linkage in several important ways. First, gPDC is directly derived from the VAR model fitted to the IBI data, thus bypassing the estimation of RSA. This is an appealing feature when the duration of ECG measurement is short, such as when studying transient social interactions. In these scenarios, the number of RSA values that can be extracted using traditional methods is small, which limits the analytic techniques available for examining interpersonal physiology. For example, with only a few repeated RSA measurements per person, researchers are often restricted to studying interpersonal physiology using models that aggregate data across dyads to produce an overall group-level estimate. This is not ideal given the large amount of heterogeneity often found in these dynamic processes (Ferrer & Steele, 2014; Gates & Liu, 2016; Gonzales & Ferrer, 2014). In contrast, gPDC provides a way to estimate RSA influences at the dyad level even with short IBI series, thus allowing researchers to answer a larger range of questions, such as predictors and consequences of interpersonal physiology.

Second, as a frequency domain statistic, gPDC provides an overall measure of directed lagged effect that is summarized across time lags. In other words, gPDC does not distinguish between effects occurring at different time scales, as long as they are well represented in the data. This is contrary to many time domain methods for assessing RSA linkage, such as the cross-lagged model, in which the temporal interval of effects (i.e., time lags) need to be specified precisely. Although the temporal interval of effects can bear important theoretical meanings, it is often difficult to determine its appropriate value in empirical studies. In addition, assuming a fixed temporal interval for the entire sample may be overly restrictive. For instance, a one-lag cross-lagged regression model assumes that an individual's physiology at time *t* depends on and only depends on the partner's physiology at time *t-1*. This may or may not reflect the reality because (a) in some studies the amount of time between *t* and *t-1* is completely arbitrary, and (b) there is likely variability in the intervals of lagged effects across dyads. In fact, interpersonal physiology is so complex and diverse that some have argued that exploratory approaches may be more suitable for studying these phenomena than parameterized models (e.g., Ferrer, 2016). Although gPDC is estimated based on a parameterized model (i.e., VAR), it is less restricted than most time domain models because it does not require a prespecified number of lags, thus allowing variability in the temporal interval of effects across dyads. As such, we argue that gPDC may be a more robust way to capture lagged relations in RSA than existing time domain methods.

It should also be noted that our empirical example only illustrates one possibility of using gPDC to study interpersonal RSA influences, namely, in dyadic interactions. Originally developed to analyze higher-dimensional time series data, the method can be easily extended to study social interactions that involve more people. With ECG measurements from a triad, for example, one can derive six gPDC measures that represent all combinations of dyadic influences, importantly controlling for influences of the third person. In addition, gPDC can be used as an idiographic method, in which statistical inferences can be drawn at the level of the social unit based on surrogate data sets. For example, if a researcher is interested in testing whether the influence from Partner A to Partner B in a given dyad is statistically different from zero, a large number of surrogate data sets can be generated whose statistical properties are identical to the original data, except that there is no lagged influence from A to B. gPDC can then be estimated from these surrogate data sets, the distribution of which represent the null distribution of the statistic and can be used for inferences. Similarly, if a researcher wants to assess RSA influences between a therapist and a client over a number of psychotherapy sessions to evaluate changes in the interpersonal dynamics, statistical testing can be conducted to compare the different gPDC values across sessions by constructing confidence intervals for each session. For more details of the surrogate data method, we refer interested readers to Liu and Molenaar (2016).

