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How to Capture Synchronization in Triads in One Single Measure: Development of the *AMPC* Measure and an Associated Significance Test

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ABSTRACT

Interpersonal synchronization is a concept often studied in psychology. Whereas most research focuses on dyads, triadic systems such as family triads warrant increased attention. A crucial challenge in taking a triadic view on synchronization is how to quantify it, since a statistical measure that captures the level of triadic synchronization in one value, while discarding dyadic synchronization only, is lacking so far. The current paper therefore investigated three existing measures that show potential to capture triadic synchronization and proposes two novel ones. We also present a significance test that allows to investigate whether the observed triadic synchronization in a triad is stronger than can be expected by chance, while accounting for potential auto-dependence in the data. By means of a simulation study, we tested (1) how the measures react to different potential synchronization patterns; (2) the Type I error rate and the power of the significance test. The results showed that only one measure, i.e., the newly proposed adapted multiplication of pairwise correlations (*AMPC*), can effectively capture triadic synchronization, while discarding dyadic synchronization. We then applied the *AMPC* measure to intensive longitudinal data on attachment-related measures in families, showing that *AMPC* can detect meaningful triadic synchronization in empirical data.

KEYWORDS

Triadic data; synchronization; time series; significance test

Introduction

Interpersonal synchronization, or synchrony, has become an increasingly popular construct in psychology. When people's internal states or behaviors are coupled and covary over time, they are said to be synchronized (Meier & Tschacher, 2021). Accordingly, interpersonal synchronization can be defined as the global covariance among the behavior or internal states of different people across time. Many theories in psychology, such as the temporal interpersonal emotion systems (TIES) theory of Butler (2011), the Interpersonal Synchronization (In-Sync) Model of psychotherapy (Koole & Tschacher, 2016) and biobehavioral theories of attachment (Feldman, 2012, 2017) have paid attention to this construct. Moreover, other theoretical notions have been forwarded that also boil down to interpersonal covariance across time, such as coherence (e.g., Ferrer et al., 2010; Hsieh et al., 2011), similarity (e.g., Wood et al., 2022), coupling (Meier & Tschacher, 2021) or behavioral mimicry (e.g., Chartrand & Lakin, 2013).

Apart from being the focus of several theories, interpersonal synchronization has also been observed in many empirical studies. For example, in clinical psychology, synchronization has been found between the movements (Altmann et al., 2020; Ramseyer & Tschacher, 2011), nervous systems (Karvonen et al., 2016), and vocal expressions (Imel et al., 2014) of clients and therapists. Another field where synchronization has been widely investigated is family research. At a behavioral level, mothers and children tend to behave more similarly (Suveg et al., 2016), or gaze in the same direction (de Mendonça et al., 2011). At a physiological level, members of the same family can have the same brain activities (Levy et al., 2017), respiratory sinus arrhythmia (Woody et al., 2016), and hormone levels (Ruttle et al., 2011), across time.

One of the reasons why synchronization has received so much attention is that it is an important predictor of many psychological outcomes. In clinical psychology, it can predict therapy outcomes: whereas movement synchrony between therapists and patients

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has been found to be associated with the improvement of social anxiety (Altmann et al., 2020), better client-therapist relationships, and higher self-efficacy of the clients (Ramseyer & Tschacher, 2011), vocal synchronization is related to a higher empathy rating (Imel et al., 2014). Similarly, in family research, synchronization can predict many developmental outcomes: behavioral synchrony between family members is associated with negative experiences in high-risk situations (Suveg et al., 2016), physiological synchrony has been found predictive of self-regulation in early childhood (Kochanska et al., 2008) and better mother-child synchrony is predictive of healthier maternal styles and more positive child outcomes (Leclère et al., 2014).

Until now, synchronization has mostly been studied in a dyadic way, focusing on the associations between responses of two people across time. Synchronization has been quantified by means of statistical association measures describing dyadic relationships, like the Jaccard coefficient or Cohen's Kappa (e.g., Bodner & Ceulemans, 2022; Julien et al., 2000), specific parameters in statistical models (e.g., Imel et al., 2014) and, most often, the Pearson correlation (e.g., Paulick et al., 2018; Ramseyer & Tschacher, 2011). Whereas a strictly dyadic view makes sense in some fields, for example, when studying romantic relationships, it makes less sense when the interpersonal system gets larger. Triads, as the smallest multimember system, are an inspiring starting point to shed light on how to capture group synchronization of interpersonal systems that contain at least three people. Adopting a triadic view is also theoretically sound in many psychological domains, such as child development, where multiple caregivers (e.g., a mother and father) can play an important role, or in couple therapy, involving the couple and the therapist. As Butler (2011) put it, the three people under study are part of the same interpersonal system and therefore it would be meaningful to include all three of them when investigating it. For instance, when two family members both show anger, the third one might also show anger, which indicates the occurrence of triadic synchronization. Or they might play a role of peacekeeper (Davis et al., 1998), leading to more intricate patterns. Therefore, including a third person can bring us a more complete picture of the interaction taking place in a system.

A crucial challenge in taking a triadic view on synchronization is how to define and quantify it. Regarding definition, we take a strict view by defining triadic synchronization as all three persons covarying positively across time. This strict view is needed to disentangle the "peace-keeping father" from the "synchronizing father" in the example above. Regarding quantification, some measures were developed to go beyond dyadic synchronization, but they usually focus on a specific type of data or provide only part of the information about synchronization. For example, the frequently used Kuramoto model focuses on synchronization of phase oscillators (Acebrón et al., 2005). Other researchers measure the overall interpersonal synchronization by aggregating all the dyadic synchronization strengths. A popular practice is to average the unsigned pairwise correlations (Meier & Tschacher, 2021; Wood et al., 2022). However, this practice overlooks the direction information: Do all the system members have a positive covariance and thus change in the same direction or do some have a negative covariance, implying counter synchronization. Yet other researchers attempted to study interpersonal synchronization through network methods. For example, Bodner et al. (2018) used network analysis to study the emotional interaction within a family, which boiled down to computing the pairwise associations between mother and kid, mother and father, and father and kid, and visualizing the strength of these associations in a network figure. An alternative network method captures synchronization of several emotions in a non-parametric way (Hsieh et al., 2011). While insightful, these network methods do not yield a single value for triadic synchronization, which makes it difficult to study the relationship between triadic synchronization and other psychological constructs. Therefore, it is needed to develop a valid statistical measure of triadic synchronization, which can capture the full global covariance among the variable of interest of the three people across time in one value but discards scenarios in which not all three persons covary positively.

The current research therefore aims to introduce and evaluate measures to capture triadic synchronization. Since it is common to measure interpersonal synchronization by combining dyadic synchronization strengths in a certain way, we acknowledge the potential of this practice and hence focus on seeking a valid way to combine the dyadic synchronization values. The Pearson product-moment correlation is popular in a dyadic context (Altmann et al., 2022) and can cover a large diversity of data. Therefore, we use it as the measure of dyadic synchronization and thus focus on linear covariation.

Given the above definition of triadic synchronization, we expect a useful triadic synchronization measure to satisfy the following criteria: first, it should

capture the *magnitude* of triadic synchronization. Specifically, a useful synchronization measure should increase in value when the synchronization gets stronger (i.e., when the extent to which the responses of the three persons change in the same direction increases). Moreover, when there is only dyadic synchronization happening, which means that the scores of only two people correlate, while the scores of the third person change independently, a useful triadic measure should in principle equal 0. Second, it should capture the direction of triadic synchronization with its *sign*. In case the scores of one of the three persons change in the other direction, the obtained synchronization value should be negative. Third, a useful measure should capture both the magnitude and the sign in *one value*, so that it allows researchers to treat triadic synchronization as one variable and investigate its associations with other psychological constructs.

We also provide a significance test that allows to establish whether an observed triadic synchronization value is significantly larger than zero. Since the responses under study will often be repeatedly measured within the members of a triad across time (time series data), which will often be auto-correlated, the significance test accounts for auto-dependence. We evaluate both the behavior of the considered measures and the performance of the significance test in an extensive simulation study.

The remainder of this paper is organized into five additional sections. In the next section, we discuss the five candidate measures and hypothesize how they will react to different synchronization scenarios. In the third section, we introduce our significance test. In the fourth section, we test the candidate measures and the significance test through a simulation study and present the results, to pinpoint which of the candidate measures is truly useful. In the fifth section, we apply the useful measure(s) to empirical diary data about triadic synchronization in families. In the final section, we discuss the results from both statistical and empirical perspectives.

Potential triadic synchronization measures

In this section, we will introduce five potential measures of triadic synchronization. The measures assume that three variables X, Y and Z have been assessed at the same T time points. To give equal weight to the three variables in the computations, we impose that X, Y, and Z have been standardized (i.e., transformed to z-scores). To put forward predictions about the usefulness of the measures, we use four data examples with $T = 200$ and an auto-dependence, β, of 0.5 to show how each candidate measure performs in four different scenarios:

- *Counter synchronization*, where two variables change in the same direction, while the other changes in the opposite direction, which should lead to a negative result (Figure 1(a), the pairwise correlations between the entire time series of X and Y, X and Z, and Y and Z are .84, −.87, and −.87);
- *No synchronization*, where all three variables change independently, preferably yielding a synchronization value of zero (Figure 1(b), the pairwise correlations between the entire time series of X and Y, X and Z, and Y and Z are −.02, −.08, and −.02);
- *Dyadic synchronization*, where two variables change in the same direction, while the third one is independent, which should also result in a synchronization value of zero (Figure 1(c), the pairwise correlations between the entire time series of X and Y, X and Z, and Y and Z are .84, .02, and .04);
- *Triadic synchronization*, where all variables change in the same direction, which should yield a positive value which moreover increases when the strength of triadic synchronization increases (Figure 1(d), the pairwise correlations between the entire time series of X and Y, X and Z, and Y and Z are .84, .85, and .87).

