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MULTIMODAL MEASUREMENT IN PSYCHOTHERAPY RESEARCH

A multi-modality and multi-dyad approach to measuring flexibility in psychotherapy

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Abstract
Introduction Flexibility, the ability of an individual to adapt to environmental changes in ways that facilitate goal attainment, has been proposed as a potential mechanism underlying psychopathology and psychotherapy. In psychotherapy, most findings are based on self-report measures that have important limitations. We propose a multimodal, multi-dyad approach based on a nonlinear dynamical systems framework to capture the complexity of this concept.
Method A new research paradigm was designed to explore the validity of the proposed conceptual model. The paradigm includes a psychotherapy-like social interaction, during which body movement and facial expressiveness data were collected. We analyzed the data using Hankel Alternative View of Koopmann analysis to reconstruct attractors of the observed behaviors and compare them.
Results The patterns of behavior in the two cases differ, and differences in the reconstructed attractors correspond with differences in self-report measures and behavior in the interactions.
Conclusions The case studies show that information provided by a single modality is not enough to provide the full picture, and multiple modalities are needed. These observations can serve as an initial support for our claims that a multi-modal and multi-dyad approach to flexibility can address some of the issues of measurement in the field.

Keywords: psychotherapy; multimodal measurement; nonlinear dynamics; flexibility; dynamical systems

Clinical or methodological significance of this article: The findings of the present study suggest that automatic multimodal measurement of interpersonal behaviors in psychotherapy may be the key to measuring flexibility in a way that captures the full extent of this construct. This will enable researchers and clinicians ecological and automatic assessment of flexibility in the psychotherapy setting, accompanied by a method of analysis that can describe the intricate dynamics of such data. Thus, the measurement paradigm outlined here has the potential to facilitate a leap forward in psychotherapy research on predictors and mechanisms of change.

Introduction

The average response rate to therapy is estimated at around 50% (Cuijpers et al., 2014; Cuijpers et al., 2019), meaning that many individuals suffering from psychopathology do not find relief for their suffering. This problem is being addressed in psychotherapy through research on meaningful constructs that may serve as predictors or

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mechanisms of change. Predictors help identify individual differences between patients that may have implications for their ability to benefit from treatment (e.g., treatment moderators; Lutz et al., 2021), and ones that may be the target of future interventions (e.g., mechanisms of change; Kazdin, 2009). The present study focuses on flexibility as a mechanism that has been proposed as having the potential to meet these two aims: to differentiate between patients in their trait-like characteristics before the start of treatment (Ong et al., 2023), and to serve as a mechanism that can be targeted to facilitate state-like changes during treatment (Stockton et al., 2019).

Flexibility can be defined as the ability to: (1) perceive and tolerate changes in demands imposed by the environment; (2) have a wide repertoire of emotional, mental, and behavioral strategies that can be used to adapt to changes in the environment; (3) choose and implement the strategies that fit with the demands of a given situation and the chosen goal (Cherry et al., 2021; Kashdan & Rottenberg, 2010). Deeply rooted in evolutionary perspectives, the general idea is that a flexible individual is able to adapt to changing environments by responding to them in such a way that facilitates valued goal pursuit. In an interpersonal context such as psychotherapy, a more or less consistent ability to adapt and change one's responses over time whenever situational demand arises, can be associated with a better ability to benefit from psychotherapy (Greenberg & Safran, 1987; Yasinski, 2016). Considering that different environments merit different responses, a flexible individual is more likely to be able to adapt to the ever-shifting environment of intra- and interpersonal conflicts and relationships that make up human life (Hayes & Strosahl, 2004; Kashdan & Rottenberg, 2010). Conversely, inflexible individuals who do not possess these abilities are less likely to be able to cope with changing environmental demands, and thus adapt less successfully and face challenges. Patterns of inflexible behavior are theorized to increase the probability of developing mental health symptoms and disorders (Cherry et al., 2021; Hayes et al., 2006; Kashdan & Rottenberg, 2010). This idea is supported by studies that show individuals who are less flexible tend to suffer more from a range of psychopathologies such as depression (McCracken et al., 2021), anxiety and general distress (Masuda & Tully, 2012), eating disorders (Bluett et al., 2016), chronic pain (De Boer et al., 2014), and externalizing behaviors in individuals with PTSD (Dutra & Sadeh, 2018).

In recent years flexibility was theorized to be important for psychotherapy process and outcome (Hayes et al., 2006). Flexibility has even been suggested as a potential mechanism of change across psychotherapies. For example, in Acceptance and Commitment Therapy, increasing an individual's flexibility is a central and explicitly stated goal, as it is hypothesized to curb experiential avoidance and supposedly promotes adaptive behavior and mindful contact with life's experiences. This in turn is expected to help alleviate mental symptoms and improve well being (Ciarrochi et al., 2010). Researchers both within the ACT movement and outside it have directed efforts to test these hypotheses, and findings indeed show that increases in flexibility in the process of psychotherapy are linked to decreases in symptoms of depression (Atzil Slonim et al., 2011; Yasinski et al., 2020), anxiety (Fisher & Newman, 2016; Shalom et al., 2018), and eating disorders (Pellizzer et al., 2018). These results are rather consistent across studies and provide support for the identification of flexibility as a mechanism of change, and a facet of healthy functioning. Most of this literature is based on self-report measures (Cherry et al., 2021; Doorley et al., 2020), in which the participants are asked about their level of flexibility directly (e.g., "I feel open to change") or indirectly (e.g., "It's ok to remember something unpleasant"). The latter example is taken from the most common self-report measure of flexibility, the Acceptance and Action Questionnaire (AAQ-II; Bond et al., 2011), which indirectly measures levels of flexibility by asking about aspects of flexibility such as experiential avoidance.

One of the most important shortcomings in the current literature on flexibility in psychotherapy is the strong reliance on few self-report measures (Cherry et al., 2021; Doorley et al., 2020). Although self-reports have advantages such as the ease of use and adequate face validity, they have their limitations. Therefore, assessing flexibility in a way which will complement self-reports should include the same individual in differing circumstances that require differing responses. To capture the dynamics of responding to the ever-shifting environment, automatic moment-to-moment measures such as body movement and facial expressiveness can prove very useful.