Whereas gPDC provides a flexible way to assess interpersonal RSA influences, it is certainly not a one-size-fits-all method. When selecting a proper analytic approach, several restrictions of gPDC need to be taken into consideration. Most importantly, gPDC assesses influences between individuals at the same frequency band. Hence, it is only appropriate when the social partners share the same RSA frequency band (e.g., adult to adult). In other words, it cannot be used to assess RSA influences between adults and young children. In addition, because gPDC is bounded between 0 and 1, it does not distinguish between positive and negative influences. In some cases, the sign of an effect may have important theoretical implications. For example, a negative effect, especially in the context of a stressful situation, is often interpreted as one individual downregulating another individual's physiology, and thus corresponds to a morphostatic process where social partners coregulate each other's physiology so that they stabilize within optimal bounds (Butler, 2011; Butler & Randall, 2013). On the other hand, a positive effect may be interpreted as one individual promoting or exacerbating another individual's physiological responses, which corresponds to a morphogenic process that eventually leads to a downward spiral of negative reactions. To distinguish between these different processes, researchers will need to select alternative modeling methods that capture the sign of an effect, such as the cross-lagged regression model, estimated either at the dyad level or the sample level (Gates & Liu, 2016; Helm et al., 2014).

Another limitation of gPDC is its reliance on stationarity, an assumption of the data to have time-invariant statistical properties (e.g., mean and variance). In empirical data, this assumption may be violated. For example, although we did not find significant trends in the differenced IBI series in this study, there may be systematic trends in RSA that bear important meanings. If researchers are interested in capturing interpersonal linkage in these trends, gPDC would not be appropriate. Instead, time domain methods for modeling multivariate change trajectories, such as growth curve analysis (Laurenceau & Bolger, 2005; Reed, Randall, Post, & Butler, 2013) and dynamical correlation (Liu, Zhou, Palumbo, & Wang, 2016), may be considered. Even if there is no systematic trend, the stationarity assumption may still be violated if influences between social partners change over time. For example, it could be that during a 10-min marital interaction, the husband has a medium influence on the wife in the first 5 min (gPDC = 0.3), and no influence in the last 5 min (gPDC = 0). If we estimate gPDC from the husband to the wife using data from the whole 10-min period, we will obtain a gPDC of 0.15, which represents the average strength of influence. Although this value is still informative for examining between-dyad associations, information on within-dyad variation is lost. In studies where within-dyad variation is the focus, researchers may consider extending the current approach by utilizing a sliding window method, which involves sliding the data into shorter time windows and estimating gPDC within each time window (e.g., Boker, Rotondo, Xu, & King, 2002; Gates et al., 2015; Liu, Molenaar, Rovine, & Goodwin, 2012). Importantly, the sliding window approach still assumes local stationarity within each window and hence is not suitable for representing quickly changing processes. In the latter cases, researchers will need to consider truly time-varying models, such as the time-varying effects model (e.g., Shiyko, Lanza, Tan, Li, & Shiffman, 2012), state-space models (e.g., Chow, Zu, Shifren, & Zhang, 2011), and the generalized additive models (Bringmann et al., 2017), for appropriately analyzing the data.

It should also be noted that gPDC is essentially a composite of the cross-lagged regression coefficients, which can contain information on both the direct and indirect influences between partners. Hence, if the major research question involves determining whether or not partners directly influence each other in a social context, it is not sufficient to carry out null hypothesis testing on gPDC alone. Palumbo et al. (2016) discuss several ways that researchers can improve the internal validity of research, such as carrying out permutation tests with randomly paired dyads, and measuring physiological linkage in a baseline condition where no direct influence is expected.

Finally, other than lagged influences, RSA linkage can take various forms, which may be better represented by other methods. For instance, time domain correlational statistics (Gates et al., 2015; Liu et al., 2016) provide measures for concurrent synchrony, whereas differential equation models (Ferrer & Helm, 2013; Ferrer & Steele, 2014) allow researchers to examine coupling effects in change, rather than level, of the data. At this point, there is not sufficient research on interpersonal physiology for accurately predicting how these distinct forms of linkage may have different implications. However, there has been important theoretical work distinguishing between different types of linkage as well as methodological pieces that summarize the various ways of assessing them (e.g., Butler, 2011; Gates & Liu, 2016; Palumbo et al., 2016). With increasing interests in this area due to technological developments in measuring autonomic activities, it is our hope that more empirical evidence will be gained to provide better answers to these important questions.

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SUPPORTING INFORMATION

Additional Supporting Information may be found in the online supporting information tab for this article.

Data S1

Data S2

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