Averaged second-order cross-correlation

Computation

The first candidate measure is the averaged second-order cross-correlation (*ASOC*, Dale et al., 2020). To compute this measure, we first divide X, Y and Z into P slices of roughly equal size s (e.g., 20 slices; see Figure 2(a)). Then, within each slice, the three pairwise correlations of X, Y and Z are calculated, yielding three new variables r^{XY}, r^{XZ}, and r^{YZ} with P values (yellow values in Figure 2(b)). It is worth noting that *ASOC* is the only measure that uses data-slicing. For the remaining measures introduced later, no data-slicing is needed. Next, the second-order cross-correlations (*SOC*) can be calculated as the correlations between r^{XY} and r^{XZ}, r^{XY} and r^{YZ}, as well as r^{XZ} and r^{YZ}, yielding $SOC_{r^{XY}r^{XZ}}$, $SOC_{r^{XY}r^{YZ}}$ and $SOC_{r^{XZ}r^{YZ}}$ (orange values in Figure 2(c)). These three values are averaged to obtain the averaged second-order cross-correlation (*ASOC*, blue values in Figure 2(c)):

$$ASOC_{XYZ} = mean(SOC_{r^{XY}r^{XZ}}, SOC_{r^{XY}r^{YZ}}, SOC_{r^{XZ}r^{YZ}}).$$

Data examples and resulting predictions

Part of the data of our four examples are presented in Figure 2(b). To compute the *ASOC*, each variable was

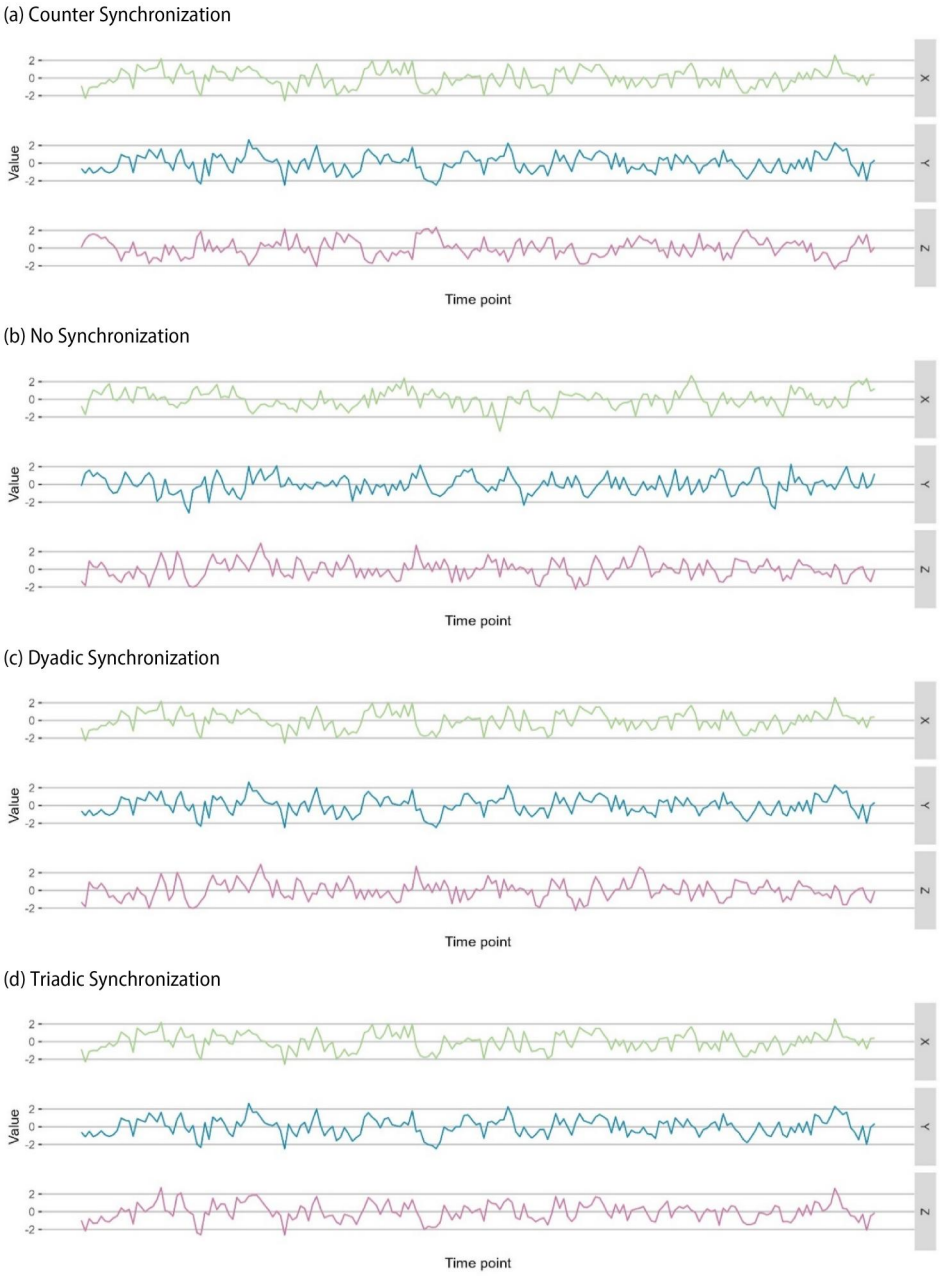


Figure 1. Illustration of different synchronization scenarios. (a) Counter Synchronization. (b) No Synchronization. (c) Dyadic Synchronization. (d) Triadic Synchronization.

divided into 20 slices, with 10 scores in each slice. The results (see Table 1 and Figure 2(c)) show that *ASOC* yields a negative value for counter synchronization, which is what we want given that Z changes in a different direction than X and Y. When there is no synchronization, *ASOC* generates a negative value closer to 0. *ASOC* yields a positive value when there is triadic synchronization in the data. However, when there is only dyadic synchronization present in the data, *ASOC* also yields a value that seems clearly higher than 0, which is not desirable. Based on these data examples, we predict that *ASOC* might fail to distinguish between dyadic and triadic synchronization.

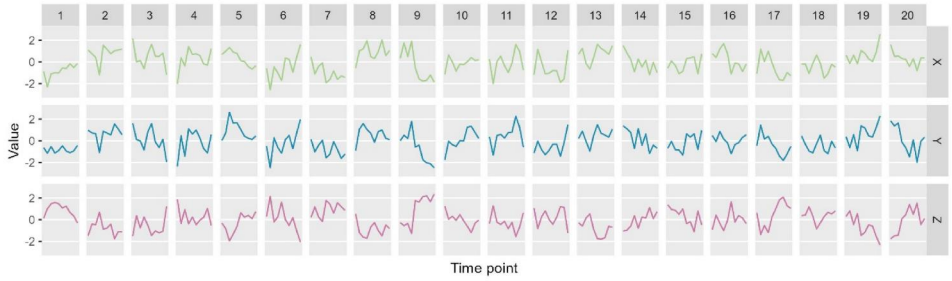
Cronbach's α

Computation

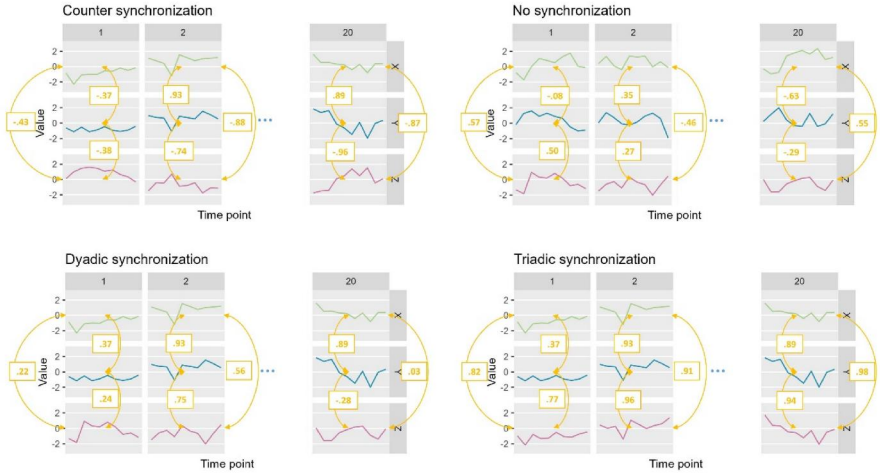
The second measure is Cronbach's α (Cronbach, 1951), which combines the pairwise correlations between X, Y and Z:

$$\alpha = \frac{3}{3-1}\left(1 - \frac{S_X^2 + S_Y^2 + S_Z^2}{S_{X+Y+Z}^2}\right)$$
$$= \frac{3}{3-1}\left(1 - \frac{S_X^2 + S_Y^2 + S_Z^2}{S_X^2 + S_Y^2 + S_Z^2 + 2S_{XY} + 2S_{XZ} + 2S_{YZ}}\right).$$

(a) Data-slicing



(b) Calculation of Pairwise Correlations



(c) *SOC*s (Orange) and *ASOC*s (Blue) of Data Examples

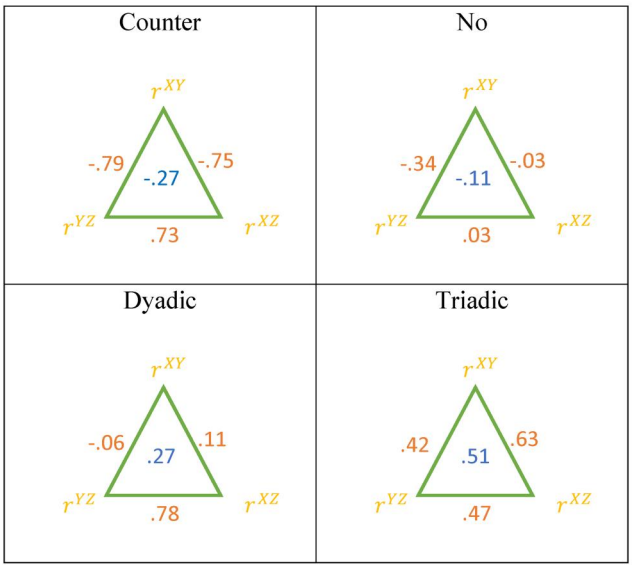


Figure 2. Calculation of *ASOC*. (a) Data-slicing. (b) Calculation of Pairwise Correlations. *(c) SOCs* (Orange) and *ASOCs* (Blue) of Data Examples.

