ЭКСПЕРИМЕНТАЛЬНЫЕ И ЭМПИРИЧЕСКИЕ ИССЛЕДОВАНИЯ

A comparative analysis of automated methods for nonverbal synchrony quantification in psychological counseling

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Nonverbal synchrony (NVS) has been investigated in relation to key psychotherapy and counseling process variables, such as therapeutic alliance and session quality, with empirical evidence suggesting a potential association. However, findings remain inconsistent, and the concordance between different automated methods of quantifying NVS is still understudied. This study contributes to the limited body of methodological research by comparing two principal NVS quantification approaches – the Ramseyer-Tschacher and Altmann methods – analyzing their relationship under both homogeneous (uniform) and heterogeneous parameter settings (method-specific). An analysis of 13 counseling sessions revealed strong positive correlations between most NVS measures under homogeneous settings (ρ = 0,17 to 0,92), particularly for overall synchrony strength and frequency. In contrast, under heterogeneous settings, while internal correlations within each method remained stable, cross-method correlations became weak or negative (ρ = –0,30 to 0,25). Notably, measures of synchrony strength within synchrony intervals showed distinct patterns of correlation relative to other NVS indicators, suggesting that they may reflect different aspects of synchronous behavior. These findings highlight the critical impact of parameter settings on NVS measurement and emphasize the need for greater methodological standardization in this field. Furthermore, the results indicate that different quantification methods may be sensitive to different temporal characteristics of synchrony, which has implications for both research and clinical applications. Additionally, these findings suggest that automated NVS quantification could potentially serve as an objective alternative to questionnaire-based assessments of counseling session quality, though substantial validation work addressing parameter sensitivity would be required before implementing such applications. This study contributes to the growing body of research on NVS by addressing key methodological considerations for future investigations.

Keywords: nonverbal synchrony, movement synchrony, motion energy analysis, time-series analysis, psychotherapy, counseling

Introduction

One of the processes underlying interpersonal interaction is interpersonal synchrony, which can be defined as the alignment of various features of interacting people in time and space [Hu et al., 2022]. Synchrony plays a fundamental role in human communication, promoting social bonding, enhancing mutual understanding, and facilitating coordinated actions [Chetouani et al., 2017]. It can occur across multiple modalities, including speech patterns, physiological responses, and body movements, reflecting the dynamic nature of social interaction [Feldman, 2017].

Of particular interest is nonverbal synchrony (NVS), which refers to the alignment of movements, gestures, and nonverbal cues and can also represent a dimension of interaction quality [Nyman-Salonen et al., 2021]. Recent studies have examined the role of NVS in various contexts, with findings suggesting a positive correlation between higher levels of NVS and improved social outcomes and interaction quality [Atzil-Slonim et al., 2023; Cohen et al., 2021; Galbusera et al., 2018; Hu et al., 2022; Mende, Schmidt, 2021; Vodneva et al., 2024]. Nevertheless, some studies showed a mixed association between NVS and outcomes [Jennissen et al., 2024; Prinz et al., 2021]. It may also be reduced in individuals with autistic spectrum disorders [Bowsher-Murray et al., 2022; Macpherson, Miles, 2023], depression [Altmann et al., 2021], or anxiety [Macpherson, Miles, 2023; Schoenherr et al., 2021].

The importance of measuring NVS extends far beyond academic research, with potentially transformative applications across multiple domains [Zampella et al., 2020; Altmann et al., 2021; Jennissen et al., 2024]. In health care, understanding interpersonal synchrony could revolutionize therapeutic interventions, particularly for populations with communication challenges such as autism spectrum disorders or depression, where nonverbal coordination may be impaired [Zampella et al., 2020; Altmann et al., 2021]. Educational settings could also benefit by potentially developing more effective teaching strategies that improve student-teacher interactions and learning outcomes (Shetty S.V. Non-verbal cues. https://www.timeshighereducation.com/campus/nonverbal-cues-learn-how-use-them-effectively-teacherstudent-communication) In organizational settings, synchrony research has implications for improving team collaboration, leadership effectiveness, and interpersonal communication (Hall A. The power of synchrony. https://aaronhall.com/the-power-of-synchrony-how-leaders-connect-and-inspire/). Understanding nonverbal synchrony could help organizations develop more effective team-building strategies, improve workplace interactions, and enhance conflict resolution techniques [Ibid.]. Furthermore, as artificial intelligence and robotics advance, insights from synchrony research might inform the development of more nuanced, human-like interaction protocols for social robots and virtual assistants, bridging the gap between technological innovation and human social experience.

Thus, NVS plays a crucial role in various interpersonal processes. One particularly relevant context for empirical research is the field of psychological help, with its complex interpersonal dynamics, various psychotherapeutic approaches, and emphasis on collaborative work aimed at improving clients' well-being. Empirical evidence underscores the important role of NVS in psychotherapeutic interactions, where movement coordination facilitates better therapeutic outcomes [Wiltshire et al., 2020; Oreshina, Zhukova, 2023]. However, the positive relationship between NVS and therapy outcomes is not always consistent, as meta-analyses investigating NVS show mixed results [Ayache et al., 2021; Atzil-Slonim et al., 2023; Gregorini et al., 2025].

