Gesture Dynamics and Therapeutic Success in Patient-Therapist Dyads

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Abstract

We investigated gesture dynamics by examining wrist-worn accelerometer data from 28 patient-therapist dyads involved in multiple sessions of mentalization-based therapy. We sought to determine if there were long-term correlations in the signals and evaluate the degree of complexity matching between patient and therapist. Moreover, we looked into the relationship between complexity matching and the level of therapeutic success (operationalized by change in mentalization and the severity of symptoms). The results indicated that the patient and therapist gesture dynamics were significantly different than long-term correlations produced by white noise. Further, six patient-therapist dyads matched each other in complexity across sessions, but no systematic relationship between the patient and therapists' was observed and there were no relationships between these dynamics and measures of therapeutic success.

Keywords:

fractal scaling; DFA; complexity matching; reflective functioning; mentalization

Introduction

Humans are highly complex beings that utilize myriad mechanisms to interact with one another. One such mechanism is *mentalization*, which entails the socio-cognitive processes that enable humans to make sense of both themselves and others by means of mental states (Bateman & Fonagy, 2004; Shaw, Lo, Lanceley, Hales, & Rodin, 2020). A deficiency in mentalizing capacities has been associated with a number of mental disorders like borderline personality disorder (Bateman, Campbell, Luyten, & Fonagy, 2018), autism (Baron-Cohen, Leslie, & Frith, 1985), and affective mental disorders (Inoue, Tonooka, Yamada, & Kanba, 2004). Psychotherapeutic interactions can help individuals to overcome deficiencies in their mentalizing abilities and bring about positive change in people engaged in the process.

Importantly, recent approaches have suggested that there may be common features to social interactions that ultimately drive not only therapeutic effectiveness (Wampold, 2015), but also successful teamwork (Gorman, Dunbar, Grimm, & Gipson, 2017) and relationships (Deits-Lebehn, Baucom, Crenshaw, Smith, & Baucom, 2020). Through interactions with caregivers, for example, children have been shown to develop the ability to mentalize (Fonagy & Target, 1996). Interpersonal coordination in psychotherapy, more generally, contributes to positive outcomes (Wiltshire, Philipsen, Trasmundi, Jensen, & Steffensen, 2020), with the sensitive responsiveness of the therapist providing a potential interactional scaffold for healing mentalizing difficulties (Allen & Fonagy, 2006). Toward this end, we examine the role of gesture-based fractal dynamics of patient-therapist interactions and investigate the relationship between this form of non-verbal bodily interaction and patients' mentalizing capacity as well as changes in symptomatology.

Mentalization. The ability to mentalize enables humans to understand both intrapersonal and interpersonal situations in terms of mental processes and subjective states (Allen & Fonagy, 2006). Co-morbid mentalizing deficiencies and psychiatric conditions are particularly challenging though. Because psychiatric patients often suffer from attachment traumas, they are less willing to take in new knowledge from others as trustworthy, generalizable, and relevant (i.e., *epistemic trust* (Fonagy & Allison, 2014). Damaged epistemic trust manifests as difficulties in personal and professional relationships. And, this mistrust of information from others makes therapeutic change challenging. In other words, impaired mentalization complicates social interactions (Sperry, 2013).

Mentalization-based therapy (MBT) (Bateman & Fonagy, 2004; Vogt & Norman, 2019) focuses on creating an attachment relationship that makes it possible for the patients to increase their mentalization abilities and it has been shown to be effective for a range of mental disorders. In such cases, interactional or "ostensive cues" such as eye contact, accurate turn-taking, and contingent tone of voice, play an essential role in making these 'hard to reach' patients feel understood and helping them to restore their capacity to learn from experience and build epistemic trust. Put differently, interpersonal coordination and adaptation have been proposed to be one of the most fundamental common factors among psychotherapeutic treatments (Sperry, 2013; Wiltshire et al., 2020), and thus, this relational and interactional context and its dynamics are necessary to characterize and develop mentalization abilities and bring about positive change.

Fractal Dynamics. Fractals are geometric and statistical structures that can exhibit self-similarity over temporal and spatial scales. Fractals are present in natural structures (e.g., trees, coastlines, and cardiovascular networks) and processes (e.g., physical, physiological, psychological, and social) (West, 2017). They have received considerable interest from the scientific community including the cognitive (Van Orden, Holden, & Turvey, 2003; Likens, Fine, Amazeen, & Amazeen, 2015), movement (Hausdorff et al., 2001), and health sciences (Goldberger et al., 2002). Fractal characteristics are identifiable in those contexts by measuring patterns of autocorrelation in noisy time series data (see Detrended Fluctuation Analysis section below). Fractal processes tend to exhibit a slowly decaying form of autocorrelation that has been termed Long-Range Correlation (LRC). These patterns have been observed in a number of time series relevant for studying interpersonal interactions, including: reaction times (Van Orden et al., 2003), eye movements (Stephen & Mirman, 2010), postural sway (Palatinus, Kelty-Stephen, Kinsella-Shaw, Carello, & Turvey, 2014), neurophysiology (Hardstone et al., 2012; Wiltshire, Euler, McKinney, & Butner, 2017), and limb movements (Stephen, Anastas, & Dixon, 2012).