Table 1. Values obtained with the candidate triadic synchronization measures for the data examples.

Candidate	Counter	No	Dyadic	Triadic
ASOC	−0.27	−0.11	.27	.51
Cronbach's α	−2.25	−0.12	.56	.95
Triadic correlation	.09	.02	.02	−0.07
MPC	.86	−0.03	.09	.85
AMPC	−0.86	.03	.09	.85

$S^2{}_X$, $S^2{}_Y$, and $S^2{}_Z$ are the variances of X, Y and Z; $S^2{}_{X+Y+Z}$ is the variance of the sum of them at each time point; and S_{XY}, S_{XZ} and S_{YZ} are the covariances between X and Y, X and Z, and Y and Z. Because X, Y and Z are standardized, the variances equal 1 and the covariances equal the correlations. Thus:

$$\alpha = \frac{3}{3-1}\left(1 - \frac{1+1+1}{1+1+1+2r^{XY}+2r^{XZ}+2r^{YZ}}\right) = \frac{3}{2}\left(1 - \frac{3}{3+2r^{XY}+2r^{XZ}+2r^{YZ}}\right).$$

r^{XY}, r^{XZ}, and r^{YZ} here and in the following sections denote the pairwise correlations between the entire time series of X and Y, X and Z, and Y and Z.

Data examples and resulting predictions

The Cronbach's α values for the four data examples can be found in Table 1. Cronbach's α yields negative values[1] for counter synchronization and no synchronization, and positive values for dyadic and triadic synchronization. The relatively high value for dyadic synchronization follows from taking the pairwise sum of the correlations in the denominator of the formula, where a strong correlation between two variables cannot be canceled out by the zero correlations with the other variable. Hence, we predict that Cronbach's α might fail in distinguishing triadic synchronization from dyadic synchronization. Moreover, although the counter case yielded a clearly negative α value here, this is not guaranteed. For example, if two variables are strongly positively correlated with each other, while the third is negatively correlated with them, but to a smaller extent, the sum and thus α may still be positive and incorrectly indicate triadic synchronization. Hence, we hypothesize that Cronbach's α might not be able to detect whether the three variables are changing in the same direction.

[1]The value of Cronbach's α is generally considered to lie between 0 and 1 when used as an indicator of internal consistency. This is because all the items under investigation are assumed to be homogeneous (Cho & Kim, 2015; Cronbach, 1951), hence the pairwise correlation between each pair of items is always positive and Cronbach's α will also be positive. However, in triadic interactions, the pairwise correlations between the scores of two members can be negative, so it is possible for the value of Cronbach's α to be negative or even smaller than −1.

Triadic correlation

Computation

The third measure is the triadic correlation, proposed by Pires and Perdigao (2015). This measure multiplies the correlations between each original variable and the product of the two others, yielding the following formula:

$$cor_3(X,Y,Z) = \left[r^{X,YZ}r^{Y,XZ}r^{Z,XY}\right]^{1/3}.$$

$r^{X,YZ}$, $r^{Y,XZ}$, and $r^{Z,XY}$ denote the pairwise correlations between the entire time series of X and the product of Y and Z, the entire time series of Y and the product of X and Z, and the entire time series of Z and the product of X and Y. Note that we take the cubic root of the product to obtain a value that can be interpreted as a correlation again.

Data examples and resulting predictions

Given the complexity of its computation, the performance of the triadic correlation is difficult to predict based on the formula only. Table 1 shows the triadic correlation values of the four data examples. We obtain a value close to 0 for all four synchronization patterns. Based on the data example, we predict that triadic correlation may not distinguish among different synchronization patterns.

Multiplied pairwise correlations

Computation

Given that none of the existing measures yielded positive values for pure triadic synchronization only, we propose a new measure that combines the pairwise correlations in a different way. As mentioned above, Cronbach's α is a function of the sum of all three pairwise correlations, with precisely this summation yielding drawbacks for our purpose. Combining the pairwise correlations through multiplication rather than summation (i.e., the key feature of triadic correlation) might solve these drawbacks partly, since one pairwise correlation equal to zero (as in the dyadic synchronization case) will set the product to zero as well. We label this measure the multiplied pairwise correlation (*MPC*):

$$MPC(X,Y,Z) = \left[r^{XY}r^{XZ}r^{YZ}\right]^{1/3}.$$

Data examples and resulting predictions

MPC values for the four data examples are presented in Table 1. *MPC* generates a value close to 0 for no synchronization and for dyadic synchronization, and a positive value for triadic synchronization, as expected. However, when there is counter synchronization in the data, *MPC* generates a positive value as well. This

happens because the multiplication neutralizes the two negative signs in the pairwise correlations. Hence, *MPC* cannot distinguish counter synchronization from triadic synchronization, and thus fails our criterion of sign.

Adapted multiplied pairwise correlation

Computation

To solve the fact that the *MPC* might give positive values for counter synchronization, we propose the following adaptation:

$$AMPC(X,Y,Z) = \begin{cases} |r^{XY}r^{XZ}r^{YZ}|^{1/3}, r^{XY}>0, r^{XZ}>0, \text{ and } r^{YZ}>0 \\ -|r^{XY}r^{XZ}r^{YZ}|^{1/3}, \text{ otherwise} \end{cases}.$$

The adaptation implies that the adapted *MPC* (*AMPC*) value can only be positive when all the underlying pairwise correlations are positive, which means that all the variables are changing in the same direction. Otherwise, the *AMPC* value will be negative.

Data examples and resulting predictions

From the *AMPC* values in Table 1, we see that the only difference with the *MPC* values is that we now obtain a negative value rather than a positive one for the counter synchronization case. Hence, we predict that this measure will only be clearly positive in case of triadic synchronization and thus might be a promising candidate.

Testing the significance of triadic synchronization through a permutation test

Apart from a measure, also a significance test is needed to help decide whether the magnitude of triadic synchronization in empirical data is stronger than expected in the absence of triadic synchronization. Hence, the null hypothesis of the test states that there is no triadic synchronization occurring. Under this null hypothesis, no, dyadic and counter synchronization are all admitted.

To decide whether this null hypothesis can be rejected, one needs to compare the observed synchronization value for an empirical data set to a sampling distribution of possible synchronization values under the null hypothesis. This sampling distribution should be formed under the null hypothesis that states that there is no triadic synchronization. We propose to obtain the sampling distribution through a surrogate data generation procedure, where we shuffle the observed scores on the variables *X*, *Y*, and *Z* and compute the synchronization value on the shuffled data. This shuffling step is repeated a large number of times (i.e., 1000). Next, the *p*-value is derived by computing the proportion of shuffled data sets that yield the observed synchronization value or a higher one. If the *p*-value is smaller than the α level one chooses in advance, the null hypothesis is rejected.

There are two core problems in setting up this significance test for triadic synchronization: (1) how to shuffle the observed data in such a way that any potential triadic synchronization is removed, but possible dyadic synchronization is kept, since this form of synchronization is admitted under the null hypothesis; and (2) how to deal with the time series properties, primarily auto-dependence, of the variables.

Destroying only triadic synchronization

To generate surrogate data, one would usually simply permute the scores on each variable separately, which would destroy all forms of synchronization. To break triadic synchronization only, while keeping potential dyadic synchronization intact, we therefore propose to permute only the variable that is not involved in the highest correlation in the observed data (Figure 3(b)). This permutation plan is called *Permut-One* in the following section, where we compare its performance with that of the standard permutation plan (*Permut-All*), in which all three variables *X*, *Y*, and *Z* are permuted (Figure 3(a)). *Permut-All* will also destroy dyadic synchronization; we therefore predict that it may lead to too high Type I error rates in case of dyadic synchronization patterns.

Accounting for auto-dependence

In behavioral time series, it is common to observe auto-dependence. The permutation testing, which shuffles all individual scores in each time series, will break both the synchronization and the auto-dependence at the same time, leading to inflated Type I error (Bodner et al., 2021). To account for auto-dependence, we propose to use segment shuffling of the variables when generating surrogate data (Moulder et al., 2018). This method requires researchers to cut a time series into *S* segments of (almost) equal length *m* (e.g., 10 segments, see Figure 3(a,b)) and shuffle the segments instead of the scores at individual time points, maintaining the auto-dependence within each segment. Combining segment shuffling with the strategy to only break triadic synchronization

yields a third permutation plan that we call *Segment-One* (Figure 3(b), where the cells represent segments rather than individual timepoints for *Segment-One*). To be complete, we also include a fourth permutation plan, where we permute all the segments of all three variables (Figure 3(a)), which is called *Segment-All* in the following sections.

Simulation study

In this section we present the simulation study that we ran to evaluate the five candidate synchronization measures and the hypotheses that we formulated about their validity. We also assess the performance of the significance tests, when using the four surrogate data generation plans.