The variability in findings can be attributed, in part, to methodological challenges in measuring NVS. As a readily observable aspect of human interaction, NVS can be analyzed through behavioral coding or expert ratings [Fujiwara et al., 2021]. However, to avoid time-consuming manual analysis, automated methods have been developed to identify movement patterns [Delaherche et al., 2012]. One widely used approach for automated human movement analysis is motion energy analysis (MEA), which represents interaction dynamics over time as continuous time series data [Schoenherr et al., 2019c]. Notably, various tools and protocols based on MEA can be used to generate movement time series and compute NVS, which may contribute to methodological discrepancies. Cross-methodological studies comparing various synchrony quantification approaches are needed to clarify these inconsistencies.

Measuring NVS is inherently complex, requiring sophisticated computational approaches that capture different aspects of interpersonal coordination. Two primary methodological approaches have emerged for quantifying NVS: windowed cross-lagged correlation (WCLC) and windowed cross-lagged regression (WCLR). Both methods segment movement data into time windows and analyze coordination at different lags to assess temporal dynamics. WCLC computes correlations between movement patterns across these shifting windows, while WCLR extends this approach by incorporating predictive modeling. Specifically, WCLR compares two models – one predicting an individual's future movements based solely on their own past behavior and another that also includes their partner's prior movements – allowing for a more nuanced examination of NVS [Altmann et al., 2022].

These methods yield several key metrics for assessing NVS. *Synchrony frequency* refers to the proportion of interaction time during which significant synchrony is observed, indicating how often coordination occurs. *Overall synchrony strength* provides a global measure of coordination by averaging movement correlations across the interaction. *Synchrony strength within synchronization intervals* focuses on the intensity of coordination during specific periods of alignment, known as synchronization intervals [Schoenherr et al., 2019c].

A literature review revealed limited cross-methodological research comparing synchrony quantification approaches. To date, we found only two comprehensive studies have examined the concordance between different NVS measurement methods using MEA. These studies compared synchrony measures using two distinct parameter configurations (or settings). The first configuration, referred to as heterogeneous parameter settings, employed default parameter settings typically found in the existing literature for each specific analysis method. These settings can vary widely between research teams, reflecting the current lack of standardization in NVS measurement [Altmann et al., 2022]. Researchers using this configuration use the original developers' recommended parameters, which may differ in window width, step size, maximum time lag, and correlation calculation methods. In contrast, the second configuration, called homogeneous parameter settings, deliberately standardized all parameters across different methods to maximize direct comparability. By using identical computational settings, researchers can effectively isolate method-specific differences in synchrony quantification [Schoenherr et al., 2019c].

The existing comparative studies show contrasting results. Schoenherr et al. [2019c] found significant positive correlations (r > 0,5) between most of the resulting synchrony scores under both parameter configurations. In contrast, Altmann et al. [2022] reported substantially lower concordance when analyzing clinical interviews, with correlations ranging from strongly positive to significantly negative. This variability highlights the complexity and methodological challenges of measuring NVS and the critical need for more systematic comparative research. The divergent results suggest that different computational approaches may capture distinct aspects of interpersonal coordination, emphasizing the importance of understanding how various measurement techniques relate to and potentially complement each other.

Therefore, the purpose of this study was to conduct an exploratory investigation of the concordance between the distinct methods for NVS quantification in psychological counseling. To provide a comprehensive understanding, we examined this concordance under both homogeneous and heterogeneous parameter settings. Based on previous findings indicating both similarities and distinctions in the relationship between synchrony scores across methods, we developed several hypotheses. First, when using homogeneous parameter settings, we expected strong correlations between synchrony measures across different methods. In contrast, we expected weaker correlations under heterogeneous parameter settings. It should be noted that the primary goal of this paper was not to identify the most effective algorithm for synchrony quantification. Rather, the goal was to examine the extent to which different algorithms produce consistent NVS scores when applied to the same counseling interactions. In doing so, this study aims to refine methodological approaches to NVS analysis and contribute to the development of standardized frameworks for synchrony quantification, ultimately facilitating more reliable and generalizable research in this field.

Methods

Sample and Design

The study employed a quasi-experimental design. All participants gave their informed consent for study participation. Each counselor-client dyad was assigned a unique identifier to ensure confidentiality. Sessions were conducted according to the counselors' usual practice close to the usual session day and time. All sessions were video recorded, and to ensure privacy, the research team left the room for the duration of the session. A video camera was placed on a tripod to ensure that both participants were fully visible throughout the session. If participants stood up at any point, the counselors reported this to the research team, and these segments were excluded from analysis. Otherwise, no specific instructions were given to the counselors or clients. The study was approved by the local Bioethics Committee.

Thirteen dyads participated in the study, consisting of 12 clients and 2 experienced counselors (one dyad participated twice). The counselors were a 51-year-old woman trained in Acceptance and Commitment Therapy, and a 35-year-old man trained in Cognitive Behavioral Therapy (CBT). Of the 12 clients, 7 were female. The mean age of all clients was 27,17 years (SD = 8,14). All clients had at least a bachelor's degree. To qualify, clients had to have a request for psychological counseling and show no signs of acute or relapsing mental illness. At the end of the study, all participants received a bookstore gift card.