A Multi-modal and Multi-dyad Approach in Psychotherapy Research

It has been suggested that as individuals are exposed to a variety of circumstances in everyday life, displaying variability over time and across contexts can serve as an indicator of a system able to integrate and adapt to internal and external demands, which may result in better mental health (Atzil Slonim et al., 2011; Fisher & Newman, 2016). A multimodal approach to measuring flexibility may provide a lens through which an individual's level of flexible response can be assessed (Bakhchina et al., 2018; Stange et al., 2023), both as part of the pre-treatment assessments and as an assessment of the process of change as the result of treatment. Such flexibility may manifest pre and during treatment as distinct responses to interpersonal contexts in which one individual (patient) is sharing an emotional experience with another individual (therapist). It can be expected that patients who come to treatment with higher trait-like tendencies to show flexibility, may respond better to situations in which they need to respond in manners that are distinct from their interpersonal tendencies. For example, some patients may find it difficult to share a painful experience, receive feedback from the therapist on what they share, or bring up their own concerns about the progress of therapy. For those individuals, an ability to overcome this difficulty could result in therapeutic progress (Greenberg et al., 2007). From the perspective of flexibility, individuals need to be able to respond in manners that are distinct from their interpersonal tendencies, to be able to be able to work effectively in treatment. When patients are not characterized by higher levels of flexibility, increasing flexibility may become the goal of treatment in itself. In such circumstances, flexibility becomes a mechanism of change.

Working effectively in treatment is a possible long-term goal that the flexible patient may pursue, which may require sacrificing short-term goals such as avoiding difficult emotions. Consistently pursuing such a goal over time, situations, and different therapeutic relationships, requires implementing various interpersonal responses. Based on literature suggesting that automatic moment-to-moment measures are able to assess interpersonal relationships and therapeutic processes (Cohen et al., 2021), we propose that meaningful aspects of the flexible ebb and flow of interpersonal responses can be measured using automatic measures such as facial expressiveness and body movement.

Facial expression generation and perception are an integral part of successful communication between individuals, and they contain information about the *kind* of emotions that are being conveyed (Ekman & Friesen, 1978). Facial expressiveness (overall facial movement activity across a given frame) provides information about the amount of facial movements that have transpired during an interaction as individuals attempt (both consciously and unconsciously) to communicate experiences (Salah et al., 2011) and manage their partner's attention (Sawada & Sato, 2015). Observing the moment-to-moment changes in facial expressiveness of a patient in therapy provides information about the dynamics governing expression of emotions that are being communicated (Lin et al., 2019). Implementing this nonverbal mode of communication differently when interacting with different caretakers or the same caretaker at different time-points, may signify an ability to adapt one's way of communicating to changes in relationship dynamics.

However, facial expressiveness alone is not enough as the meaning behind such behavioral changes may differ drastically depending on context. For example, a patient might become more expressive when attempting to facilitate the therapist's understanding of their experience at one time but at other times they might do so to avoid another topic. Consequently, the same behavior may be considered flexible or inflexible depending on the goal it serves and its outcomes. Thus, we propose that at least one more modality of behavior be considered to remedy this (if only partly) by providing useful context. The second modality that we consider is the amount of body movements as they hold information regarding the *intensity* of emotions, as well as some information regarding their quality (Aviezer, Trope, & Todorov, 2012; Wallbott, 1998). Observing patterns of momentary changes in body movement may shed light on the ebb and flow of emotional arousal during a therapy session. Thus, changes in the patterns of arousal occurring between different sessions or interactions with different caretakers might provide a hint that the emotional experience was somehow changed in its intensity or quality.

Taken together, changes in the patterns of body movement that are not accompanied by changing patterns of facial expressiveness might indicate that something is being felt but not communicated overtly in or between sessions, making it more possible for goal pursuit to be disrupted. However, changes in facial expressiveness patterns may occur along with changes in body movement patterns or without them. In our view, the former could occur when what is being felt might also be expressed overtly, while the latter may occur when the act of expression itself allows to keep patterns of arousal relatively unphased. Finally, an absence in both types of changes might indicate either that these adaptations were not required by the changing situation in or between sessions or that situational demand was left unattended, in which case goal pursuit would be disrupted.

Flexibility Through the Lens of a Dynamical Systems Approach

The dynamics of facial expressiveness and body movement in theory, as well as the actual dynamics displayed by such data (Moulder et al., 2021), are all complex and nonlinear in nature. Such an understanding of these modalities is in line with a Nonlinear Dynamical Systems Theory (NDST) framework of interpretation and analysis. Dynamical Systems Theory contains both linear and nonlinear methods, both of which give rise to powerful analytic tools. In the case of flexibility, a linear approach using more traditional methods would be inappropriate (Van Montfort et al., 2018). A more suitable approach for studying flexibility in psychotherapy would have to derive from nonlinear methods, which allow for both qualitative and quantitative descriptions of systems that exhibit complex and unpredictable behavior (de Felice et al., 2022; Schiepek et al., 2021).

A linear system can only ever exhibit some combination of exponential growth or decay to a baseline and periodic fluctuations (Strogatz, 2018). Higher levels of flexibility, in general and in the therapeutic context in particular, depict behavior as adaptive, sensitive to environmental changes and inputs, and highly complex. Body movements and facial expressiveness during psychotherapy sessions do not adhere to either monotonous growth, decay, or oscillation. As we mentioned above, the same behaviors in therapy can mean either progress, problems, or hold no meaning depending on the goal and context underlying them. This not only justifies the use of NDST, but makes it crucial for studying and analyzing therapeutic datasets.

To study and analyze flexibility in therapeutic datasets, we propose using attractor reconstruction techniques (Takens, 2006) to approximate the underlying attractors of body movement and facial expressiveness in psychotherapy sessions. An attractor is a representation of the entirety of a system's dynamics in the long term, which can be rendered visually for qualitative examination, and its properties may be estimated computationally (Haken, 2006). Using such methods, attractors of the two modalities belonging to the same patient, stemming from different therapy sessions may be compared to assess their flexibility. Qualitative comparisons of attractor structures may be used to detect whether the dynamics of each modality changed between therapy sessions. This may also be supported by changes in the values of quantitative metrics estimated for the attractors: e.g., the Lyapunov exponent and the Correlation Dimension. Thus, individuals who exhibit greater changes in their attractor structures and these two metrics between therapy sessions or interactions with multiple caregivers might be more reactive, and possibly adapt more to changing inputs. For example, during the therapy session, the therapist and patient may exhibit a variety of movements and facial expression dynamics over time, which may be described as a reconstructed attractor and estimated matrix. Qualitative comparisons of attractor structures of different phases of the same therapy session or different sessions result in quantifying the level of flexibility of the patient.

In addition to serving as quantifiable metrics that can be compared between attractors, The Lyapunov exponent and the Correlation Dimension contain information to complement the information provided by the attractor. Lyapunov exponents can serve as measures of the unpredictability of the behavior exhibited in a therapy session (Taylor, 2010). Higher Lyapunov exponent values may indicate reactivity to what is happening in the session, which may signal a flexible behavior. While Lyapunov exponents may be construed as measuring the predictability of behavior, the Correlation dimension may signify the complexity of that behavior. The larger its value, the more dimensions are needed to aptly describe the dynamics (Sprott & Rowlands, 2001). In psychotherapy (and possibly other interpersonal contexts), one possible interpretation of the value of the Correlation Dimension is that it quantifies the number of different behaviors, of body or facial movement, that are implicit in the dynamics. Both metrics can thus provide an understanding of the number of behaviors available to an individual and the predictability of their use. We expect that low values of these metrics represent less flexible characteristics of individuals in the therapeutic context.