Studying these forms of variability is important because fractal patterns have been associated with qualities such as adaptability, expertise, and health (Cavanaugh, Kelty-Stephen, & Stergiou, 2017; Nourrit, Delignières, Caillou, Deschamps, & Lauriot, 2003; Goldberger et al., 2002). Adaptive forms of variability tend to produce patterns consistent with LRC, whereas non-adaptive forms of variability often lack temporal correlation (Goldberger et al., 2002). Fractal patterns are thought to emerge from the interaction of many nested components (Ihlen & Vereijken, 2010). For example, maintaining balance in an upright stance requires multiple regions of the body to work in parallel (such as visual, vestibular, and musculoskeletal system) (Duarte & Zatsiorsky, 2000). In social interactions, these same subsystems are nested within individuals which are nested within the superordinate group (Likens, Amazeen, Stevens, Galloway, & Gorman, 2014). Fractal variability in social interactions may even reflect important information such as the quality of team coordination (Likens et al., 2014). Thus, we contend that measuring fractal variability of gestures may be important for characterizing patient-therapist interactions.

Patient-therapist dyads: fractal organization and complexity matching. In the context of physical therapy, multifractal movement patterns—patterns exhibiting multiple fractal structures— have been shown to be crucial for the physiological ability of the movement structure to interrelate (Cavanaugh et al., 2017). Those fractal movement patterns have been suggested to reflect an optimal form of variability that allows people to flexibly adapt their movements to novel circumstances and respond to unexpected perturbations. The fractal structure has also been suggested to reflect similar qualities in cognitive and social dynamics (Likens et al., 2014; Stephen & Mirman, 2010). We expect that fractal movement patterns may also reflect the quality of therapist-client interactions because nonverbal coordination has been shown to be important in predicting the success of psychotherapy (Paulick et al., 2018; Wiltshire et al., 2020).

As far as we are aware, this is the first study to investigate the relationships between fractal movement dynamics, mentalization, and therapeutic success. We posited that fractal movement patterns measured from patient-therapist dyads' gestures may reflect the quality of their therapeutic interactions. This entails three interrelated predictions. First, we expected that wrist movements of both patients and therapists would produce fractal scaling exponents coinciding with "pink noise" (Van Orden et al., 2003) as evidenced by contrast with white noise signals. Second, we expected that there would be correlations between the scaling exponents exhibited by patient-therapist dyads. This so-called *complexity matching* has been observed in numerous situations involving dyadic coordination (Abney, Paxton, Dale, & Kello, 2014, 2021; de Jonge-Hoekstra, Cox, van der Steen, & Dixon, 2021; Marmelat & Delignières, 2012; Delignières, Almurad, Roume, & Marmelat, 2016). More generally, complexity matching takes place when two processes that exhibit fractal scaling have similar dynamics (i.e., their dynamics are correlated). Theoretically, this is important as systems that exhibit complexity matching are able to maximize information exchange (Delignières et al., 2016). Lastly, our third prediction was that if patient fractal scaling exponents can serve as an index of health and adaptability, and the complexity matching estimates as an index of information exchange and interaction quality, then these two measures should have a systematic relationship with two key measures of therapeutic success: increased mentalization and decreased symptomatology.

Thus, in our study, we investigated whether patient and therapist gestures display fractal dynamics, evaluated whether those dynamics were correlated (i.e., complexity matching), and determined whether those fractal dynamics and complexity matching estimates had a relationship with therapeutic success.

Methods

Participants and Study Design

Twenty-eight patients from an outpatient hospital in a Northern European country who were being treated for anxiety or personality disorder with Mentalization-based Therapy were included in the study. All patients and therapists provided informed consent and the study was given ethical approval by the participating hospital. Therapy sessions were given weekly and lasted approximately 40 - 60 minutes. The number of sessions varied between 5 - 35 sessions (M = 16.85).

Data Collection

The data was collected using BioNomadix wearable devices. Accelerations were measured using the BN-ACCL3 Reciever+Transmitter attached to the dominant wrists of the therapist and the patient. All signals were transmitted to a Biopac MP160 data acquisition unit connected to a wireless amplifier and stored using AcqKnowledge software. Accelerometers capture movement in three dimensions (X, Y, and Z) and were sampled at 125 HZ. For dimensionality reduction, we calculated the point-wise three-dimensional Euclidean distance from each observation. This common approach, also known as an *interpoint distance time series*, captures the overall moment-to-moment movement magnitude (Davis, Brooks, & Dixon, 2016). The average length of the interpoint distance time series was 2,790,076.42 (*SD* = 624,611.36) with min length = 87,584 and max = 4,504,885.