All 13 sessions were recorded with a GoPro HERO 10 Black. The duration of the sessions was not strictly controlled, with an observed mean duration of 56,69 min (SD = 10,33 min). The recording conditions were consistent with the optimal parameters described by Ramseyer and Tschacher [2011] and Altmann [2013]. To ensure comparability of the video files, they were converted to MP4 format with a resolution of 1280x720 pixels, a frame rate of 25 frames per second, and a bit rate of 4240 kbit per second using Movavi Video Converter 18.3.0 Premium.

Time Series Data Collection and Preprocessing

The Motion Energy Analysis (MEA) is a video analysis method based on a frame-difference algorithm [Grammer et al., 1999]. The algorithm detects motion by analyzing changes in pixel coloration between consecutive frames. By defining a region of interest (ROI), the motion of specific body parts, such as a person's head or torso, can be tracked throughout the video recording. The grayscale pixel differences in successive frames within the ROI are analyzed to generate a motion energy time series. By using multiple ROIs, a multivariate time series of motion activity can be generated for each video, with each ROI representing a specific body part of each individual. In this study, MEA was applied to the video files using MATLAB vR2023a and scripts developed by Altmann (accessible at https://github.com/10101-00001/MEA). Schoenherr et al. [2019b] demonstrated a high correlation (r = 0,996) between MEA in MATLAB and MEA software.

Factors such as ROI size, foreground-background ratio, video resolution, frame rate, and noise-to-signal ratio can affect the time series values. Therefore, maintaining consistency across sessions is crucial for accurate analysis [Ramseyer, 2020]. To accommodate the higher video resolution and ensure comparability, minor adjustments were made to the original MEA code. Background ROIs, used for noise filtering, were scaled to align with the original 10x10 squares (for 640x480), resulting in 18x18 squares for all videos. A single ROI was highlighted per individual, integrating head and body movements. In our sample, the threshold used for MEA (99th percentile of the difference values for the background ROI pixel) was 6.

Following MEA, several preprocessing steps were applied following the recommendations of Altmann and Schoenherr [Schoenherr et al., 2019a]. Each time series was standardized by dividing the motion energy values by the corresponding ROI size and multiplying by 100, adjusting values to range from 0 to 100, representing range from no ROI activity to full ROI activation. If motion energy in the background ROIs exceeded 5% or if the body ROI motion changed by more than 15% between consecutive frames, the affected values were set to missing and linearly interpolated. The time series were then smoothed using a moving median with a five-frame bandwidth and were logarithmically transformed.

For algorithms comparison, all raw time series also underwent preprocessing according to rMEA as recommended by Kleinbub and Ramseyer [2020]. This involved removing outliers (values greater than 10 times the standard deviation of each time series), smoothing using 0,5-second moving averages, and rescaling based on standard deviation. The correlation between the results of two preprocessing approaches was high (Spearman's r ≈ 0,97, p < 0,0001), leading to the exclusive use of Altmann and Schoenherr preprocessing for further analysis to ensure comparability. Once the time series data have been preprocessed, synchrony scores are computed using time series analysis methods, typically through windowed cross-lagged correlation (WCLC) or windowed cross-lagged regression (WCLR)

Time Series Analysis

The WCLC method calculates correlations between paired time series across different time lags. The analysis starts by computing the correlation between the first windows (segments) of both time series without delay (lag = 0). Then, one window is shifted by a single lag point, and the correlation is recalculated at each new lag. A positive lag indicates that changes in the first time series (e.g., Person 1) precede those in the second (Person 2), while a negative lag suggests the inverse relationship. This process continues until a predetermined maximum lag is reached. Once the maximum lag is analyzed, both windows are shifted by a specified step size, and the procedure is repeated until all windows from the time series have been evaluated [Ramseyer, Tschacher, 2011].

The WCLR method integrates elements of both cross-lagged regression and WCLC by computing window-wise interrelations with variations in both the reference window position and the time lag. Two models are applied to each pair of windows: Model 1 predicts future behavior based solely on an individual's previous behavior (thus accounting for autocorrelation only), while Model 2 incorporates the partner's previous behavior as an additional predictor variable. Synchrony is considered identified when Model 2 significantly outperforms Model 1, as determined by an R^2 difference test [Altmann, 2011; Altmann, 2013].

Two primary methodological approaches illustrate the application of these techniques. The approach by Fabian Ramseyer and Wolfgang Tschacher is grounded in systems theory and dynamic systems models, which conceptualize human interactions as inherently reciprocal, nonlinear, and time-dependent [Ramseyer, Tschacher, 2006]. Their framework posits that NVS is an emergent property arising naturally from the mutual influence of interacting partners, reflecting underlying psychological and emotional processes consistent with embodied cognition theories [Mahon, 2015]. This approach utilizes the "MEA" software [Ramseyer, 2020] for extracting movement time series data and the rMEA package in R [Kleinbub, Ramseyer, 2020] to compute WCLC (referred to as $WCLC_1$ in this paper for clarity) and derive average synchrony strength scores (average cross-correlation coefficients) across various time lags. To confirm that the observed synchrony is not merely a product of random dynamical alignment, a shuffling method is typically used to compare synchrony in real interactions against pseudosynchrony generated by combining time series from different dyads.