The Current Study

In light of all the above, we propose a research paradigm for assessing flexibility in the context of psychotherapy, that leans on multimodal and multi-dyad measurement and is nested within a NDST analytical framework. This manuscript compares two cases of experimental participants assigned to the roles of pseudo-patients, as a preliminary demonstration of the type of information our operationalization is geared to collect. We conducted the current study having two hypotheses: (1) The proposed paradigm would allow us to differentiate between the two individuals in terms of their levels of flexibility in a way that would coincide with their self-report measures, as well as with the theoretical definition of flexibility. (2) This differentiation will only be possible by assessing and interpreting the patterns of both facial expressiveness and body movement modalities. Facial expressions are expected to signify the emotions the patient explicitly communicates in the interaction. In contrast, the movement is expected to signify the level of arousal. Combining these two modalities is capable of shedding light on the level of concordance between the two modalities. Thus, we expected that changing patterns of body movement between interactions would signify flexible behavior only when accompanied by changing patterns of body movement.

Method

Design

Participants underwent the Flexibility Interaction Paradigm (FIP) procedure (described below), which consists of several social interactions designed to resemble psychotherapy, as well as self-report questionnaires before the interactions.

Flexibility Interaction Paradigm (FIP)

This paradigm was designed to resemble the patient's process of sharing interpersonal experience in short-term psychodynamic psychotherapy for depression. To achieve this, we adapted the first session of the supportive-expressive psychodynamic therapy protocol (SET: Luborsky, 1984; Luborsky et al., 1995), in which the patient is asked to share Relationship Episodes (RE's) with the therapist. RE's are interactions between the patient and important figures in their life, in which the patient felt some kind of discomfort, tension, disagreement, or hurt (Gibbons, 2017). The "pseudo-patients" (from now on we will refer to them as "speakers") recruited for the FIP were asked to provide three RE's in advance, the order of which was randomized to determine which RE would be discussed in each interaction. In each of the FIP interactions, the "speaker" was asked to discuss RE's from their lives with another participant who was assigned to the role of "pseudo-therapist" (from now on we will refer to them as "listeners"). As we were interested in assessing the behavior of each speaker as they interacted with different listeners, each speaker participated in three separate interactions, each of them with a different listener. Additionally, we were interested in manipulating the level of familiarity and closeness in the interactions, to strengthen the claim that these interactions impose different situational demands on the speakers.. Thus, some listeners were strangers to the speaker, while others were the speaker's close friends.

The instructions provided to the speakers were based on the SET protocol's definition of RE's (Gibbons, 2017). Additionally, the experimenters explicitly stated to the speakers that their goal is to tell the RE's to the listeners. These instructions were given twice: once to speakers and listeners apart, and once more together with the listeners before the start of each interaction. The length of each interaction was 15 min, which was determined in a few trial runs as a feasible time for strangers to be able to converse, while still providing us with enough time to measure the desired behaviors (Ramseyer, 2020b; Reich et al., 2014). All interactions were recorded on video to allow for the collection of behavioral data.

Measures

Behavioral measures. Motion data. The Motion data were collected from video recordings of FIP interactions. The interactions were filmed with cameras installed in the room positioned at equal distances from both speaker and listener, with a sampling rate of 25 frames per second. The video recording was then cropped (using Corel VideoStudio software, Ottawa, Ontario, Canada) to make sure that they contained only segments where the speaker and listener were interacting, and not the parts where the instructions were being given by the experimenters. The quantity of motion in the cropped videos was assessed using Motion Energy Analysis (MEA; Ramseyer, 2020b), in which Regions of Interest (ROIs: the head and body of therapist and patient) were manually selected, and the number of pixels changing from frame to frame was calculated in each ROI. The resulting data were then smoothed, averaging every half-second window using a moving average function.

Facial expressiveness. Data were collected from video recordings of the interactions using the OpenFace software (Baltrušaitis et al., 2016) which is based on the Facial Action Coding System (Ekman & Friesen, 1978). OpenFace identifies the intensity of activation of facial muscle groups (termed "Action Units") in the video frames and provides values that represent the level of each of 14 action unit's activation in each frame. This is achieved after OpenFace identifies facial landmarks in each frame that serve as reference points.

Once the raw OpenFace data had been extracted, we calculated the overall level of expressiveness in each frame across the 14 action units. This was achieved by addressing each frame as a point in a

14-dimensional Cartesian space, with 14 sets of coordinates. Then we used the "numpy.linalg.norm" function in the "Numpy" library (Harris et al., 2020), using Python (Python 3.6.8; Van Rossum & Drake, 2009), to calculate the distance between each two consecutive frames. The resulting values are difference scores between frames that represent the amount of movement in the facial expression from one frame to the next. Higher scores indicate that a lot of movement has occurred while at the lower end, a score of zero indicates that no movement has occurred at all.

Self-report measures. Psychological Flexibility Questionnaire (PFQ; Ben-Itzhak et al., 2014**).** A 20-item self-report questionnaire for measuring the psychological flexibility of an individual. The 20 items assess psychological flexibility across 5 domains: (1) positive perception of change; (2) characterization of the self as flexible; (3) self-characterization as open and innovative; (4) a perception of reality as dynamic and changing, and (5) a perception of reality as multifaceted. Each of the 20 items is rated on a scale ranging from 1 (strongly disagree) to 6 (strongly agree), thus higher scores indicate greater psychological flexibility. Good reliability (Cronbach's $a = .92$) and validity of the PFQ have been demonstrated (Ben-Itzhak et al., 2014).

Acceptance and Action Questionnaire (AAQ-2; Bond et al., 2011**).** A 10 item self-report questionnaire used for measuring psychological flexibility as defined in ACT, where flexibility is a core concept. This questionnaire measures flexibility by asking questions about experiential avoidance, immobility, and acceptance tendencies. Each item is rated on a scale from 1 (never true) to 7 (always true), such that higher scores on the AAQ-2 represent more experiential avoidance and thus—less flexibility. Good reliability (Cronbach's a ranges between .78 and .88) and validity for the AAQ-2 have been demonstrated (Bond et al., 2011).

Outcome Questionnaire (OQ-30; Wells et al., 1996**).** A 30-item self-report questionnaire designed for repeated measurement of progress in psychotherapy along three main scales: (a) level of symptom distress, including symptoms of commonly diagnosed disorders such as depression, anxiety and substance abuse. (b) The interpersonal relationships scale assesses problems in relationships, feelings of isolation, inadequacy and withdrawal. (c) The social role performance scale assesses satisfaction with work and personal life. Variable reliability (Cronbach's ɑ coefficient ranges between .47 and .75) and validity for the Outcome Questionnaire have been reported (Gross et al., 2015; Wells et al., 1996). In the current study, the OQ was used as a measure of general distress.