Measures

At the beginning and end of treatment (and at three-month intervals), patients completed a battery of questionnaires to assess their progress. For the present study, the Reflective Functioning Questionnaire (Fonagy et al., 2016) and the Symptoms Checklist (SCL-92) (Olsen, Mortensen, & Bech, 2004) were used. Only 19 patients completed a pre- and post-treatment questionnaire and were thus suitable for questionnaire-based analyses.

To assess the levels of mentalization present from pre- to post-treatment, the Reflective Functioning Questionnaire (RFQ) was used (Fonagy et al., 2016). The RFQ is the operationalization of the mental processes that underpin the ability to mentalize. Patients' level of mentalizing capacities may influence outcomes, and RF can be a possible moderator and/or predictor of outcome, but also as a mediator of change (Katznelson, 2014). This type of questionnaire relies on the "meta-perspective" of the subject, testing the degree to which they can accurately assess the affective and cognitive states that they experience (Fonagy et al., 2016). The RFQ questionnaire utilizes a 7-point Likert scale and is typically assessed in two factors: certainty (RFQc) and uncertainty (RFQu). When low, the RFQc indicates hypermentalizing (i.e., excessive and inaccurate mentalizing) and when high, RFQc indicates genuine mentalizing (Sharp et al., 2011). High scores on the RFQu indicate an almost complete lack of mentalization capacity (Fonagy et al., 2016). Only the RFQc scores were used. We took the difference from pre- (first measurement) to post-treatment (last measurement).

The SCL-92 (Olsen et al., 2004) was used to keep track of the change in symptoms reported by the patients. 92 items were rated on a 5 point Likert scale and are associated with nine factors: somatization, obsession-compulsion, interpersonal sensitivity, depression, anxiety, phobic anxiety, hostility, paranoid ideation, and psychoticism. We utilized the Global Severity Index (GSI), which is the total score across all items on the questionnaire divided by total possible. Higher GSI values correspond to more severity of symptoms. Like with the RFQ, we took the delta from the first to last measurement.

Detrended Fluctuation Analysis

One of the most widely used techniques for detecting LRC is Detrended Fluctuation Analysis (DFA) (Peng et al., 1994). DFA has been described extensively elsewhere (Kantelhardt, Koscielny-Bunde, Rego, Havlin, & Bunde, 2001); so we provide a brief summary here. DFA entails splitting a time series into several small bins (e.g., 16). In each bin, the least squares regression is fit and subtracted within each window. Residuals are squared and averaged within each window. Then, the square root is taken of the average squared residual across all windows of a given size. This process repeats for larger window sizes, growing by, say a power of 2, up to N/4, where N is the length of the series. In a final step, the logarithm of those scaled root mean squared residuals (i.e., fluctuations) is regressed on the logarithm of window sizes. The slope of this line is termed α and provides a measure of LRC. When $\alpha > 0.5$, this indicates the presence of LRC; when $\alpha < 0.5$, this indicates negative autocorrelation. Lastly, when $\alpha = 0.5$, this signals the absence of autocorrelation.

We performed DFA on the interpoint distance time series for patient/therapist using the fractalRegression R package (Likens & Wiltshire, 2021) with the following parameters: minimum scale = 16; maximum scale = N/4, scale ratio = 2, and a linear detrending function. Additionally, to determine whether the observed α scaling exponents were non-random, we ran DFA on matched-length white noise time series (*M* = 0.50, *SD* = 0.007) to compare the scaling exponents.

When a time series is stationary with a stable mean and variance, α equals the Hurst exponent (H), although it is suitable for both stationary and non-stationary signals. DFA has relaxed assumptions of stationarity (Peng et al., 1994) and the main issue introduced by strong non-stationarity is cross-over points, indicating multiple scaling regions (Hu, Ivanov, Chen, Carpena, & Stanley, 2001). None of our α values were greater than one suggesting stationarity and we also inspected the log-log plots for cross-over points prior to subsequent analyses (Kantelhardt et al., 2001).

Estimating Complexity Matching

We evaluated the evidence for complexity matching in three ways. First, the degree of complexity matching was estimated as the correlation of α exponents between patient and therapist across sessions. Evidence of complexity matching at this level of granularity would be evidenced by non-zero estimates. We tested this using the cor.test() function in R. More specifically, per dyad, two vectors containing the scaling exponents for both patient and therapist across sessions were used as input to the function resulting in complexity matching coefficients and confidence intervals. Additionally, we ran an overall mixed model that included estimates of the therapists' α scaling exponents as predictors of patient α exponents. Lastly, we ran a mixed model that included the absolute value of the difference between patient and therapist α exponents ($\mid patient_{\alpha} - therapist_{\alpha} \mid$) as a predictor ($\Delta\alpha$). The rationale for multiple methods for assessing complexity matching is that the correlational analysis provides an idiographic depiction, the $therapist_{\alpha}$ as a predictor gives an indicator of the trend across sessions, and the difference score ($\Delta\alpha$) is a direct index of matching (zero indicates a perfect match).