Data generation

On a conceptual level we imagine triadic synchronization as a shared latent experience that transpires in the scores of each person involved (Butler, 2011). Hence, we simulated data through a factor model with one factor (i.e., one latent variable). Meanwhile, we also add auto-dependence in each of the three variables, which comes about through two separate mechanisms (Ariens et al., 2023): auto-dependence of the latent common state and auto-dependence of the unique experience of each person (i.e., auto-dependence of the residuals). Specifically, the data are generated as follows:

$$
\begin{aligned}
(X_t, Y_t, Z_t)' &= \boldsymbol{\lambda}\alpha_t + \boldsymbol{\epsilon_t} \\
\alpha_t &= \beta_\alpha \alpha_{(t-1)} + e_{\alpha,t} \\
e_{\alpha,t} &\sim N\left(0, 1-\beta_\alpha^2\right) \\
\boldsymbol{\epsilon_t} &= \boldsymbol{diag}(\boldsymbol{\beta_\epsilon})\boldsymbol{\epsilon}_{t-1} + \mathbf{e}_{\boldsymbol{\epsilon},t} \\
\mathbf{e}_{\boldsymbol{\epsilon},t} &\sim \mathrm{MVN}(0, \boldsymbol{\Sigma}_{\boldsymbol{e_\epsilon}}) \\
\boldsymbol{\Sigma}_{\boldsymbol{e_\epsilon}} &= \boldsymbol{I} - \boldsymbol{diag}(\boldsymbol{\lambda}\cdot\boldsymbol{\lambda}') - \boldsymbol{diag}\left(\boldsymbol{\beta_\epsilon}\cdot\boldsymbol{\beta_\epsilon}'\right)
\end{aligned}
$$

X_t, Y_t, and Z_t are the standardized scores of the three persons at time point t ($t = 1, 2, \ldots, T$). $\boldsymbol{\lambda} = (\lambda_X, \lambda_Y, \lambda_Z)'$ is a 3×1 vector, holding the loadings of

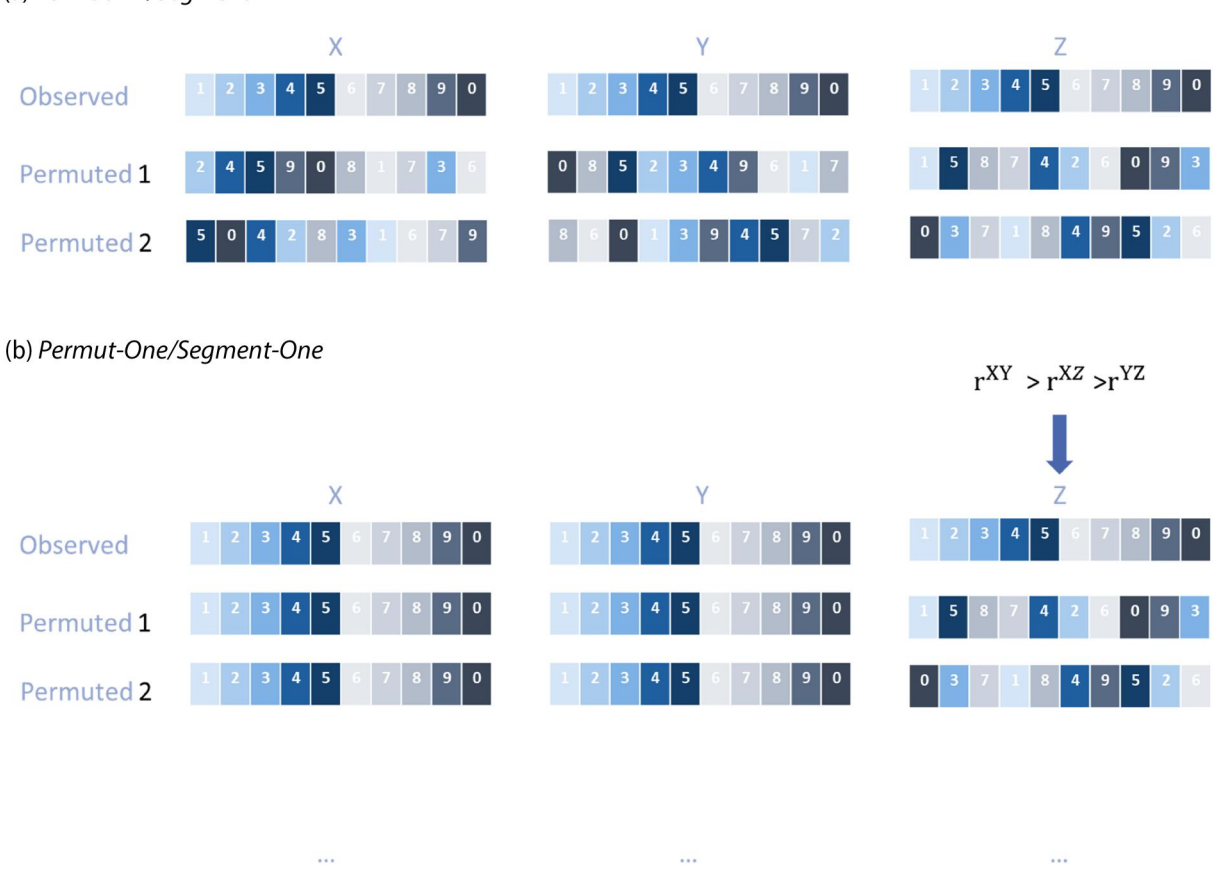


Figure 3. Comparison between *Permut-All/Segment-All* and *Permut-One/Segment-One*. *Note*. A comparison between Permut-All/Segment-All (upper panel) and Permut-One/Segment-One (lower panel). If Permut-All/Segment-All is used, all the variables will be shuffled. If Permut-One/Segment-One is used, the correlations between each pair will first be computed, and the variable (here, Z) that does not contribute to the highest correlation will be shuffled. For Permut-All/Permut-One, each cell in the figure represents an individual time point, while each cell represents a segment for *Segment-All/Segment-One*.

X, Y and Z on the latent variable. The loadings, which vary between −1 and 1, represent the extent to which X, Y and Z reflect the latent variable and thus the extent to which the corresponding persons synchronize. α_t is the factor score representing the latent state at time point t, which is related to the latent state at the previous time point t-1, $\alpha_{(t-1)}$, with the strength of this autoregressive relation being expressed by β_α. The residuals $e_{\alpha,t}$ of the factor scores are sampled from a normal distribution with a mean of 0 and a variance of $1-\beta_\alpha^2$, to set the variance of α_t to be 1.[2] $\boldsymbol{diag}(\boldsymbol{\beta_\epsilon})$ is a 3×3 diagonal matrix, the diagonal elements of which, $\boldsymbol{\beta_\epsilon} = \left(\beta_{\epsilon_X},\ \beta_{\epsilon_Y},\ \beta_{\epsilon_Z}\right)'$, represent the auto-dependencies of the residuals. $\mathbf{e_{\epsilon,t}}$ is sampled from a multivariate normal distribution with 0 as the mean vector and $\boldsymbol{\Sigma_{e_\epsilon}}$ as the variance-covariance matrix. In the current study, all the autoregressive effects are constrained to have the same value β (i.e., $\beta = \beta_\alpha = \beta_{\epsilon_X} = \beta_{\epsilon_Y} = \beta_{\epsilon_Z}$) for convenience.

The synchronization pattern is controlled by the loadings in $\boldsymbol{\lambda}$. For example, when $\lambda_X = 0$, $\lambda_Y = 0.8$, and $\lambda_Z = 0.8$, the scores on Y and Z can to a large extent be explained by the latent variable, while X is unrelated, implying that the synchronization is dyadic. When $\lambda_X = 0.8$, $\lambda_Y = 0.8$, and $\lambda_Z = 0.8$, X, Y and Z can be explained by the latent variable, and there is triadic synchronization. The data examples in the second section were generated using $\lambda_X = -0.8$, $\lambda_Y = 0.8$, and $\lambda_Z = 0.8$ for counter synchronization, $\lambda_X = 0$, $\lambda_Y = 0.8$, and $\lambda_Z = 0.8$ for dyadic synchronization, $\lambda_X = 0$, $\lambda_Y = 0$, and $\lambda_Z = 0$ for no synchronization and $\lambda_X = 0.8$, $\lambda_Y = 0.8$, and $\lambda_Z = 0.8$ for triadic synchronization. We introduced auto-dependence by setting set $\beta = .5$. The number of time points was fixed to $T = 200$.

Design

The simulation design consisted of 246 cells, obtained by crossing the following five parameters:

1. λ_X: −.2, −.5, −.8, 0, .2, .5, .8;
2. λ_Y: 0, .2, .5, .8;
3. λ_Z: 0, .2, .5, .8;
4. Number of time points T: 50 or 200;
5. Auto-dependence β: 0, .2, .5.

[2] $Var(\alpha_t) = Var\left(\beta_\alpha\alpha_{(t-1)} + e_{\alpha,t}\right) = \beta_\alpha^2 Var(\alpha_{(t-1)}) + 2\beta_\alpha Cov(\alpha_{(t-1)}, e_{\alpha,t}) + Var(e_{\alpha,t})$. $Var(\alpha_t)$ indicates the variance of α_t and $Cov(\alpha_{(t-1)}, e_{\alpha,t})$ indicates the covariance between $\alpha_{(t-1)}$ and $e_{\alpha,t}$. Since $e_{\alpha,t}$ is randomly sampled from a normal distribution, it is independent from α_t and the covariance is 0. If the variances $Var(\alpha_t)$ and $Var(\alpha_{(t-1)})$ are constrained to be 1, $Var(e_{\alpha,t}) = Var(\alpha_t) - \beta_\alpha^2 Var(\alpha_{(t-1)}) - 2\beta_\alpha Cov(\alpha_{(t-1)}, e_{\alpha,t}) = 1 - \beta_\alpha^2 - 0 = 1 - \beta_\alpha^2$.

It is worth noting that at first sight the number of cells should be 672, rather than 246. However, some combinations of the loadings can be considered equivalent in that they can be transformed into each other by multiplying all loadings by −1 and (or) changing the order of the loadings. For example, the case where ($\lambda_X = -0.2$, $\lambda_Y = 0$, and $\lambda_Z = 0.5$) is equivalent to the case where ($\lambda_X = -0.5$, $\lambda_Y = 0$, and $\lambda_Z = 0.2$). Only one of these cases is retained. Within each of the 246 cells, we generated 1000 simulated data sets and computed the five candidate measures as well as the p-value through the four versions of the significance test.

Magnitude and sign

To evaluate whether the five measures can adequately capture the magnitude of triadic synchronization and distinguish it from counter, no or dyadic synchronization, we plotted the average obtained values on the five measures as a function of the four synchronization scenarios, loading patterns (i.e., synchronization patterns) and auto-dependence (Figure 4). A valid triadic measure should be able to detect the synchronization magnitude and give only a positive value for triadic synchronization. Specifically, a measure should yield 0 for both no synchronization and dyadic synchronization, a positive value for triadic synchronization and a negative or zero value for counter synchronization.

As predicted, all three candidate measures that were taken from the literature fail in some of the settings and can therefore be dismissed. Specifically, Figure 4 shows that *ASOC* and Cronbach's α can take on positive values in the counter, dyadic and triadic scenarios, which means that when a positive value is observed, researchers cannot tell whether one is encountering triadic synchronization, or one of the two other scenarios. Similarly, negative values can be indicative of the counter as well as the dyadic scenarios, and values close to 0 can be representative of counter, dyadic or no synchronization scenarios, which indicates that the two measures cannot distinguish among the three non-triadic synchronization scenarios, either. The triadic correlation performs quite bad: No matter which synchronization scenario is present in a triad, it always yields a value close to 0, indicating that it can neither inform about the underlying pattern nor about the magnitude of triadic synchronization. To summarize, none of the three existing measures can distinguish between any of the synchronization scenarios apart.