Experience in Close relationship (ECR; Brennan et al., 1998**).** A 36-item self-report measure of adult attachment, in which individuals report their thoughts, feelings, and experiences in interpersonal relationships on a 7-point Likert scale from 1 (disagree) to 7 (highly agree). The scale produces scores on two dimensions: anxious attachment and avoidant attachment. Adequate reliability (Cronbach's ɑ for anxious and avoidant attachment are .89 and .90 respectively) and validity of the scores has been reported (Brennan et al., 1998).

Inventory of Interpersonal Problems (IIP-32; Alden et al., 1990**;** Horowitz et al., 1988**).** A 32-item self-report measure for assessment of interpersonal distress and social adjustment level. The items are rated on a 5-point Likert scale, ranging from 0 (not at all) to 4 (extremely). The total score, which is the indicator for the severity of difficulties in interpersonal functioning, is computed by averaging the item scores. Higher scores indicate poorer interpersonal functioning, which can manifest as difficulties expressing affection, being assertive or aggressive, being overly disclosing, etc. Adequate validity and reliability (alpha = .86) have been reported for the IIP-32 (Barkham et al., 1996).

Participants

In the current study, participants were recruited from the community via social media and volunteered to participate in exchange for monetary compensation. We enrolled two participants for the Flexibility Interaction Paradigm (FIP; described below) in the roles of "speakers". Each one of them interacted with three additional participants that were enrolled in the role of "listeners". Four listeners (two for each speaker) were enrolled in the same way, and two more (one for each speaker) were close friends of the speakers, recruited through them. Thus, each speaker interacted with a total of three listeners, two of whom were strangers, and one of whom was a friend. All details bearing on the participants' identity (e.g. name, gender, age, occupation) have been disguised in this study.

Speaker 1—Ted: Ted is a male in his twenties, single, and studying for a graduate degree in social work. Ted identifies as a Jewish man of European descent and reported his family's income to be below average. On the self-report measures taken at baseline (see Table I), Ted reported experiencing

Table I. Self-report measures taken at baseline.

Measure	Ted's values	Keely's values
PFQ (total score)	78	63
AAQ-II (total score)	20	54
OQ-30 (total score)	29	70
ECR (average score)		
Anxiety axis	3.72	3.78
Avoidance axis	2.89	4.94
IIP-36 (average score)	1.28	2.44

low levels of symptoms such as stress and irritability, and reported having a happy life with which he was satisfied (total OQ score = 29). Additionally, Ted reported a slight tendency towards anxious attachment, (ECR anxiety scale score = 3.72) and avoidance (ECR avoidance scale score = 2.89), and low levels of interpersonal problems (IIP score = 1.28). Finally, Ted showed moderate to high levels of self-reported psychological flexibility (PFQ score = 78), as well as low levels of experiential avoidance and distress (AAQ-II score = 20). During the FIP paradigm, Ted interacted with three listeners in the following order: a male stranger, a female stranger, and a male close friend.

Speaker 2—Keely: Keely is a female in her thirties, single, studying finance and working as a sales representative. Keely identifies as a Jewish woman of European descent and reported her family's income to be average. On the self-report measures taken at baseline (see Table I), Keely reported experiencing high levels of symptoms, among which were: stress, worries, loneliness, depressed mood, and a lack of satisfaction and happiness in life (total OQ score = 70). Additionally, Keely reported a slight tendency towards anxious attachment (ECR anxiety scale score = 3.78) and a significant tendency towards avoidance (ECR avoidance scale score = 4.94), as well as low levels of interpersonal problems (IIP score = 2.44). Finally, Keely showed moderate levels of self-reported psychological flexibility (PFQ score = 63), as well as high levels of experiential avoidance and distress (AAQ-II score = 54). During the FIP paradigm, Keely interacted with three listeners in the following order: a female close friend, a female stranger, and a male stranger.

Procedure

First, participants who contacted the research team were randomized to either the role of a "speaker" or a "listener". Then, the research team briefed them about the goals of the study and the study's requirements (i.e., the role they were expected to play), and provided them with an informed consent form. After signing, the participants filled out online questionnaires (Demographics and OQ), and speakers were asked to write down three short descriptions of REs for the FIP. The participants were then invited to come to the lab for the next stage of the study.

Once at the lab, another set of questionnaires (IIP-32, PFQ, ECR) was administered before entering the first FIP interaction. Once 15 min of interaction had passed, the experimenter came into the room to stop the conversation. At this point, the listener was debriefed while a new listener was being prepared for interaction. The speaker received the instructions again in preparation for interaction as well. The speaker was debriefed after three FIP interactions conducted in this way.

Statistical Analysis

Producing a reconstructed attractor: Hankel Alternative View of Koopman analysis (HAVOK; Brunton et al., 2017**).** We analyzed the data of two cases using Hankel Alternative View of Koopmann analysis, to reconstruct attractors of the observed behaviors, and compare them. HAVOK analysis was used to model the time-series of behavior modalities (body movement, facial expressiveness) generated by the speaker in the FIP. HAVOK is a method derived from NDST which is able to reconstruct the nonlinear dynamics of an observed system within an entirely linear framework. To accomplish this, HAVOK analysis uses time-delay embedding techniques (Takens, 2006) via a Hankel matrix approach to reconstruct the attractor of a system using time-series data.

To conduct a HAVOK analysis, a time-series of interest is first embedded into a time-delayed matrix with a Hankel matrix structure. This time-delay matrix then undergoes Singular Value Decomposition (SVD). The right singular values of the SVD represent a new matrix of orthogonal latent time series which share the least amount of linear information with one another and that are ordered in terms of the proportion of variance explained in the original time-delay matrix. The matrix of orthogonal latent time-series then undergoes a regularization and sparsification process to reduce its dimensionality from its original dimensionality (D) to a reduced rank dimensionality (r). If done correctly, the final column of the matrix of orthogonal latent time-series will represent the amount of non-linear forcing present in the system at any given time. Generally, this final column will show a spiking behavior, indicating times when a

Table II. HAVOK parameters—sets of parameters for each modality.

Modality	rmax	stackmax	labda	dt
Facial expressivenes	20	100	0.01	0.04
Body movement	16	100	0.01	0.04

system is undergoing some sort of nonlinear behavior.