In contrast, Uwe Altmann's methodology employs a peak-picking algorithm that isolates distinct peaks in the cross-correlation function to identify moments of maximal synchrony rather than relying on continuous correlation measures. Rooted in dynamic systems theory [Altmann et al., 2022], Altmann's approach uses MATLAB scripts to extract motion time series data (also via the MEA approach) and compute synchrony scores using both WCLC (referred to as $WCLC_2$) and WCLR. This method not only assesses the strength of synchrony but also quantifies its frequency (quantity) by determining the proportion of interaction time during which significant synchrony occurs. The underlying premise is that synchrony is not an ever-present continuous phenomenon but rather occurs intermittently during interactions. To minimize false positives, the algorithm stipulates that for each detected peak, the correlation value must be the highest within a specified lag window, ensuring that the identified synchrony reflects a meaningful phase alignment rather than random fluctuation. Desiree Schoenherr [et al., 2019a] further refined this approach by introducing a cut-off value for synchrony intervals to additionally control for spurious correlations.

Both approaches were examined under both homogeneous and heterogeneous parameter settings. For heterogeneous settings, we implemented each method according to its developers' recommended default parameters to reflect how these methods are typically applied in the literature. The Ramseyer and Tschacher method was implemented with the rMEA package (v1.2.2) in R (v4.4.2) with their default parameters: a time window of 60 seconds (designed to capture longer-term synchrony patterns), a step size of 30 seconds (reducing computational load while maintaining adequate temporal resolution), and a maximum time lag of 5 seconds (sufficient to capture typical interpersonal coordination delays while minimizing spurious correlations). This resulted in the synchrony measures $WCLC_1$ (average synchrony strength across all time lags) and WCC_1 (average synchrony strength without a time lag). In the Altmann methodology, MATLAB scripts (developed by Altmann and accessible at https://github.com/10101-00001/sync_ident) were used to calculate synchrony scores using their recommended default parameter settings: a window width of 5 seconds (prioritizing detection of immediate NVS), a step size of 2 frames (0,08 seconds, allowing high temporal precision), a maximum time lag of 5 seconds, and a cut-off value for the strength of synchrony intervals (R^2) of 0,25 (implemented to reduce false positives). We focused on three primary measures: total synchrony frequency ($WCLC_{2F}$ and $WCLR_F$), overall average strength across all time lags ($WCLC_{2SO}$ and $WCLR_{SO}$), and average strength of synchrony across all time lags within synchrony intervals ($WCLC_{2SW}$ and $WCLR_{SW}$).

For homogeneous settings, we deliberately selected identical parameters across both methods to maximize direct comparability: a window width of 5 seconds, a step size of 2 frames (0,08 seconds), and a maximum time lag of 5 seconds. These unified parameters allowed us to isolate most of the computational differences between the approaches while controlling parameter variation. We also attempted NVS quantification using the rMEA-recommended parameters (60-second windows, 30-second step) with the Altmann approach, but this resulted in the absence of detectable synchrony intervals, highlighting the sensitivity of these methods to parameter selection. Therefore, only the Altmann-recommended default settings were used for homogeneous settings comparison.

Statistical Analysis

Following the NVS quantification, statistical analysis was performed to examine the associations between the various synchrony scores using Bayesian nonparametric Spearman correlation analysis. Normality of the distribution was not formally tested due to the limited sample size, which inherently reduces the reliability of such tests. Given the potential for Type II errors (failure to detect non-normality) and the low power of normality tests in small samples, a nonparametric approach (Spearman correlation) was used to ensure robustness and minimize assumptions about the data distribution. In addition, Bayesian methods were used to provide a probabilistic interpretation of the strength and direction of the relationships.

The analysis was performed in R (v.4.4.2), starting with data import using the "readxl" package (v.1.4.3) and subsetting the relevant synchrony measures (which are described above). The "correlation" package (v.0.8.6) was then used to compute the Bayesian Spearman correlations. The Bayesian analysis was performed using a symmetric beta distribution prior with a wide "rscale" parameter, representing a weakly informative prior. This choice provided a balanced framework for the analysis, ensuring that the prior did not overly influence the posterior estimates.

To assess the sensitivity of the results to the prior specifications, a series of sensitivity analyses was conducted in accordance with the guidelines for reporting Bayesian analysis [Kruschke, 2021]. This involved computing the Bayes factor (BF) ratios between the BF obtained with the wide prior and those computed with alternative prior parameters (medium, narrow, and ultrawide), which variably adjust the beta distribution.

The anonymized data supporting the results of this study, including the motion energy analysis results, the final data set for statistical analysis, and the statistical analysis code, are available at https://doi.org/10.6084/m9,figshare.27959469.