(a) $N = 50$

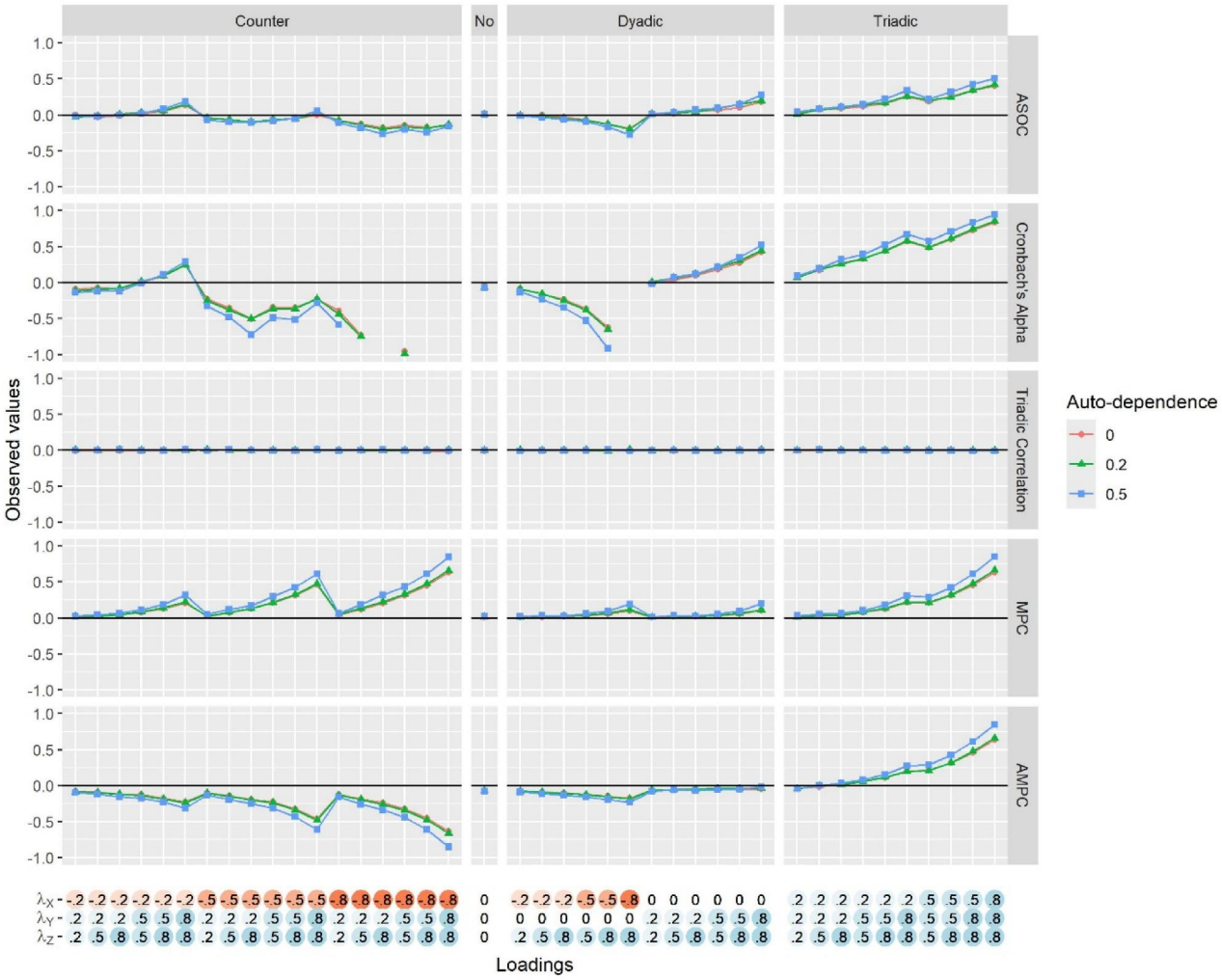


Figure 4. Average values of the five candidate synchronization measures. *Note*. Observed values of the five candidate triadic synchronization measures as a function of synchronization scenarios, loading patterns and auto-dependences. Each point represents the results of one loading pattern, the exact loadings of which (λx, λy and λz) are shown in the colored dots on the x-axis, where coral dots indicate negative values, blue dots indicate positive values, and the transparency indicates the strength of the loading. The different line colors representing data with different auto-dependences. The values are calculated based on 1000 simulated data sets for each simulation setting. The data examples used for illustrating the candidate measures in Section 2 are plotted in red dots in Figure 4(b). The horizontal black lines, placed at zero, provide a reference line of 0. Note that the *y*-axis in each panel is fixed to the interval [−1, 1]. Hence, values larger than 1 or smaller than −1 are not shown in the figure, which results in discontinuity in some lines (e.g., in the panel of Cronbach's α).

The performance of *MPC* and *AMPC* is consistent with our predictions. Both of them generate (close to) 0 values for dyadic and no synchronization scenarios. The difference between both measures is that *MPC* yields positive values for both counter and triadic synchronization, which means it cannot distinguish them, while *AMPC* yields positive values for triadic synchronization and negative values for counter synchronization. This means that when researchers obtain a positive *AMPC* value, they can claim that they observed triadic synchronization. Finally, we observe that the *AMPC* values for triadic synchronization increase when the underlying loadings increase, which implies that the measure is sensitive to synchronization strength. We conclude that only *AMPC* can be considered a useful triadic synchronization measure. We will focus on this measure in the remainder of this paper.

Regarding the influence of auto-dependence, all measures tend to generate more extreme values (i.e., stronger deviation from 0) when the auto-dependence is high (i.e., 0.5), compared to when there is weak (i.e., 0.2) or no (i.e., 0) auto-dependence. Regarding time point, all measures generate similar values when there are 50 and 200 time points.

(b) $N = 200$

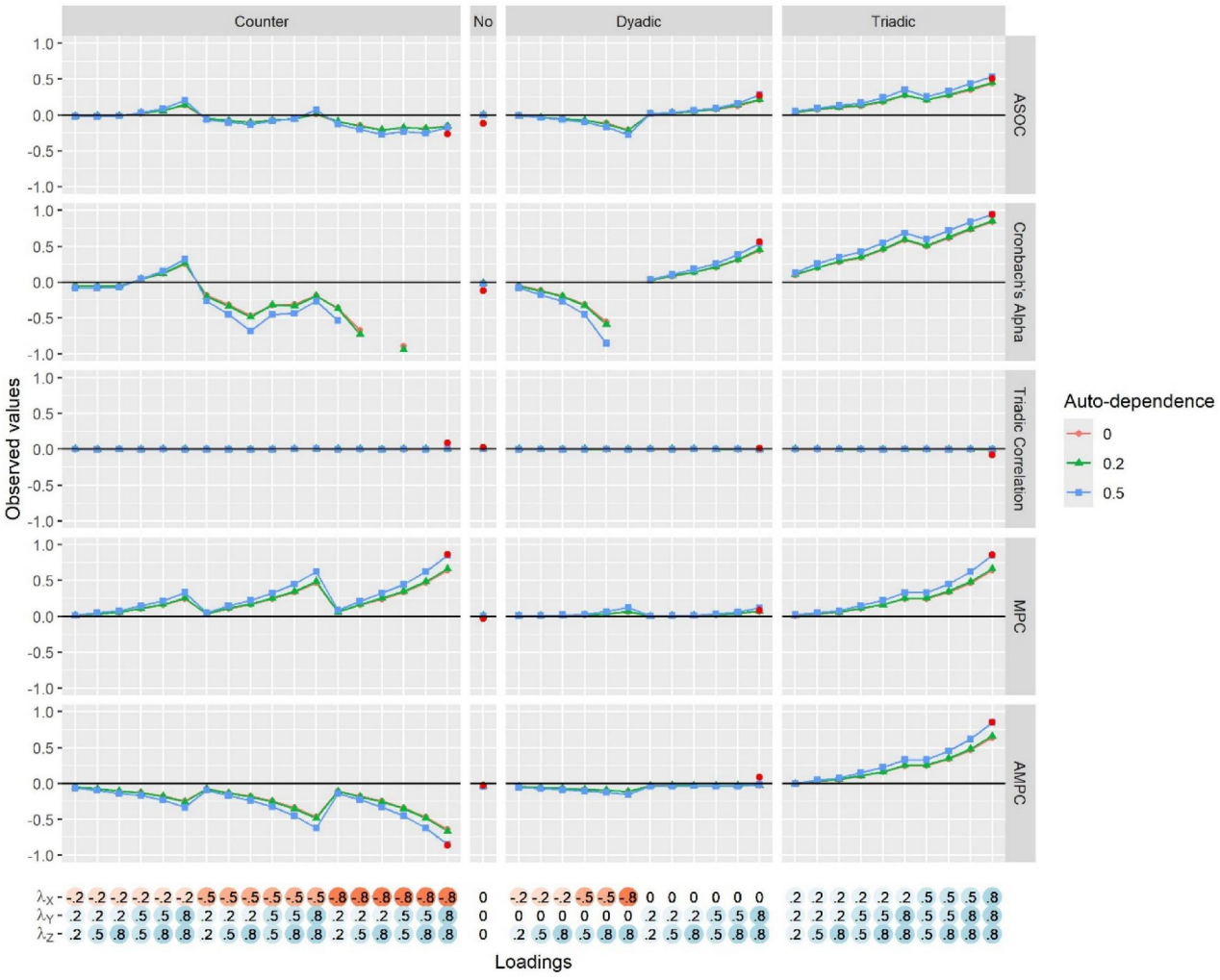


Figure 4. Continued

Type I error of the significance test

We first investigated for *AMPC* the Type I error rate of the proposed significance test at the 0.05 significance level, using all surrogate data generation plans (i.e., *Permut-One*, *Permut-All*, *Segment-One* and *Segment-All*). To this end, we inspected the test results in the 186 design cells without triadic synchronization.