A continuous-time state-space model may then be constructed regressing the first derivatives of the time-series in the SVD matrix of orthogonal latent time-series on the first r-1 components of the SVD matrix of orthogonal latent time-series and treating the *r*th component of the SVD matrix as an exogenous forcing component. The result of this process is a function that is meant to model the behavior of the original time-series data in time:

$$\dot{X} = AX + BU$$

where X is the matrix of first derivatives of the first r-1 columns of the SVD matrix of orthogonal latent time-series, U is the *r*th column of $\dot{X}$; and A and B are parameter matrices relating X and U to $\dot{X}$. This two-part equation represents the time-series as a linear system that is intermittently forced via U. The linear term (AX) contains wave-like periodic functions, which are then displaced by the nonlinear forcing term U at points in time where it is most active (where the time-series experiences deviations from a repetitive wave pattern). Thus, when the speaker is moving (the face or the body) very predictably the forcing term will be close to zero, whereas when the speaker's movements become increasingly erratic or unpredictable the forcing term will increase in magnitude.

HAVOK analysis results are highly dependent on hyperparameters that define how many columns of the SVD matrix are to be used ("rmax"), what time difference exists between measurements in a time-series ("dt"), number of rows to be used in creating the Hankel matrix ("stackmax"), and a sparsification threshold ("lambda"). In the current study, we used the "phavok" function from the HAVOK R package (Moulder et al., 2021) to find hyperparameter values that would best fit the dataset in each modality via a large grid-search of possible parameters. Thus, we found two sets of parameters (see Table II), one for each modality (facial expressiveness and movement), that would be unchanging across time-series from all six sessions we recorded, and still facilitate good fits of the HAVOK models to the original time-series.

Estimating Quantitative Properties of the Attractors

(a) **The Lyapunov exponent.** One of the meta-metrics applicable to attractors is the Lyapunov exponent, which serves as an estimate of the system's unpredictability. This metric is estimated by taking the value of two points that neighbor each other in a certain radius of state-space at time (t), and calculating the exponential growth in distance between them as time progresses. This process is repeated numerous times to estimate the average rate of increase in exponential distance between the two points, thus providing the Lyapunov exponent. The higher this metric is, the more unpredictable the system is (Taylor, 2010).

(b) **The Correlation Dimension.** This meta-metric quantifies the number (sometimes fraction) of dimensions needed to represent the system underlying a time-series. The higher the correlation dimension, the more complex the system is, as it requires more dimensions to fully describe (Sprott & Rowlands, 2001).

Results

HAVOK Analysis Results

First, we ran "phavok" to identify sets of parameters that could be used across time-series for both Ted and Keely in each modality. We identified one such set for each modality, the sets are shown in Table II. Then we ran HAVOK using these optimal parameters to reconstruct the underlying attractor for each time-series. Figures 1 and 2 show the attractors reconstructed from body movement and facial expressiveness data (respectively), for each of three interactions Ted and Keely participated in. The reconstructed attractors shown in Figures 1 and 2 represent the time-delayed embedding of the time-series (after it had undergone Singular Value Decomposition) in three dimensions. The resulting shapes represent the dynamics underlying facial expressiveness and body movement in time, in each interaction. We will analyze the resulting attractor shapes both through qualitative description of the dynamics, and through quantitative comparison. Qualitative analysis allows us to describe features that are visually apparent in the attractor shapes but difficult to quantify. To analyze the attractors quantitatively we used the two metrics: the Lyapunov exponent and correlation dimension. Tables III and IV show the values of these metrics for all reconstructed attractors shown in the previous section.

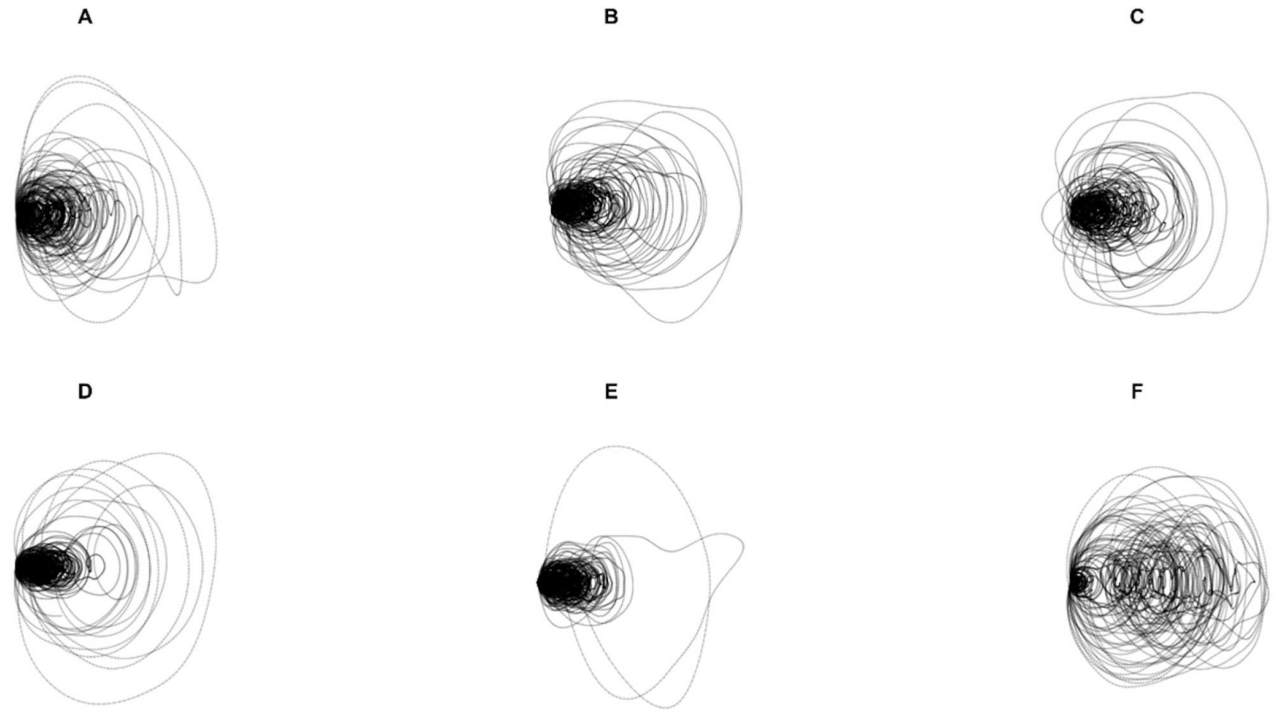

Figure 1. Attractors reconstructed from body movement.
Note: These figures show the attractors reconstructed from body movement data for each of three interactions Kelley and Ted participated in. Attractors A, B, and C represent Ted's three interactions—1, 2, and 3—respectively. Attractors D, E, and F represent Kelly's three interactions—1, 2, and 3—respectively.