Results

Homogeneous parameters. The analysis of synchrony scores using homogeneous parameter settings revealed predominantly positive correlations across all measures, with correlation coefficients ranging from $\rho = 0{,}17$ to $\rho = 0{,}92$ (Table 1). Within the Ramseyer and Tschacher's approach, $WCLC_1$ and WCC_1 showed an extremely strong correlation ($\rho = 0{,}91$, 95% CI [0,77, 0,97], BF = 6553,69), indicating high consistency between the time-lagged and non-lagged variants of synchrony. Within Altmann's approach, most of the scores were strongly positively correlated with each other, with the lowest correlations observed between scores involving synchrony strength within synchrony intervals ($WCLR_{SW}$ and $WCLC2_{SW}$). For example, a strong correlation was found between $WCLR_F$ and $WCLR_{SO}$ ($\rho = 0{,}88$, 95% CI [0,72, 0,98], BF = 2195,06), both scores from Altmann's approach but measuring different aspects of synchrony (frequency and overall strength, respectively).

When comparing between methods, the strongest relationships were observed between $WCLC_1$ and $WCLR_{SO}$ ($\rho = 0{,}92$, 95% CI [0,77, 0,99], BF = 17040,52), $WCLC_1$ and $WCLR_F$ ($\rho = 0{,}86$, 95% CI [0,68, 0,97], BF = 1222,17), and WCC_1 and $WCLR_{SO}$ ($\rho = 0{,}83$, 95% CI [0,60, 0,95], BF = 384,25), suggesting substantial agreement between measures of overall synchrony strength and frequency. However, certain measures demonstrated weaker relationships, particularly those involving $WCLR_{SW}$ and $WCLC_{2SW}$. These measures showed significantly lower correlations with other scores, with BFs generally < 3, indicating insufficient evidence for meaningful relationships. It should be noted, however, that these two measures were strongly correlated with each other ($\rho = 0{,}79$, 95% CI [0,53, 0,94], BF = 187,01).

The sensitivity analysis revealed that the choice of prior width significantly affected the results, with sensitivity ratios varying from 0,82 to 6,62 for the medium (M 1,97 ± SD 1,37), from 0,72 to 73,07 for the narrow (M 8,26 ± SD 15,36), and from 0,31 to 1,28 for the ultrawide (M 0,84 ± SD 0,29) prior width. This variation suggests that the correlation estimates were to some extent dependent on the chosen prior distribution, indicating the need for careful consideration of prior selection.

Heterogeneous parameters. The analysis of synchrony scores using heterogeneous parameter settings revealed a markedly different pattern of correlations compared to the homogeneous condition, with cross-methods correlation coefficients ranging from $\rho = -0{,}30$ to $\rho = 0{,}25$, Within the Ramseyer and Tschacher's approach, $WCLC_1$ and WCC_1 maintained their strong correlation ($\rho = 0{,}91$, 95% CI [0,79, 0,98], BF = 9077,14), suggesting consistent agreement under varying settings. However, the re-

Table 1

Bayesian Correlation Matrix of Synchrony Scores Using Homogeneous Parameter Settings

Parameter1	Parameter2	rho	CI_low	CI_high	pd_%	ROPE_%	BF
$WCLC_1$	WCC_1	0,91	0,77	0,97	100	0	6553,69
$WCLC_1$	$WCLC_{2F}$	0,64	0,23	0,90	99,98	0,63	17,10
$WCLC_1$	$WCLC_{2SW}$	0,60	0,26	0,88	99,78	0,7	10,14
$WCLC_1$	$WCLC_{2SO}$	0,77	0,51	0,93	100	0	136,77
$WCLC_1$	$WCLR_F$	0,86	0,68	0,97	100	0	1222,17
$WCLC_1$	$WCLR_{SW}$	0,32	–0,19	0,70	89,38	14,15	1,08
$WCLC_1$	$WCLR_{SO}$	0,92	0,77	0,99	100	0	17040,52
WCC_1	$WCLC_{2F}$	0,62	0,26	0,87	99,8	0,7	11,67
WCC_1	$WCLC_{2SW}$	0,59	0,16	0,87	98	2	8,31
WCC_1	$WCLC_{2SO}$	0,73	0,41	0,90	100	0	61,36
WCC_1	$WCLR_F$	0,78	0,53	0,95	100	0	187,01
WCC_1	$WCLR_{SW}$	0,33	–0,18	0,71	89,25	13,95	1,06
WCC_1	$WCLR_{SO}$	0,83	0,60	0,95	100	0	384,25
$WCLC_{2F}$	$WCLC_{2SW}$	0,33	–0,17	0,71	89,93	12,78	1,08
$WCLC_{2F}$	$WCLC_{2SO}$	0,81	0,54	0,94	100	0	316,58
$WCLC_{2F}$	$WCLR_F$	0,71	0,40	0,95	100	0,4	43,63
$WCLC_{2F}$	$WCLR_{SW}$	0,17	–0,31	0,60	74,43	23,2	0,58
$WCLC_{2F}$	$WCLR_{SO}$	0,65	0,25	0,89	99,7	0,2	18,57
$WCLC_{2SW}$	$WCLC_{2SO}$	0,56	0,16	0,87	99,2	2,83	6,50
$WCLC_{2SW}$	$WCLR_F$	0,41	–0,04	0,77	94,95	9,03	1,66
$WCLC_{2SW}$	$WCLR_{SW}$	0,79	0,53	0,94	100	0	187,01
$WCLC_{2SW}$	$WCLR_{SO}$	0,61	0,20	0,87	98,55	1,83	11,67
$WCLC_{2SO}$	$WCLR_F$	0,75	0,42	0,94	100	1,13	89,55
$WCLC_{2SO}$	$WCLR_{SW}$	0,44	–0,04	0,76	95,35	6,63	2,12
$WCLC_{2SO}$	$WCLR_{SO}$	0,81	0,59	0,95	100	0	263,37
$WCLR_F$	$WCLR_{SW}$	0,19	–0,32	0,61	77,5	22,43	0,61
$WCLR_F$	$WCLR_{SO}$	0,88	0,72	0,98	100	0	2195,06
$WCLR_{SW}$	$WCLR_{SO}$	0,41	–0,03	0,79	94,73	9,2	1,72