Figure 5 shows the Type I error as a function of the different synchronization scenarios, loading patterns, and auto-dependence. A valid surrogate data generation plan should generate a Type I error rate that equals the 0.05 significance level, although Type I error rates lower than significance level are not problematic either. For *AMPC*, the Type I error rate is always close to 0 in the counter scenario. In both the no and dyadic synchronization scenarios, the Type I error rate remains at 0.05 if *Segment-One* is used, while it gets larger in the dyadic scenario, when *Permut-All* or *Segment-All* is used. For *Permut-One*, the Type I error remains at 0.05 if there is no ($\beta = 0$) or weak ($\beta = 0.2$) auto-dependence, while it increases when there is a stronger ($\beta = 0.5$) auto-dependence in the data. The results show the superiority of *Segment-One*.

Power

We also examined the power of the significance test in the 60 simulation cells that implied triadic synchronization. We again used all four surrogate data generation plans and the 0.05 significance level. Figure 6 shows the power as a function of the loading patterns and the number of time points. We observe that power increases when the synchronization strength (i.e., one or more of the loadings increase) or the auto-dependence increases and decreases when only 50 time points are available. The power is lower for

(a) $T = 50$

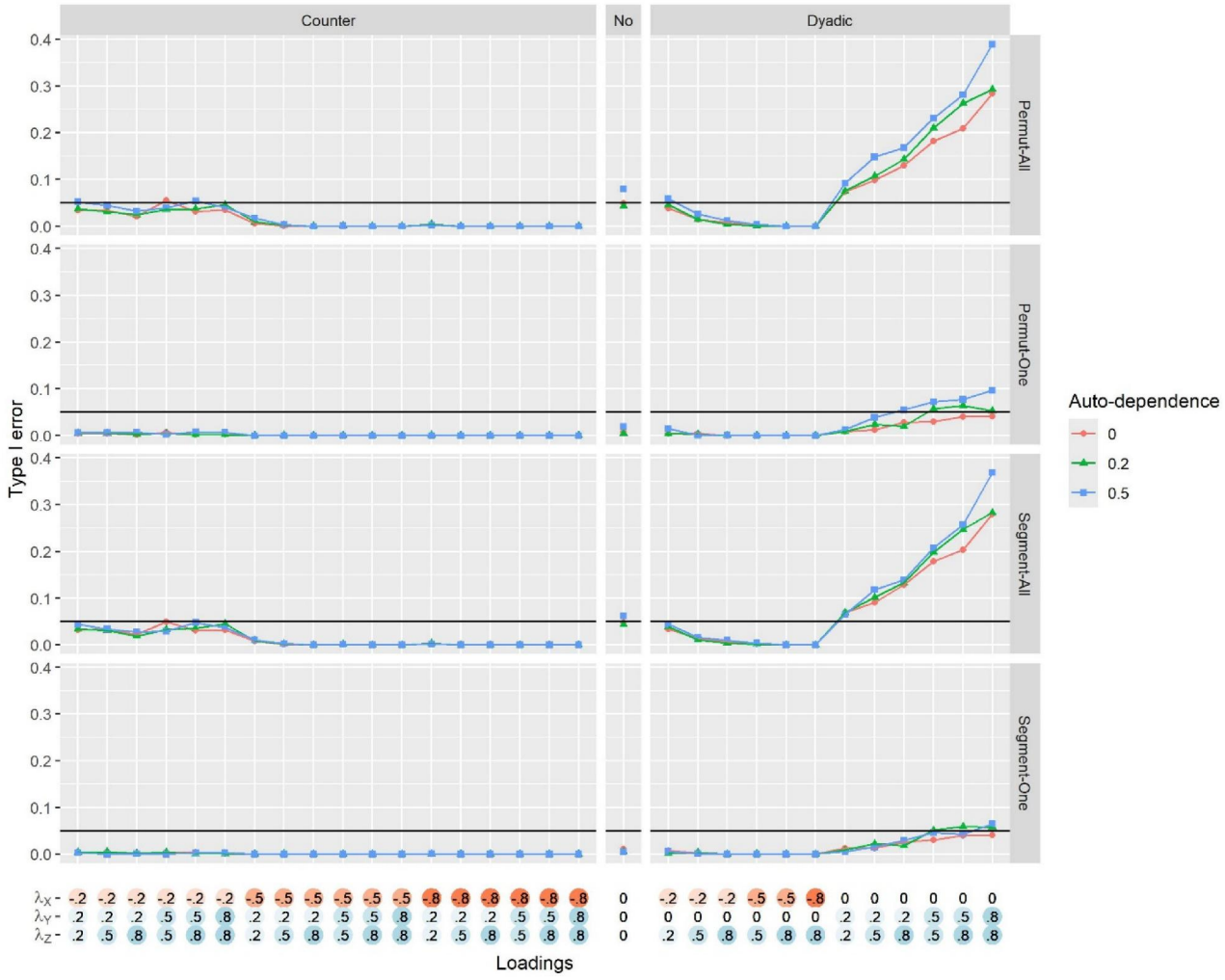


Figure 5. Type I error rates of *AMPC*. *Note*. Type I error rate of the significance test of *AMPC* as a function of synchronization scenarios, loading patterns and auto-dependences. Each point represents the results of one loading pattern, the exact loadings of which (λx, λy and λz) are shown in the colored dots on the x-axis, where coral dots indicate negative values, blue dots indicate positive values, and the transparency indicates the strength of the loading. The different line colors representing data with different auto-dependences. The values are calculated based on 1000 simulated data sets for each simulation setting. The horizontal black lines indicate the .05 significance level. The rows show results using (1) *Permuat-All*, (2) *Permut-One*, (3) *Segment-All*, and (4) *Segment-One* as permutation plan.

Permut-One and *Segment-One*. It is also worth noting that when one variable has a low loading (e.g., $\lambda = 0.2$), the power tends to be low, especially when *Permut-One* or *Segment-One* is used. This indicates that *AMPC* might be less sensitive to the loading patterns where one variable synchronizes limitedly with the other two.

Empirical data

The simulation results show that if there is triadic synchronization in the data, *AMPC* can detect it, as well as reflect its magnitude and direction. In this section, we further demonstrate the usefulness of AMPC by applying it to empirical data.

Theoretical motivations

Children's attachment security to their parents has been found to fluctuate over time (e.g., Bosmans et al., 2014), showing state-like features. Secure attachment states are associated with a sense of security, resulting from the experience of parental sensitivity and support during stressful events (Bosmans et al.,

(b) $T = 200$

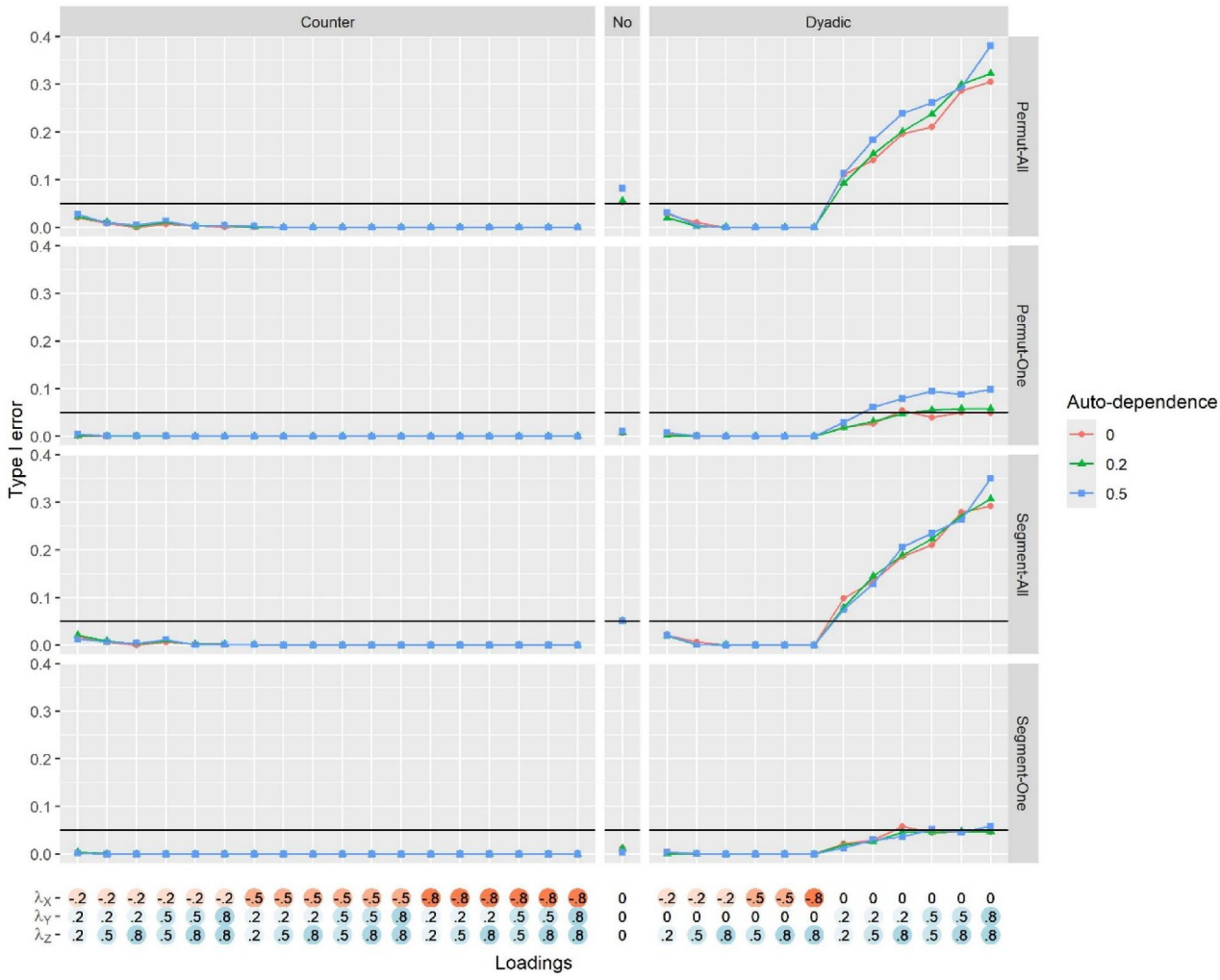


Figure 5. Continued

2020; Verhees et al., 2023). Parental sensitivity is defined as the ability of parents to appropriately perceive and promptly respond to their child's signals (Ainsworth et al., 1974). Apart from this, parents will perceive their partner as more sensitive when their partner shows more parental sensitivity toward their child (Cross et al., 2021). Hence, children's state attachment security, parents' self-reported sensitivity and their partners' perception of their sensitivity can be expected to synchronize within families.