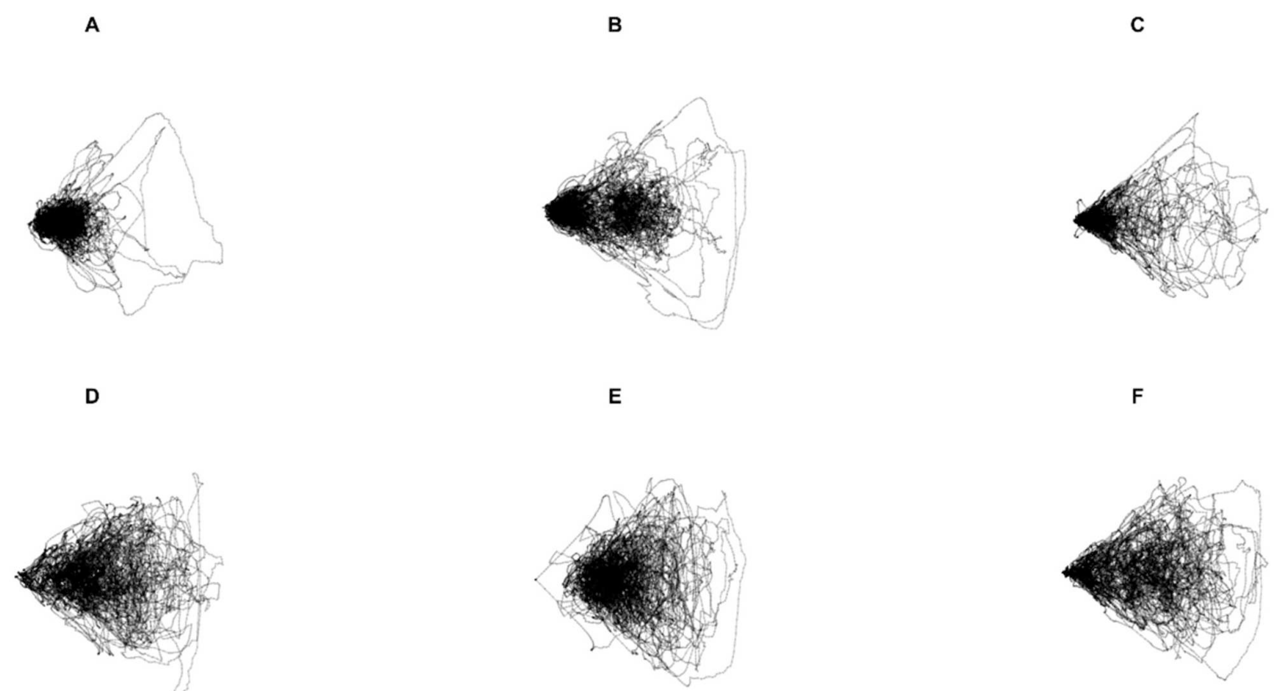

Figure 2. Attractors reconstructed from facial expressiveness.
Note: These figures show the attractors reconstructed from facial expressiveness data for each of three interactions Kelley and Ted participated in. Attractors A, B, and C represent Ted's three interactions—1, 2, and 3—respectively. Attractors D, E, and F represent Kelly's three interactions—1, 2, and 3—respectively.

Before we proceed to report on the results, it is important to show that these shapes differ greatly from attractors that would have resulted from random data. Figure 3 shows an example of three attractors, where one is obtained from a purely mathematical system (A); one is obtained from a HAVOK reconstruction of data presented in this manuscript (B); and one from random Gaussian noise (C). While the attractor structure obtained from our observed data is not as visually smooth and clean as a purely mathematical system, it does show meaningful order and structures compared to random noise. This indicates that our data signal is picking up meaningful dynamics of behavior as opposed to only measurement error.

Ted's Results

Description of interactions. Ted interacted with three different listeners both in terms of their familiarity to him, as well as their behavior in the interactions. The first listener was a very energetic and engaged same-sex stranger who offered verbal feedback with enthusiasm. The second was a stranger of the opposite sex who seemed to engage much less, moved less, and barely spoke back to Ted. Finally, Ted met a same-sex friend who reacted mildly but was engaged throughout the interaction. In the three interactions Ted was able to meet the goal set by the FIP paradigm, namely, to tell his RE's from start to finish and have a conversation about them with his listeners. Additionally, Ted was very responsive to engagement from his listeners, and seemed to revel in their reactions and feedback. This was reflected in Ted's movements, which were characterized by a relaxed posture on one hand, and hand gestures that were used to illustrate his words and imbue them with the intensity he wished on the other. While listening to the responses of listeners, Ted would sit rather still and nod his head from time to time. Ted's facial expressions also showed a similar pattern: when speaking, Ted's expressions would change quickly to match the tone of his words. However, when being spoken to, Ted would adopt a rather unchanging but friendly face while keeping eye contact. While this description was generally true for all three interactions, it changed visibly in the second. As the second listener responded to Ted minimally, Ted's efforts to "pull him into the RE's story" (with both gestures and expressions) became more pronounced on the background of the times Ted spent awaiting a response without moving.

Reconstructed attractors. Ted's body movement attractors across sessions (see Figure 1(A–C)) show a rather similar structure: each attractor has a dense center with perturbations encircling it and expanding out. The general pattern of the three attractors shows that ted spent most of the time in the interaction moving rather mildly, with larger movements happening once in a while. This reflected Ted's behavior in the video recordings, as described above, so that the dense center could represent the times spent not listening, smiling and nodding, whereas the perturbations reflect the more active behaviors.

Ted's facial expressiveness attractors exhibit different patterns (see Figure 2(A–C)): the general shape of the attractors resembles the shapes observed in body movement attractors, in that generally the attractors possess some kind of dense center. The attractors for interactions one (A) and three (C) have a defined dense center with large perturbations encircling it, however the first attractor's center seems denser, and the perturbations less frequent than those of the third. The attractor for the second (B) interaction seems to possess two pronounced

Table III. Lyapunov exponent values, means, and ranges for each speaker.

Modality	speaker	interaction	Lyapunov exponent value	mean	range
Facial expressivenes	Ted	1	1.428	1.015	1.285
		2	0.166		
		3	1.451		
	Keely	1	0.655	0.739	0.32
		2	0.621		
		3	0.941		
Body movement	Ted	1	1.682	1.568	0.669
		2	1.845		
		3	1.176		
	Keely	1	0.871	0.765	0.169
		2	0.702		
		3	0.723		

Table IV. Correlation dimension values, means, and ranges for each speaker.

	Speaker	Interaction	Correlation dimension value	Mean	Range
Facial Expressiveness	Ted	1	10.152	5.640	7.332
		2	2.82		
		3	3.949		
	Keely	1	4.048	4.451	3.042
		2	6.173		
		3	3.131		
Body Movement	Ted	1	1.662	2.291	1.335
		2	2.215		
		3	2.997		
	Keely	1	3.187	2.593	1.165
		2	2.57		
		3	2.022		

dense centers, which represent the frequent switching of Ted's face from an unmoving state of awaiting, to trying to grab the listener's attention when speaking.