Note: rho = Spearman's correlation coefficient; CI = credible interval (lower and higher bounds); pd = probability of direction; ROPE = region of practical equivalence; BF = Bayes factor value. $WCLC_1$ = average synchrony strength across all time lags calculated using rMEA; WCC_1 = average synchrony strength without a time lag calculated using rMEA. $WCLC_{2F}$ and $WCLR_F$ = total synchrony frequency calculated using peak-picking algorithm (correlation and regression methods); $WCLC_{2SO}$ and $WCLR_{SO}$ = overall average strength across all time lags calculated using peak-picking algorithm (correlation and regression methods); $WCLC_{2SW}$ and $WCLR_{SW}$ = average strength of synchrony across all time lags within synchrony intervals calculated using peak-picking algorithm (correlation and regression methods).

Table 2

Bayesian Correlation Matrix of Synchrony Scores Using Heterogeneous Parameter Settings

Parameter1	Parameter2	rho	CI_low	CI_ high	pd_%	ROPE_%	BF
$WCLC_1$	WCC_1	0,91	0,79	0,98	100	0	9077,14
$WCLC_1$	$WCLC_{2F}$	–0,28	–0,69	0,20	85,15	16,4	0,84
$WCLC_1$	$WCLC_{2SW}$	0,03	–0,47	0,47	54,45	30,35	0,45
$WCLC_1$	$WCLC_{2SO}$	–0,25	–0,66	0,23	84,05	19,8	0,77
$WCLC_1$	$WCLR_F$	–0,30	–0,71	0,17	88,48	15,4	0,92
$WCLC_1$	$WCLR_{SW}$	0,12	–0,37	0,59	67,43	25,73	0,51
$WCLC_1$	$WCLR_{SO}$	–0,29	–0,70	0,19	87,23	14,8	0,92
WCC_1	$WCLC_{2F}$	–0,20	–0,64	0,30	76,85	21,93	0,61
WCC_1	$WCLC_{2SW}$	0,15	–0,32	0,61	72,13	26,43	0,53
WCC_1	$WCLC_{2SO}$	–0,13	–0,57	0,37	69,83	26,58	0,52
WCC_1	$WCLR_F$	–0,15	–0,61	0,32	72,48	26,38	0,54
WCC_1	$WCLR_{SW}$	0,25	–0,24	0,68	82,35	19,63	0,72
WCC_1	$WCLR_{SO}$	–0,15	–0,61	0,30	71,63	25,78	0,53

Note: rho = Spearman's correlation coefficient; CI = credible interval (lower and higher bounds); pd = probability of direction; ROPE = region of practical equivalence; BF = Bayes factor value. $WCLC_1$ = average synchrony strength across all time lags calculated using rMEA; WCC_1 = average synchrony strength without a time lag calculated using rMEA. $WCLC_{2F}$ and $WCLR_F$ = total synchrony frequency calculated using peak-picking algorithm (correlation and regression methods); $WCLC_{2SO}$ and $WCLR_{SO}$ = overall average strength across all time lags calculated using peak-picking algorithm (correlation and regression methods); $WCLC_{2SW}$ and $WCLR_{SW}$ = average strength of synchrony across all time lags within synchrony intervals calculated using peak-picking algorithm (correlation and regression methods).

lationships between cross-methodology correlations showed a notable shift, with all correlations becoming weak or even negative with all BFs < 1, For example, $WCLC_1$ demonstrated negative correlations with $WCLR_{SO}$ (ρ = –0,29, 95% CI [–0,70, 0,19], BF = 0,92), $WCLC_{2SO}$ (ρ = –0,25, 95% CI [–0,66, 0,23], BF = 0,77), and $WCLR_F$ (ρ = –0,30, 95% CI [–0,71, 0,17], BF = 0,92).

The sensitivity analysis revealed that the choice of prior width continued to influence the results, with sensitivity ratios varying from 0,80 to 5,61 for the medium (M 1,42 ± SD 1,10), from 0,67 to 50,31 for the narrow (M 4,43 ± SD 10,04), and from 0,34 to 1,31 for the ultrawide (M 1,04 ± SD 0,30) prior width. This variation suggests that the correlation estimates remained dependent on the chosen prior distribution, reinforcing the need for careful prior selection across different parameter settings.