Statistical Tests

A series of independent samples Welch's t-tests and Wilcoxon Signed-Rank tests were used to compare the following combinations of scaling exponents to white noise: 1) patient and therapists α exponents collectively, 2) patient α exponents individually, and 3) therapist α exponents individually. Further, one-way t-tests were used to evaluate whether the change in patients' reflective functioning (Δ RFQc) and symptom severity (Δ GSI) were different than zero.

Furthermore, we ran a series of mixed-effects models that included the patient α estimate for a given session as the outcome variable, with either the corresponding therapist α from that session or the absolute value of the difference between patient and therapist α exponents ($| \, patient_{\alpha} - therapist_{\alpha} \, |$) for that session, as a level 1 predictor. The patients' change in reflective functioning (Δ RFQc) and symptom severity (Δ GSI) were included as level 2 predictors with a random intercept effect for the ID of the patients. Several random effect structures, as well as potential interactions, were tested as well and model fit was compared (additional details in the Results section). The models were run in R using the lme4 (Bates, Mächler, Bolker, & Walker, 2015) and lmerTest (Kuznetsova, Brockhoff, & Christensen, 2017) packages, with p-values estimated on the t-tests with the Satterthwaite degrees of freedom approximations. Models were fit using restricted maximum likelihood (REML). Model assumptions and fit were checked using the performance R package (Lüdecke, Ben-Shachar, Patil, Waggoner, & Makowski, 2021). One highly influential data point was removed.

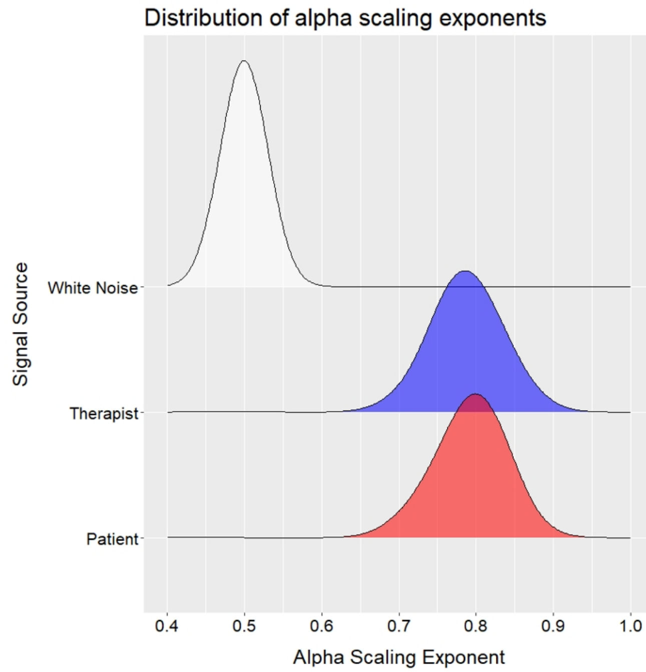

Figure 1: Density plots for patient, therapist, and white noise α scaling exponents

Results

Change in Patient Symptomatology and Reflective Functioning

We sought to determine if patients exhibited a change in their symptomatology (Δ GSI) and reflective functioning (Δ RFQc) from pre- to post- treatment. Results from a set of one-way t-tests showed that overall the global severity of symptoms was reduced for all patients (M = -0.40, SD = 0.60, $t(18)$ = -2.90, $p < .001$, CI_{95} = [-0.69, -0.12], but reflective functioning did not systematically change across all patients (M = -0.09, SD = 8.29, $t(18)$ = -0.05, p = 0.52, CI_{95} = [-4.09, 3.90].

Comparison of the α Exponents with White Noise

The α scaling exponents for both patients and therapists, as well as white noise signals, are presented in the density plot in Figure 1. On average, the α scaling exponents for patients (M = 0.792, SD = 0.042, CI_{95} = [0.788, 0.796]) were similarly distributed to the α scaling exponents for therapists (M = 0.786, SD = 0.045, CI_{95} = [0.78, 0.79]).