Lyapunov exponent and correlation dimension metrics. As shown in Table III, Lyapunov exponent values derived from Ted's data were all positive, meaning that distances between nearby trajectories on the attractors increase exponentially as time passes. Ted's mean value of Lyapunov exponents in facial expressiveness data were lower than the mean value of the same metric in the body movement data (1.02 and 1.57 respectively). Additionally, the range of Lyapunov exponent values in facial expressiveness data were larger than in body movement data (1.29 and 0.67 respectively). These differences are mainly due to a sharp drop in the Lyapunov exponent value for facial expressiveness in the second interaction. This suggests that Ted's facial expressiveness attractors differ in terms of their predictability more than his body movement attractors do. The mean value and range of the correlation dimension (see Table IV) metric was much higher in Ted's facial expressiveness data than in body movement (means: 5.64 and 2.29 ranges: 7.33 and 1.34 respectively). This suggests that Ted's facial expressiveness attractors vary much more between themselves, and are generally more complex than his body movement attractors.

Keely's Results

Description of interactions. Keely also interacted with three different listeners: she first interacted with a same-sex friend of many years, who was very agreeable. Then she interacted with a same-sex stranger who was very enthusiastic about giving positive feedback, as well as presenting her own perspective during the interactions. Finally, Keely interacted with another stranger of the opposite sex, who was more assertive and self-expressive than the others. Upon inspecting the interaction recordings, we found that Keely did not stay on-task and did not share the RE's with her listeners. Rather, she made small talk with them on topics related to the RE's she was supposed to discuss. For example: when interacting with the stranger in the third interaction, she did not tell him about the political argument that arose between her and a colleague. However, she did choose politics as a general subject of discussion with the listener. The interactions seemed pleasant to both sides, however they shared a similar behavioral pattern: Keely would speak more than the listeners, with her face constantly switching between moments of stillness and sharp movement, mostly keeping a commanding and assertive, yet friendly voice. She tended to interrupt the speakers when they offered feedback, often adding a proclamation such as: "This is what I am, and it's not going to change". This verbal behavior was mostly accompanied by a sharp increase in body movement and hand gesturing. This pattern seemingly became more pronounced with each interaction.

Reconstructed attractors. Keely's body movement attractors across sessions (see Figure 1(D–F)) differ in structure more than Ted's: the first two attractors (D and E) follow roughly the same structure as Ted's, however; the center seems to be denser. Additionally, the perturbations from the dense center seem to be less frequent but larger in magnitude, especially in Keely's attractor for the second interaction (E). Keely's attractor from the third interaction (F) differs greatly from the first two, exhibiting no defined center, and a rather uniform density in space that is the result of constant large motions. This pattern coincides with the behavior observed in the video recordings described above at its most severe. In the third interaction, Keely's

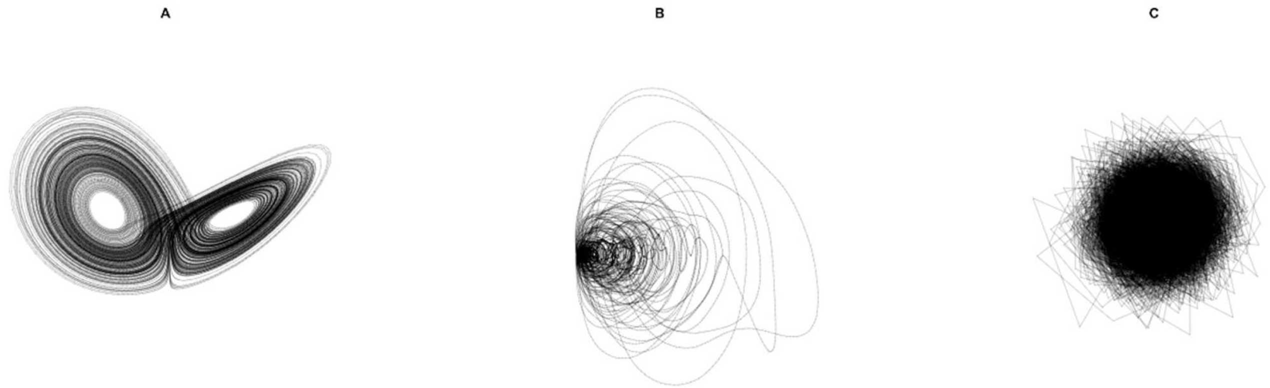

Figure 3. An example of different attractors.
Note: Attractor A represents is an example of an attractor obtained from the purely mathematical Lorenz system. Attractor B was obtained using HAVOK analysis with data presented in this manuscript. Attractor C is an attractor reconstructed from random Gaussian noise.

swinging between little motion and large sharp hand gesturing was the most erratic.

Keely's facial expressiveness attractors (see Figure 2(D–F)) look similar to each other, having an arrow-like shape like Ted's but with no clearly defined center. The state-space seems to be uniformly filled by trajectories, coinciding with the consistent but large changes in facial expressions during the interactions.

Lyapunov exponent and correlation dimension metrics. As shown in Tables III, Lyapunov exponent values derived from Keely's data were all positive, meaning that distances between nearby trajectories on the attractors increase exponentially as time passes. Keely's mean value of Lyapunov exponents in facial expressiveness data were very similar to the mean value of the same metric in the body movement data (0.74 and 0.77 respectively). Additionally, the range of Lyapunov exponent values in facial expressiveness data were larger than in body movement data (0.32 and 0.17 respectively). This suggests that Keely's facial expressiveness attractors in both modalities do not strongly differ in terms of their predictability. The mean value and range of the correlation dimension metrics (see Table IV) were much higher in Keely's facial expressiveness data than in body movement (means: 4.45 and 2.69, ranges: 3.04 and 1.17 respectively). This suggests that Keely's facial expressiveness attractors vary much more between themselves and are generally more complex than her body movement attractors.

Integration of HAVOK Analysis Results and Case Descriptions

During the FIP interactions, it seems that of the two speakers described here, Ted was the only one who stayed on-task and was able to discuss his RE's with the listeners consistently, regardless of their reactivity and collaboration with him. Additionally, both the quantitative and qualitative analyses of the speakers' facial expressiveness attractors show Ted's attractors to differ between interactions, as evidenced by the shapes described above, and the larger ranges of Lyapunov exponent and correlation dimension values. These results correspond with Ted's behavior in the interactions, where he used changing facial expressions to communicate and react to his listeners as he was speaking, and was less expressive as they were replying, seemingly attending to their words. Of great interest is the change in Ted's behavior during the second interaction, where the listener was much less active both verbally and non-verbally. In this interaction, Ted's face seemed to switch between two modes of behavior that alternated repetitively. The first was characterized by relative motionlessness and a flat facial expression, while the second mode seemed to contain attempts to excite the listener into reacting by accompanying pieces of dialogue with a smile. This pattern might explain the sharp decrease in the value of the Lyapunov exponent in this interaction as well as the appearance of a second dense area in the attractor, thus exemplifying Ted's adaptation to differences between listeners. While the results indicate Ted's facial expressiveness behavior varies between interactions, this is not true for his body movements. During the interactions, Ted's way of moving was fairly consistent, including relaxed hand gestures accompanying speech, and larger movements such as adjusting the sitting pose. This relatively small and consistent selection of behaviors seems to be reflected in the lower values of correlation dimension, as well as in the attractors that have very similar shapes. However, the larger range values of both metrics indicate that the attractors differed in their level of predictability and complexity more than Keely's.