Discussion

The purpose of the present study was to conduct a comparative analysis of two automated methods for quantifying NVS in psychological counseling. Specifically, we aimed to assess the degree of agreement between the synchrony scores derived from the two approaches. The analyses were exploratory in nature, with the goal of generating preliminary findings that could inform future studies with larger sample sizes. It was hypothesized that there would be strong correlations between synchrony measures across methods when using homogeneous parameter settings and weak correlations when using heterogeneous parameter settings. In addition, we hypothesized that within each parameter setting type, synchrony strength scores would show moderate Spearman correlations, whereas correlations between strength and frequency scores would be weak. The results generally support these hypotheses.

The findings demonstrate a complex pattern of relationships between different NVS quantification methods, which is partially consistent with previous research but also provides new insights. Under homogeneous parameter settings, we observed strong positive correlations between most synchrony measures, particularly for overall strength and frequency measures, which is consistent with the findings of Schoenherr et al. [2019c]. This suggests that these measures may capture similar underlying aspects of NVS when computational parameters are standardized. Synchrony strength refers to the overall coordination between interaction partners, reflecting the intensity of synchrony across the entire interaction, whereas frequency measures quantify how often synchrony occurs during the interaction. As hypothesized, we found moderate correlations between synchrony strength and frequency scores within homogeneous parameter settings. However, the measures of synchrony strength within synchrony intervals (which assess synchrony strength only during specific interaction periods) showed significantly weaker correlations with the other measures, while maintaining a strong correlation with each other, suggesting that these measures may capture a different facet of synchronous behavior.

The results from heterogeneous parameter settings revealed a remarkable contrast. While the internal consistency within each method remained stable, the cross-method correlations became weak or even negative. This finding is more consistent with Altmann et al.'s [2022] observations of highly variable convergent validity under heterogeneous settings. The strong difference between homogeneous and heterogeneous conditions suggests that the choice of parameter settings plays a critical role in the comparability of NVS measures across methods. This sensitivity to parameter settings raises important methodological considerations for future research, as it suggests that seemingly minor analytic choices can substantially affect the measurement of NVS.

This substantial impact of parameter settings on cross-method correlations has important implications for the interpretation and comparison of existing NVS research. Studies using different parameter settings may in fact measure different aspects of synchronous behavior, even when using seemingly similar methodological approaches. The contrasting window sizes between the methods might explain these differences: Altmann's approach with smaller windows may capture micro-level synchrony or synchronization of subtle movements, whereas Ramseyer's larger windows may detect macro-level synchrony patterns or broader movement coordination. This finding underscores the need for greater standardization of NVS measurement procedures, or at least careful consideration and reporting of parameter choices in future research.

This finding is particularly important given that existing systematic reviews of NVS research [Wiltshire et al., 2020; Ayache et al., 2021; Atzil-Slonim et al., 2023; Gregorini et al., 2025] typically aggregate results across studies without accounting for the settings of NVS calculation. Thus, our research highlights the need to consider homogeneity of settings as a potential moderating factor, as studies using different parameter settings may measure different aspects of synchronous behavior. Accounting for these parameter settings can improve the comparability of results across studies, increase the reliability of meta-analyses, and facilitate the development of standardized guidelines for future research and practice.

The sensitivity analysis revealed an additional methodological consideration for NVS research. The substantial variation in results across different prior widths suggests that statistical inference in NVS studies using Bayesian approaches requires careful attention to prior selection. This finding highlights the importance of transparent reporting and justification of analytic choices in future Bayesian analyses of NVS.

These findings have direct implications for future NVS research design and methodology. When comparing results across studies or conducting meta-analyses, researchers should carefully consider whether differences in parameter settings might explain contradictory findings. Moreover, the choice between approaches might depend on the specific research questions: studies focusing on subtle immediate responses might benefit from Altmann's approach with smaller windows, while research on broader interaction patterns might be better served by Ramseyer's method with larger windows. This suggests that researchers should not view these methods as interchangeable tools, but rather as complementary approaches that capture different temporal scales of nonverbal coordination. Future research should also examine the temporal dynamics of nonverbal synchrony within counseling sessions. Analyzing how synchrony patterns evolve across sessions, such as identifying moments of peak synchrony or comparing early and late segments, could provide important implications for counseling processes.

Given these findings, the two methods may capture different aspects of synchronous behavior, and thus, for the time being, they should probably be used concurrently for comparison and to test convergent and predictive validity. Given that convergent validity between different methods has been understudied, it is important to continue exploring how these methods align and diverge. For example, using both methods together allows researchers to cross-validate findings and determine whether they consistently reflect meaningful aspects of interpersonal synchrony across various contexts. This approach would help determine whether differences in results are due to genuine variations in synchronous behavior or are simply artifacts of methodological choices.

However, Altmann's peak-picking algorithm (especially when combined with WCLR) is much more time-consuming, which comes at the cost of a long waiting time for calculations. The computational requirements may be prohibitive for studies with large datasets or when a quick turnaround is required. On the other hand, rMEA package offers a more efficient alternative, though it may miss subtle or micro-level synchrony patterns. The cost-benefit of each approach should therefore be considered based on the specific research question, sample size, and available computational resources.