We first conducted an independent samples Welch t-test to evaluate the null hypothesis that the α exponents resulting from DFA on the accelerometry-based interpoint distance of patient-therapist dyads is significantly different than the α exponents resulting from DFA run on white noise with the same length. Results indicated that there was a significant difference between the scaling exponents of accelerometer data (M = 0.79, SD = 0.04) and white noise (M = 0.50, SD = 0.007, $t(952.17)$ = -196.87, $p < .001$, CI_{95} = [-0.29, -0.287]. Further, the effect size was large, d = 9.25. See Figure 1 for a visual comparison of these distributions.

To be sure that this effect was evident for patients and therapists individually, we conducted two additional independent samples Welch t-tests to compare patient or therapist scaling exponents to those derived from white noise. There was a difference between the scaling exponents of patient accelerometer data (M = 0.79, SD = 0.04) and white noise (M = 0.50, SD = 0.007, t (476.71) = -143.84 , $p < .001$, CI_{95} = [-0.296, -0.288] with a large effect, d = 9.58. And, there was also a difference between the scaling exponents of therapists (M = 0.786, SD = 0.045) and white noise (M = 0.50, SD = 0.007, $t(474.20)$ = -134.45, $p < .001$, CI_{95} = [-0.29, -0.28], also, with a large effect, d = 8.95. This pattern of results also held true when comparing the exponents using Wilcoxon Signed-Rank Tests, which do not assume normality.

Complexity Matching

An overview of the correlational results of complexity matching analysis is presented in Figure 2. Many of the CIs of the correlation coefficients include zero, except for six patient-therapist dyads.

Mixed Modeling Results

First, we examined whether patient$_{\alpha}$ could be predicted by therapist$_{\alpha}$ as well as patient change in mentalization (Δ RFQ) and symptomatology (Δ GSI). Our iterative model evaluation procedure showed that no additional interactions between the fixed effects or random effect structures improved the original model fit (see Statistical Tests section).

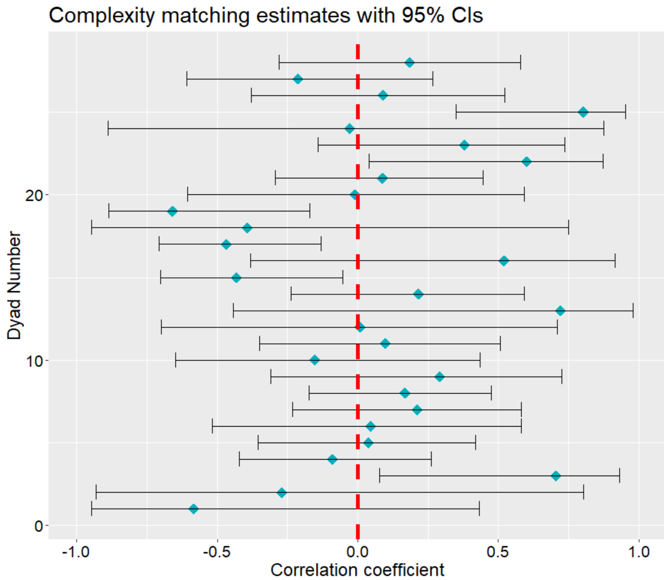

Figure 2: Dot and whisker plot for each patient-therapist dyads' complexity matching estimates

Table 1 shows the results from the mixed model using Therapist$_\alpha$ as an index of complexity matching. Overall, there did not appear to be any systematic relationships between the patient α exponents and therapist exponents across sessions, nor with the change in symptom severity or reflective functioning (Patient ID random effect: SD = 0.025; Residual: SD = 0.032). While the model accounts for 41% of the variability in patient$_\alpha$ exponents across sessions (R^2c = 0.41), fixed effects accounted for only 5% (R^2m = 0.047).

Table 1: Fixed effects for model with Therapist$_\alpha$.

	Coef.	SE	df	t	p
(Intercept)	0.75	0.04	341.45	20.00	0.00
Therapist$_\alpha$	0.05	0.05	361.27	1.00	0.32
Δ SCL92	0.00	0.01	15.15	0.23	0.82
Δ LRFc	-0.00	0.00	15.11	-1.35	0.20

Lastly, we examined whether patient$_\alpha$ could be predicted by the complexity matching indicator $\Delta\alpha$ ($|\ patient_\alpha - therapist_\alpha\ |$) as well as patient change in mentalization (Δ RFQ) and symptomatology (Δ GSI). Evaluation of model performance showed that no additional interactions between the fixed effects improved the model fit, but including a random slope for $\Delta\alpha$ did. Thus, we report that model here.

Table 2 shows the results from the mixed model using $\Delta\alpha$ as an index of complexity matching. As with the first model, there did not appear to be any systematic relationships between the patient$_\alpha$ exponents and the absolute value of the difference in α across sessions, nor with the change in symptom severity or reflective functioning. While the model accounts for 49% of the variability in patient$_\alpha$ exponents (R^2c = 0.49), the fixed effects accounted for only 3% (R^2m = 0.03).