Sample

To explore the synchronization of children's state attachment security, parents' self-reported sensitivity and their partners' perception of their sensitivity, we analyzed data from a pilot study on stress in adolescents' daily lives (Verhees et al., 2024). In this study, both parents and children reported daily stressful events using either a daily diary paradigm (one report per day) or an experience sampling paradigm (e.g., ESM, multiple reports per day which were synchronized within the family). In total, 20 Belgian families (mom, dad, and a 11 to 13-year-old adolescent) participated (i.e., 60 individuals), ten of which received daily diaries and the others ESM. Families with participants who always reported the maximum score (i.e., 100) on at least one item (implying that synchronization cannot be meaningfully computed) were removed, resulting in three families per data collection method being excluded.

Procedure

All participants first filled in background questionnaires, then participated in the diary/ESM period, and finally

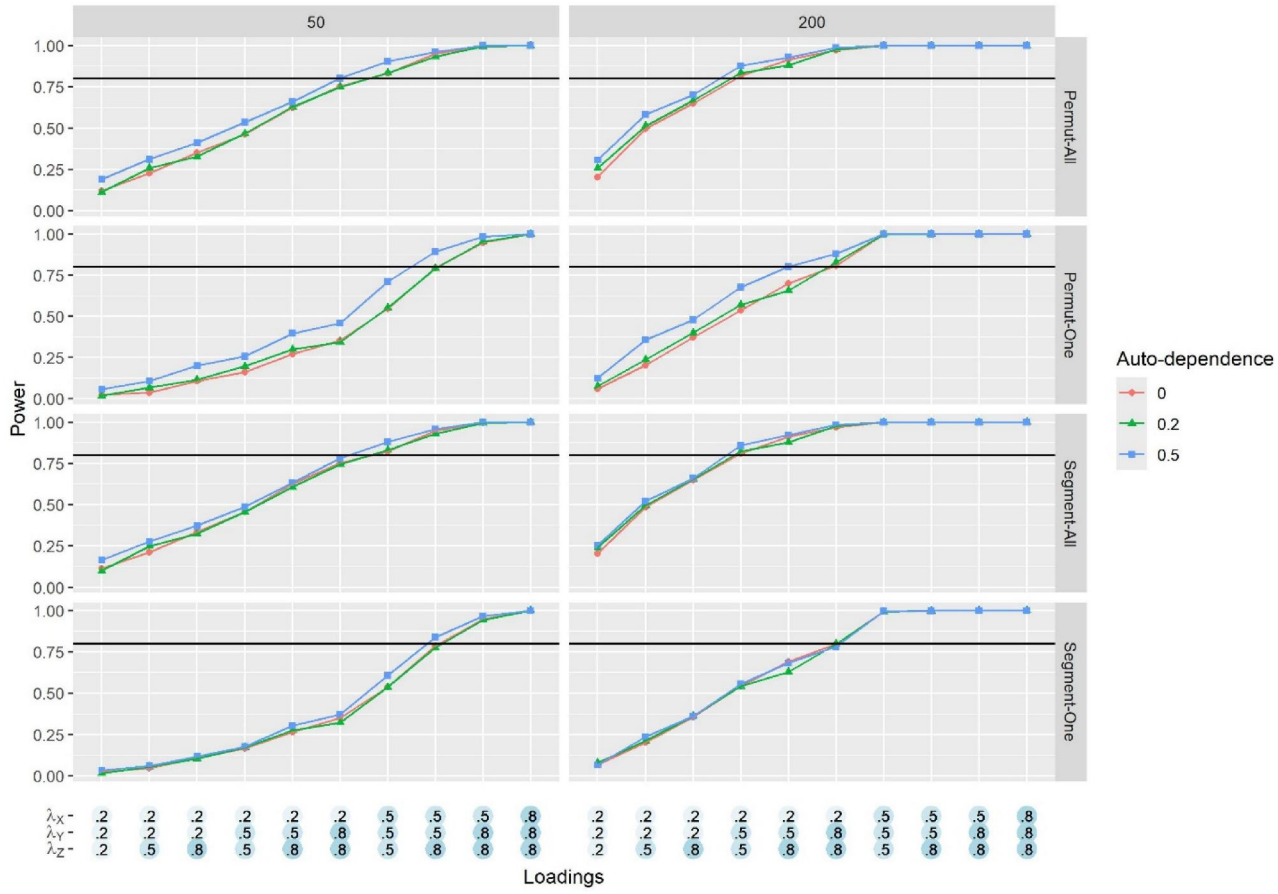


Figure 6. Power of AMPC. *Note.* Power of the significance test of *AMPC* as a function of number of timepoints, loading patterns and auto-dependences. Each point represents the results of one loading pattern, the exact loadings of which (λx, λy and λz) are shown in the colored dots on the x-axis, where, blue dots indicate positive values, and the transparency indicates the strength of the loading. The different line colors representing data with different auto-dependences. The horizontal black lines indicator the power of .8. The column on the left shows results with $T = 50$, and the column on the right shows results with $T = 200$. The rows show results using (1) *Permut-All*, (2) *Permut-One*, (3) *Segment-All*, and (4) *Segment-One* as permutation plan.

completed an evaluation questionnaire. In the diary paradigm, participants received one survey per day for 14 consecutive days. In the ESM paradigm, participants received four surveys on weekdays and nine surveys on weekend days for 10 consecutive days. The surveys were sent to members within one family at the same time. If all three family members completed the survey, the time point is defined as valid. Among families included, there were 86 valid time points in the daily diary data and 189 in the ESM data.

Measures

At each timepoint, children's attachment security was measured by items assessing their trust in mom or dad (i.e., "How much do you trust at this moment that your mom/dad would help you if you had a problem?"). Self-reported parental sensitivity was measured from both parents at each time point by two items gauging responsiveness (i.e., "At this moment I feel that I respond promptly and appropriately to my child's signals and needs.") and awareness ("At this moment I feel that I easily pick up signals from my child."). The partner-perceived parental sensitivity examined partner's perception of responsiveness (i.e., "At this moment I feel that my partner responds promptly and appropriately to our child's signals and needs.") and awareness (i.e., "At this moment I feel that my partner easily picks up signals from my child."). All items were assessed on a scale from 0 to 100.

Data analysis and results

We tested the triadic synchronization among (1) child's trust in mom, mom's self-reported responsiveness/awareness, and dad's perception of mom's responsiveness/awareness; (2) child's trust in dad, dad's self-reported responsiveness/awareness, and mom's

perception of dad's responsiveness/awareness; (3) child's trust in dad, mom's self-reported responsiveness/awareness, and dad's perception of mom's responsiveness/awareness; (4) child's trust in mom, dad's self-reported responsiveness/awareness, and mom's perception of dad's responsiveness/awareness, in both the daily diary and ESM data. In the former two cases, the trust object of the child was aligned with the sensitivity provider under examination, implying that (significant) triadic synchronization could be expected. In the latter two cases, the trust object of the child differed from the investigated sensitivity provider and thus no triadic synchronization was expected. Given the limited amount of time points per family, we pooled the data of the seven families within each data collection method and computed the *AMPC* across the seven families.

We conducted the significance test with the *Segment-One* permutation strategy, using the seven families as segments. Specifically, the order of the families in the variable to be shuffled was permuted, while the order of the time points within each family remained intact. Since families have different numbers of valid time points, the family members matched after shuffling could have different numbers of time points. For example, the child from a family with 9 valid time points could be matched with the parents from another family with 12 valid time points. In this case, only the first 9 time points of the parents were retained. This implies that the permuted data contained less time points than the observed data set.

The results are presented in Table 2. In the daily diary data, when children's trust object is the same as the sensitivity provider, *AMPC*s are positive and significant, indicating the existence of triadic synchronization. When children's trust object is different from the sensitivity provider, *AMPC*s are still positive, but lower and not significant, suggesting the absence of triadic synchronization. These results align with our hypotheses. However, in the ESM data, significant triadic synchronization was only found among children's trust in dad, dad's self-reported responsiveness/awareness, and mom's perception of dad's responsiveness/awareness, but not among children's trust in mom, mom's self-reported responsiveness/awareness, and dad's perception of mom's responsiveness/awareness. This discrepancy could result from the fact that family members had higher rates of contact in the daily diary paradigm (96%, referring to having been in contact that day) than in the ESM paradigm (57%; referring to having been in contact since the last survey (Verhees et al., 2024). If family members did not have contact, it becomes harder to be aware and respond to needs of the child or to perceive your partner's behavior, and thus the likelihood of synchronization decreases.

Table 2. Triadic synchronization results of empirical example.