Given the importance of methodological choices in measuring NVS, researchers should carefully consider the implications of parameter settings when designing studies. If the goal is to capture a broad, high-level understanding of synchrony, using larger window sizes (as in rMEA) may be appropriate. However, if a more detailed analysis of micro-level synchrony is desired, Altmann's peak-picking algorithm may be preferable, despite the higher computational cost. Researchers should not treat these methods as interchangeable but as complementary tools that can provide more comprehensive understanding when used together.

These findings also have implications for the potential use of NVS measures as objective indicators of session quality. While current practice relies heavily on questionnaire-based assessments [Sukhorukov et al., 2024], automated NVS quantification may offer a more objective alternative. However, the sensitivity of these measures to parameter settings suggests that substantial validation work would be required before such applications could be implemented, including determining which parameter settings and temporal scales are most predictive of the outcomes.

It is important to note several limitations to the findings of this study. First, the relatively small sample size (n = 13 sessions) limits the statistical power of the correlational analyses and the generalizability of the findings. Further studies with larger samples are needed to confirm these findings. Second, the discrepancy in session length may have influenced the results, as synchrony patterns can evolve and develop over time. Shorter sessions may have limited the observation of more complex synchrony dynamics, whereas longer sessions may have provided more opportunities to observe complex interactional processes. Third, the study focused exclusively on dyadic counseling sessions conducted in CBT, which may not generalize to other therapeutic modalities or group settings. Fourth, the analysis did not account for potential confounding variables such as counselors' experience level, therapeutic alliance, or client presenting problems. Finally, although the study examined different parameter settings, it did not exhaustively explore all possible combinations, leaving open the possibility that other parameter configurations might yield different results.

Nevertheless, this study advances the investigation of NVS assessment in several important ways. First, few previous studies have compared synchrony measures across different algorithms or varied settings, particularly within the context of real psychotherapy or counseling sessions. Second, unlike most research that restricts time series analysis to the initial segments of sessions (usually 15 minutes), this study examines entire sessions, providing a more comprehensive capture of NVS. Additionally, this study extends the NVS investigation to a Russian-speaking sample, representing one of the first efforts to broaden the demographic context for this research. By addressing these gaps, the study lays the foundation for future research to explore how methodological choices and cultural contexts influence NVS patterns. This broader perspective can inform the development of more standardized frameworks for measuring and interpreting NVS across diverse settings.

Conclusion

In conclusion, this study provides critical insights into the methodological complexities of NVS measurement in psychological counseling. The findings underscore the profound impact of parameter settings on synchrony quantification, demonstrating that computational choices can significantly alter the interpretation of nonverbal coordination. The strong correlations under homogeneous settings and weak correlations under heterogeneous conditions highlight the need for greater methodological standardization in

NVS research. Future investigations should prioritize transparent reporting of analysis parameters, explore the nuanced differences between micro- and macro-level synchrony measurement, and conduct more comprehensive studies that can validate and extend these preliminary findings. By drawing attention to the critical role of methodological choices, this research contributes to a more nuanced understanding of nonverbal synchrony and sets the stage for more rigorous and comparable studies in the field of psychological interaction analysis.

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Сравнительный анализ автоматизированных методов количественной оценки невербальной синхронизации в психологическом консультировании

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Невербальная синхронизация (НВС) изучалась в контексте ключевых аспектов психотерапевтического и консультационного процесса, таких как терапевтический альянс и качество сессии, причем результаты исследований указывают на возможную взаимосвязь между ними. Однако результаты остаются неоднозначными, а согласованность между различными автоматизированными методами количественной оценки НВС всё ещё недостаточно исследована. В данной работе изучалась взаимосвязь между двумя подходами к количественной оценке НВС: методами Рамзайера – Чахера и Альтманна. Для этого использовались как однородные, так и неоднородные настройки параметров. Анализ 13 консультационных сессий выявил сильные положительные корреляции между большинством показателей НВС при однородных настройках (ρ = от 0,17 до 0,92), особенно для показателей общей силы и частоты. Однако при использовании неоднородных настроек корреляции внутри методов оставались стабильными, в то время как корреляции между методами становились слабыми или даже отрицательными (ρ = от –0,30 до 0,25). Примечательно, что показатели силы синхронизации внутри синхронизационных интервалов демонстрировали особые корреляционные взаимоотношения с другими показателями НВС – это позволяет предположить, что они могут отражать отдельные аспекты синхронного поведения. Полученные результаты подчеркивают критическое влияние настроек параметров на измерение НВС и необходимость большей методологической стандартизации при исследовании ее. Результаты также указывают на то, что различные методы могут фиксировать различные временные масштабы НВС, а это, в свою очередь, может иметь значение как для исследовательских, так и для практических целей. Эта работа вносит вклад в растущий объем исследований по измерению НВС, обсуждая важные методологические аспекты для будущих трудов.

Ключевые слова: невербальная синхронизация, синхронизация движений, анализ энергии движения, анализ временных рядов, психотерапия, консультирование

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