Table 2: Fixed effects for model with $\Delta\alpha$.

	Coef.	SE	df	t	p
(Intercept)	0.79	0.01	17.15	116.45	0.00
$\Delta\alpha$	-0.04	0.11	16.62	-0.36	0.72
Δ SCL92	0.00	0.01	16.12	0.48	0.64
Δ LRFc	-0.00	0.00	14.24	-1.15	0.27

Discussion

Taken together, the main implications of our results are twofold: firstly, the patients displayed a reduction in symptoms. Secondly, the gestures of patients and therapists (as measured by accelerometers on their dominant hands) exhibited long-range correlations (i.e., fractal scaling). While we did not observe a systematic relationship between the patient and therapists' α exponents across all patients and sessions, there was evidence of complexity matching in six patient-therapist dyads. We also did not observe that the patient$_\alpha$ or therapist$_\alpha$ were related to changes in mentalization and symptomatology.

One potential reason that we did not observe this relationship could be due to the measurement of mentalization, which may not be fully captured by the RFQ (Gullestad & Wilberg, 2011). Furthermore, the severity of psychopathology should also have an effect on the mentalizing capacity where less severe pathologies show more typical levels of mentalization. This indicates that mentalization may not be a core deficit when looking at psychopathology (Katznelson, 2014). Future research could test whether there is more change in mentalization for cases with severe pathology.

While we did not directly observe the benefits of the observed movement dynamics as other research has shown (Paulick et al., 2018; Wiltshire et al., 2020), it may be that interactional dynamics relate to other elements that have not been accounted for in the present study such as the attachment relationship. Future work could, for example, focus on other outcomes and physiological dynamics or vocalizations (Wieder & Wiltshire, 2020). The time course of the fractal dynamics and complexity matching estimation methods may also be important. It could be that there is an optimal level of complexity matching associated with a "successful" therapy that is specific to stages of treatment (Paulick et al., 2018, p.14). Or it could be that a windowed DFA approach to estimate scaling exponents and complexity matching within sessions would be more sensitive (Rigoli et al., 2020). Alternatively, a multifractal analysis would give an indication of variability across scales and afford the investigation of fluctuations at a "within-session" vs. "across-session" level. Bivariate fractal regression methods may also reveal how dyads relate to each other at those scales (Likens, Amazeen, West, & Gibbons, 2019). That being said, the study of complexity matching is still developing and other promising approaches can be evaluated in future efforts (Abney et al., 2021; de Jonge-Hoekstra et al., 2021).

Further, our results indicated that roughly 35-40% of the variability is explained by the random effects of our mixed models. This pattern of results indicate that the observed patient-therapist interactions are highly idiographic. Notably, our study looked for a more general pattern of results across all patients. However, large individual differences may render generalizable findings improbable. Relatedly, different pathologies are associated with different decoding and encoding abilities, which might influence the patient-therapist interaction pattern (Ekman & Friesen, 1974). And, specific impairments in gesture performance are found in different pathologies (Dutschke et al., 2018). Future work should examine these more patient-specific characteristics and account for any potential differences due to the number of sessions or session length.

In conclusion, our study found compelling evidence of fractal scaling in gesture dynamics of patient-therapist dyads and partial evidence of complexity matching across sessions. No relationships between these dynamics and mentalization were observed. However, we find this first effort a promising direction in better understanding the functional role of gesture movement dynamics in collaborative human interactions.

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References

Abney, D. H., Paxton, A., Dale, R., & Kello, C. T. (2014). Complexity matching in dyadic conversation. *Journal of Experimental Psychology: General*, *143*(6), 2304.

Abney, D. H., Paxton, A., Dale, R., & Kello, C. T. (2021). Cooperation in sound and motion: Complexity matching in collaborative interaction. *Journal of Experimental Psychology: General*.

Allen, J. G., & Fonagy, P. (2006). *The handbook of mentalization-based treatment*. John Wiley & Sons.

Baron-Cohen, S., Leslie, A., & Frith, U. (1985). Does the autistic child have a "theory of mind"? *Cognition*, *21*(1).

Bateman, A., Campbell, C., Luyten, P., & Fonagy, P. (2018). A mentalization-based approach to common factors in the treatment of borderline personality disorder. *Current Opinion in Psychology*, *21*, 44–49.

Bateman, A., & Fonagy, P. (2004). Mentalization-based treatment of bpd. *Journal of Personality Disorders*, *18*, 36–51.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1), 1–48.

Cavanaugh, J. T., Kelty-Stephen, D. G., & Stergiou, N. (2017). Multifractality, interactivity, and the adaptive capacity of the human movement system: A perspective for advancing the conceptual basis of neurologic physical therapy. *Journal of Neurologic Physical Therapy*, *41*(4), 245.