(1) Diary

Synchronization cases (Kid-reported - Self-reported - Partner-reported)	*AMPC*	Pairwise correlations (Kid, Self)	(Kid, Partner)	(Self, Partner)	*p*
Trust in mom - Mom's resp. - Mom's resp.	.24*	.45	.18	.24	.014
Trust in mom - Mom's awar. - Mom's awar.	.27*	.45	.21	.22	.018
Trust in dad - Dad's resp. - Dad's resp.	.30*	.26	.21	.50	.038
Trust in dad - Dad's awar. - Dad's awar.	.32*	.27	.28	.40	.012
Trust in dad - Mom's resp. - Mom's resp.	.21	.16	.11	.50	.202
Trust in dad - Mom's awar. - Mom's awar.	.23	.20	.16	.40	.105
Trust in mom - Dad's resp. - Dad's resp.	.14	.25	.04	.24	.146
Trust in mom - Dad's awar. - Dad's awar.	.14	.28	.05	.22	.108

(2) ESM

Synchronization cases (Kid-reported - Self-reported - Partner-reported)	*AMPC*	Pairwise correlations (Kid, Self)	(Kid, Partner)	(Self, Partner)	*p*
Trust in mom - Mom's resp. - Mom's resp.	.10	.17	.02	.22	.214
Trust in mom - Mom's awar. - Mom's awar.	−.04	.13	.00	.16	.332
Trust in dad - Dad's resp. - Dad's resp.	.26*	.15	.30	.38	.023
Trust in dad - Dad's awar. - Dad's awar.	.23*	.11	.29	.35	.029
Trust in dad - Mom's resp. - Mom's resp.	−.13	−.03	.22	.38	.668
Trust in dad - Mom's awar. - Mom's awar.	−.12	−.03	.19	.35	.643
Trust in mom - Dad's resp. - Dad's resp.	.08	.19	.01	.22	.228
Trust in mom - Dad's awar. - Dad's awar.	−.07	.13	−.02	.16	.539

Note. All measures were assessed on a scale from 0 to 100. Data from 7 families in dairy paradigm were analyzed, including 86 valid time points. Data from 7 families in ESM paradigm were analyzed, including 189 valid time points. *resp.* is the abbreviation of *responsiveness, percp.* is the abbreviation of *perception,* and *awar.* is the abbreviation of *awareness*. (Kid, Self) stands for the correlation between kid's trust in parents and parents' self-reported sensitivity, (Kid, Partner) denotes the correlation between kid's trust in parents and partners' perceived sensitivity, and (Self, Partner) indicates the correlation between parents' self-reported sensitivity and partners' perceived sensitivity.

*$p < 0.05$.

Discussion

Triadic synchronization measures can give researchers insight into how people in a triadic system interact. This paper set out to propose a measure for capturing the presence and extent of triadic synchronization in one value, allowing to relate synchronization strength to other constructs. After providing a definition of triadic synchronization and clarifying which characteristics a useful triadic measure should have, we evaluated potential measures that use various ways to combine pairwise correlations, including three existing measures and two newly proposed measures. Both the data examples and the simulation results indicate that, only *AMPC*, the adjusted multiplication of pairwise correlations, has all the desired characteristics. Apart from the measure itself, we also proposed an associated significance test *Segment-One*. The simulation results show that the significance test has an acceptable Type I error rate. However, power heavily depends on synchronization strength and number of measurements. Finally, we showed that *AMPC* can detect meaningful triadic synchronization in empirical data.

Among the potential measures evaluated, only *ASOC* employs a data-slicing procedure, whereas the remaining measures do not. Although this discrepancy might raise concerns about the fairness of comparisons, it is important to note that data-slicing is an integral part of *ASOC*'s computation (Dale et al., 2020). Specifically, *ASOC* is calculated using a two-step procedure: in the first step, the time series are split into multiple slices to compute a series of first-order correlations, and in the second step, second-order cross-correlations are computed across these first-order correlations. Using data-slicing is thus necessary for calculating *ASOC* because the computation of a second-order cross-correlation requires multiple first-order correlations for each pair of variables. In contrast, the other measures combine first-order correlations computed over the entire time series in a specific way, without the need for data-slicing. Therefore, we believe that our comparison is sufficiently fair.

Given that the *AMPC* looks very promising, we see a number of directions for future research. First, the *AMPC* condenses the available information on triadic synchronization into one value. This is useful in that it allows researchers to treat triadic synchronization as one variable and investigate how it relates to another psychological construct. However, if researchers are more interested in the underlying synchronization patterns (e.g., who synchronizes less, who more), one could complement the *AMPC* measure with other methods like synchronization networks (e.g., Bodner et al., 2018; Bodner & Ceulemans, 2022; Ferrer et al., 2010; Hsieh et al., 2011; Veenman et al., 2024).

Second, the *AMPC* focuses on the concurrent triadic synchronization. Sometimes, delayed reactions are present in interpersonal interactions, implying that some of the variables should be appropriately lagged before computing synchronization. For example, after exposure to a stressful event, the child might feel stressed immediately, whereas the parents might only feel stressed a few minutes later when they have become aware of the child's reaction, resulting in lagging synchronization. To detect such lagged triadic synchronization, researchers need to determine how large the lag should be. In dyadic scenarios, methods like peak picking have been developed (Bodner & Ceulemans, 2023; Boker et al., 2002) for choosing the lag. Specifically, for two time series X and Y, one can compute the correlation between X at time point t and Y at time point $t+\tau$, implying a lag of τ time points later. By doing this for different τ values, one can plot how the correlation varies as a function of lag size τ (Figure 7(a)). The τ value that yields the largest correlation (i.e., the peak of the plot) is chosen as the optimal lag (shown by the red line in Figure 7(a)). When there are three time series X, Y and Z, this method can be extended by introducing a lag between X and Z, υ. One can then compute the *AMPC* value of X at time point t, Y at $t+\tau$, and Z at $t+\upsilon$. By varying the values of τ and υ, a heat map can be drawn (Figure 7(b)), plotting how the value of *AMPC* depends on τ and υ and allowing to select at which τ and υ AMPC peaks (shown by the red rectangular in Figure 7(b)). It is recommended to test the validity and applicability of this triadic extension of peak picking in the future.

Third, like all association measures, the *AMPC* assumes that the synchronization strength is stable across time. However, it makes sense to assume that this strength itself depends on other information, for instance, whether the persons under study are in contact, what kind of situations they are experiencing, etc. Therefore, future research could look into how such additional information can be incorporated when computing the measure or, in case such information is lacking, into methods for detecting different synchronization regimes in the data (e.g., Cabrieto et al., 2018), allowing to capture the dynamics of triadic synchronization.

Fourth, when applying the significance test *Segment-One*, there is a tradeoff between the choice of the number of segments S and the segment size m.

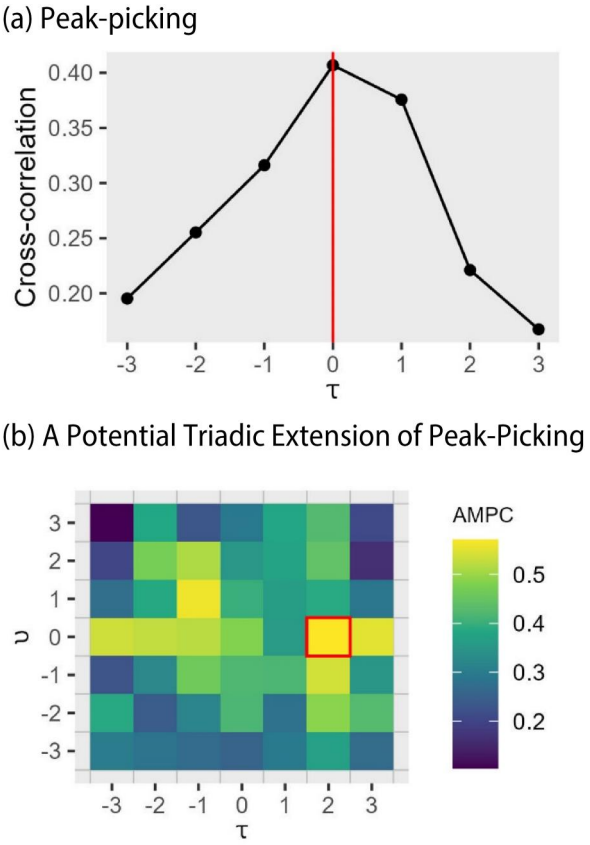


Figure 7. Illustration of peak-picking and its potential triadic extension.

On the one hand, one needs to choose a large enough number of segments to have enough possible ways to shuffle these segments. On the other hand, a large enough segment size m is also needed to maintain (most of) the auto-dependence in the time series, so that an inflated type I error can be avoided. However, when there is a limited number of time points in the time series, one cannot simply choose a large value for both m and S, but needs to carefully balance them. Hence, future research should investigate how to optimally choose the number of segments S and the segment size m, given a specific number of time points.

Fifth, the usefulness of a measure for capturing triadic synchronization is also dependent on how one defines triadic synchronization. We defined triadic synchronization as triadic covariance between the variables of interest of three people across time. Hence, scenarios in which only two persons synchronize are not admitted according to the definition, implying that a useful measure should take on a value of (about) zero. Other definitions can also be considered, obviously, but we urge researchers to make their definition of choice explicit. Specifically, they should clarify which among all possible synchronization scenarios fall under their definition of triadic synchronization. For example, in Wood et al. (2022), interpersonal synchronization among multiple musicians was measured *via* averaged unsigned correlations. This measure only yields zero values when there is no covariance at all. Hence, these researchers used a much broader definition of synchronization– covariance between at least a subset of persons across time. Moreover, given the use of the unsigned correlations, counter synchronization is also considered a form of synchronization.

Finally, although the current paper focuses on triadic synchronization, *AMPC* could potentially be extended to capture group synchronization of interpersonal systems that contain more than three people. Specifically, the extent to which all the group members covary with each other across time can be measured *via* taking the k-th root of the product of all the possible pairwise correlations within the group. Future study could further test the performance of this potential extension.

Conclusion

We have proposed the *AMPC* measure and an associated significance test as useful tools for capturing and testing triadic synchronization. We expect these tools to advance research into triadic synchronization and how it relates to other psychological constructs.

Article information

Conflict of Interest Disclosures: Each author signed a form for disclosure of potential conflicts of interest. No authors reported any financial or other conflicts of interest in relation to the work described.

Ethical Principles: The study procedure for the empirical data collection was approved by the Social and Societal Ethics Committee KU Leuven (G-2022-4703-R2). The authors affirm having followed professional ethical guidelines in preparing this work. These guidelines include obtaining informed consent from human participants, maintaining ethical treatment and respect for the rights of human or animal participants, and ensuring the privacy of participants and their data, such as ensuring that individual participants cannot be identified in reported results or from publicly available original or archival data.

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Informed Consent: All parents and children participating in the empirical study provided written informed consent.

Data Availability Statement: Materials and code are available via https://osf.io/7fw92/?view_only=6439434545a84f34af39b0cc68a1bb0a. The data used in empirical study are available from the corresponding author, upon reasonable request.

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