Davis, T. J., Brooks, T. R., & Dixon, J. A. (2016). Multiscale interactions in interpersonal coordination. *Journal of Sport and Health Science*, *5*(1), 25–34.

de Jonge-Hoekstra, L., Cox, R., van der Steen, S., & Dixon, J. (2021). Easier said than done? task difficulty's influence on temporal alignment, semantic similarity, and complexity matching between gestures and speech. *Cognitive Science*.

Deits-Lebehn, C., Baucom, K. J., Crenshaw, A. O., Smith, T. W., & Baucom, B. R. (2020). Incorporating physiology into the study of psychotherapy process. *Journal of Counseling Psychology*, *67*(4), 488.

Delignières, D., Almurad, Z. M., Roume, C., & Marmelat, V. (2016). Multifractal signatures of complexity matching. *Experimental Brain Research*, *234*(10), 2773–2785.

Duarte, M., & Zatsiorsky, V. M. (2000). On the fractal properties of natural human standing. *Neuroscience Letters*, *283*(3), 173–176.

Dutschke, L. L., Stegmayer, K., Ramseyer, F., Bohlhalter, S., Vanbellingen, T., Strik, W., & Walther, S. (2018). Gesture impairments in schizophrenia are linked to increased movement and prolonged motor planning and execution. *Schizophrenia Research*, *200*, 42–49.

Ekman, P., & Friesen, W. V. (1974). Nonverbal behavior and psychopathology. *The Psychology of Depression*, 3–31.

Fonagy, P., & Allison, E. (2014). The role of mentalizing and epistemic trust in the therapeutic relationship. *Psychotherapy*, *51*(3), 372.

Fonagy, P., Luyten, P., Moulton-Perkins, A., Lee, Y.-W., Warren, F., Howard, S., ... Lowyck, B. (2016). Development and validation of a self-report measure of mentalizing: The reflective functioning questionnaire. *PLoS One*, *11*(7), e0158678.

Fonagy, P., & Target, M. (1996). Playing with reality: I. theory of mind and the normal development of psychic reality. *International journal of psycho-analysis*, *77*, 217–233.

Goldberger, A. L., Amaral, L. A., Hausdorff, J. M., Ivanov, P. C., Peng, C.-K., & Stanley, H. E. (2002). Fractal dynamics in physiology: alterations with disease and aging. *Proceedings of the National Academy of Sciences*, *99*(suppl 1), 2466–2472.

Gorman, J. C., Dunbar, T. A., Grimm, D., & Gipson, C. L. (2017). Understanding and modeling teams as dynamical systems. *Frontiers in Psychology*, *8*, 1053.

Gullestad, F. S., & Wilberg, T. (2011). Change in reflective functioning during psychotherapy—a single-case study. *Psychotherapy Research*, *21*(1), 97–111.

Hardstone, R., Poil, S.-S., Schiavone, G., Jansen, R., Nikulin, V. V., Mansvelder, H. D., & Linkenkaer-Hansen, K. (2012). Detrended fluctuation analysis: a scale-free view on neuronal oscillations. *Frontiers in physiology*, *3*, 450.

Hausdorff, J. M., Ashkenazy, Y., Peng, C.-K., Ivanov, P. C., Stanley, H. E., & Goldberger, A. L. (2001). When human walking becomes random walking: fractal analysis and modeling of gait rhythm fluctuations. *Physica A: Statistical Mechanics and its Applications*, *302*(1-4), 138–147.

Hu, K., Ivanov, P. C., Chen, Z., Carpena, P., & Stanley, H. E. (2001). Effect of trends on detrended fluctuation analysis. *Physical Review E*, *64*(1), 011114.

Ihlen, E., & Vereijken, B. (2010). Interaction-dominant dynamics in human cognition: Beyond $1/f$ fluctuation. *Journal of Experimental Psychology: General*, *139*(3), 436.

Inoue, Y., Tonooka, Y., Yamada, K., & Kanba, S. (2004). Deficiency of theory of mind in patients with remitted mood disorder. *Journal of Affective Disorders*, *82*(3), 403–409.

Kantelhardt, J. W., Koscielny-Bunde, E., Rego, H. H., Havlin, S., & Bunde, A. (2001). Detecting long-range correlations with detrended fluctuation analysis. *Physica A: Statistical Mechanics and its Applications*, *295*(3-4), 441–454.

Katznelson, H. (2014). Reflective functioning: A review. *Clinical Psychology Review*, *34*(2), 107–117.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest package: Tests in linear mixed effects models. *Journal of Statistical Software*, *82*(13), 1–26. doi: 10.18637/jss.v082.i13

Likens, A. D., Amazeen, P. G., Stevens, R., Galloway, T., & Gorman, J. C. (2014). Neural signatures of team coordination are revealed by multifractal analysis. *Social Neuroscience*, *9*(3), 219–234.

Likens, A. D., Amazeen, P. G., West, S. G., & Gibbons, C. T. (2019). Statistical properties of multiscale regression analysis: Simulation and application to human postural control. *Physica A: Statistical Mechanics and its Applications*, *532*.

Likens, A. D., Fine, J. M., Amazeen, E. L., & Amazeen, P. G. (2015). Experimental control of scaling behavior: what is not fractal? *Experimental Brain Research*, *233*(10), 2813–2821.

Likens, A. D., & Wiltshire, T. J. (2021). *fractalregression: An r package for univariate and bivariate fractal analyses.* Retrieved from `github.com/aaronlikens/fractalRegression`

Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). performance: An r package for assessment, comparison and testing of statistical models. *Journal of Open Source Software*, *6*(60).

Marmelat, V., & Delignières, D. (2012). Strong anticipation: complexity matching in interpersonal coordination. *Experimental Brain Research*, *222*(1-2), 137–148.

Nourrit, D., Delignières, D., Caillou, N., Deschamps, T., & Lauriot, B. (2003). On discontinuities in motor learning: A longitudinal study of complex skill acquisition on a ski-simulator. *Journal of Motor Behavior*, *35*(2), 151–170.

Olsen, L. R., Mortensen, E. L., & Bech, P. (2004). The scl-90 and scl-90r versions validated by item response models in a danish community sample. *Acta Psychiatrica Scandinavica*, *110*(3), 225–229.

Palatinus, Z., Kelty-Stephen, D. G., Kinsella-Shaw, J., Carello, C., & Turvey, M. T. (2014). Haptic perceptual intent in quiet standing affects multifractal scaling of postural fluctuations. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(5), 1808.

Paulick, J., Deisenhofer, A.-K., Ramseyer, F., Tschacher, W., Boyle, K., Rubel, J., & Lutz, W. (2018). Nonverbal synchrony: A new approach to better understand psychotherapeutic processes and drop-out. *Journal of Psychotherapy Integration*, *28*(3), 367.

Peng, C.-K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., & Goldberger, A. L. (1994). Mosaic organization of dna nucleotides. *Physical Review E*, *49*(2), 1685.

Rigoli, L. M., Lorenz, T., Coey, C., Kallen, R., Jordan, S., & Richardson, M. J. (2020). co-actors exhibit similarity in their structure of behavioural variation that remains stable across range of naturalistic activities. *Scientific reports*, *10*(1), 1–11.

Sharp, C., Pane, H., Ha, C., Venta, A., Patel, A. B., Sturek, J., & Fonagy, P. (2011). Theory of mind and emotion regulation difficulties in adolescents with borderline traits. *Journal of the American Academy of Child & Adolescent Psychiatry*, *50*(6), 563–573.

Shaw, C., Lo, C., Lanceley, A., Hales, S., & Rodin, G. (2020). The assessment of mentalization: measures for the patient, the therapist and the interaction. *Journal of Contemporary Psychotherapy*, *50*(1), 57–65.

Sperry, M. (2013). Putting our heads together: Mentalizing systems. *Psychoanalytic Dialogues*, *23*(6), 683–699.

Stephen, D. G., Anastas, J. R., & Dixon, J. A. (2012). Scaling in cognitive performance reflects multiplicative multifractal cascade dynamics. *Frontiers in Physiology*, *3*, 102.

Stephen, D. G., & Mirman, D. (2010). Interactions dominate the dynamics of visual cognition. *Cognition*, *115*(1), 154–165.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology: General*, *132*(3), 331.

Vogt, K. S., & Norman, P. (2019). Is mentalization-based therapy effective in treating the symptoms of borderline personality disorder? a systematic review. *Psychology and Psychotherapy*, *92*(4), 441–464.

Wampold, B. E. (2015). How important are the common factors in psychotherapy? an update. *World Psychiatry*, *14*(3), 270–277.

West, G. B. (2017). *Scale: the universal laws of growth, innovation, sustainability, and the pace of life in organisms, cities, economies, and companies*. Penguin.

Wieder, G., & Wiltshire, T. J. (2020). Investigating coregulation of emotional arousal during exposure-based cbt using vocal encoding and actor–partner interdependence models. *Journal of Counseling Psychology*, *67*(3), 337.

Wiltshire, T. J., Euler, M. J., McKinney, T. L., & Butner, J. E. (2017). Changes in dimensionality and fractal scaling suggest soft-assembled dynamics in human eeg. *Frontiers in Physiology*, *8*, 633.

Wiltshire, T. J., Philipsen, J. S., Trasmundi, S. B., Jensen, T. W., & Steffensen, S. V. (2020). Interpersonal coordination dynamics in psychotherapy: A systematic review. *Cognitive Therapy and Research*, *44*(4), 752–773.