Keely, on the other hand, did not stay on-task, especially when interacting with strangers in interactions two and three. As described above, Keely did not truly discuss the RE's with her listeners, but rather talked *around* them, making small talk about a general topic that is remotely related to each given RE. This pattern of avoidance was accompanied by both qualitative and quantitative properties of her attractors that were different to Ted's. Keely's facial expressiveness attractors are very similar across interactions: this is reflected both by the attractor shapes as well as the lower range and mean of Lyapunov exponents in Keely's data. However, for body movement a different pattern emerged: Keely's attractor shapes differed more than Ted's, and her mean value of correlation dimension was higher than Ted's. However, Keely's mean Lyapunov exponent and the ranges of both metrics remained consistently lower than Ted's.

Discussion

The goal of the present study was to introduce a novel approach to measuring flexibility in psychotherapy, and demonstrate its use using an experimental design. We set out to achieve this goal by using a multi-dyad and multi-modal approach nested within a Nonlinear Dynamical Systems framework. The framework is based on a definition of flexibility as behaviors that vary when circumstances demand it, in a way that allows toleration of distress and promotes goal attainment (Cherry et al., 2021; Kashdan & Rottenberg, 2010). The FIP paradigm was designed to mimic therapeutic interactions between individuals in which one shares emotional experiences with another, as may happen in many clinical settings where the same individual (patient) meets with several caretakers (therapist, diagnostician, or case manager).

Our first hypothesis was that the FIP paradigm, designed as psychotherapy-based interactions, would successfully differentiate between two individuals—Ted and Keely. From the outset, we chose Ted and Keely for this demonstration because their flexibility levels differ as manifested by self-report measures of flexibility as well as psychological health and functioning levels. Ted's pre-session self-report measures indicated him as more flexible than Keely, which was accompanied by better psychological health and functioning. The results suggest that the FIP was able to differentiate between Ted and Keely's flexibility levels. Ted's behavior during the therapy-like interactions with three different partners showed more unpredictability within the interactions as well as more structural variability between them, compared to Kelly's patterns of behavior.

Our second hypothesis was that multimodal information would be crucial to reveal which of the patterns identified was indicative of flexibility and adaptive behavior. Had we looked at either modality on their own, we could have identified both individuals as flexible based on the attractor shapes. Our results indicate that Ted's facial expressiveness behavior was more varied in terms of its dynamics, predictability, and complexity than Keely's. The results for body movement emerged as less conclusive, showing that on one hand, Keely's attractor shapes differ between interactions much more than Ted's, but are still characterized by higher predictability and lower ranges of the quantitative metrics estimated. Thus, Ted's varying facial expressiveness attractors and his ability to stay on-task would have crowned him as flexible, while in the body movement modality Keely might have taken the prize. However, by putting these modalities together, minding their postulated meaning and integrating these results with the speaker's ability to stay on-task, a more complicated and richer picture emerged.

Ted showed an ability to change the dynamics of his facial expressiveness when faced with different conversation partners, which was not observed in Keely's data. In Ted's case, these changes were accompanied by rather similar attractor shapes of body movements, which may show that Ted was able to regulate the changes in his arousal at least in part. However, some variability between the attractors remained and manifested itself in the quantitative metrics of the attractors. Thus, while Ted's body movement patterns are less variable than his facial expressiveness patterns, they are still characterized by less predictability and more complexity than Kelly's. Taken together with Ted's ability to stay on-task during the interactions, Ted's better interpersonal functioning, and lower symptom distress when compared to Keely, Ted's pattern of behavior may be defined as flexible (Cherry et al., 2021; Kashdan & Rottenberg, 2010). Finally, Ted and Keely's psychological flexibility as measured by two self-report measures seems to be in line with this definition. These findings provide preliminary support for our claim that the multimodal data collected in the FIP may differentiate between patients with different levels of flexibility.

This study is the first to suggest a paradigm for the assessment of individuals' flexibility that was devised specifically to be suitable to psychotherapy as well as the theoretical definition of flexibility. In many psychotherapy settings (inpatient and outpatient clinics, and RCTs) patients meet more than a single provider of mental healthcare. Thus, the FIP paradigm might be used in such settings for ecological collection of data. Such a method requires no additional effort on the patient's part and is directly relevant to measuring flexibility in psychotherapy, thus bypassing some shortcomings of self-report measures. Integrating multimodal automatic measurement in psychotherapy will allow researchers and clinicians to observe patterns of behavior as the patient interacts with multiple caregivers, as well as the same caregiver over time (namely, as it evolves throughout different sessions). Observing differences in patterns of patient's behavior with different caretakers may serve as an indication of their trait-like flexibility at a given time (Zilcha-Mano, 2021). Conversely, state-like changes in these patterns over time might hint at changes in a patient's flexibility, which might then be related to therapy outcomes. Such research may shed light on the role of flexibility as a predictor, and a mechanism of change in psychotherapy.

Importantly, this work is also novel due to its use of nonlinear dynamical systems methods within the psychotherapy research space. Without leveraging NDST methodology, these findings would have been possible given that the metrics we used in this study (Lyapunov exponents and Correlation Dimension) are either undefined or have no equivalent within a linear analysis framework. These methods can be implemented with any kind of data that is collected frequently enough, such as vocal and physiological signals from therapy sessions (Kleinbub et al., 2020; Reich et al., 2014). Another research direction that can implement these methods is using smartphones and smartwatches before the start of treatment in an ecological manner throughout the patient's daily life. The level of flexibility of the patient can then be evaluated using these data as collected across time before the start of treatment and across types of daily life interactions (with significant others, strangers, etc.).

Our study is of course not without its limitations. Although in the current study we devised the FIP to resemble psychotherapy, we believe that the true potential of our approach will be realized once implemented in psychotherapy directly, as described above. On one hand, the FIP was created to best resemble psychotherapy but on the other there are several shortcomings of this paradigm that must be considered: (a) the interactions of the FIP were only fifteen minutes long, as opposed to the fifty minutes of a standard therapy hour; (b) due to the attempt to resemble the naturalistic setting of therapy, the goals of the participants were not manipulated as well as they could have been in a rigorous experimental setting. Thus, while operating and interpreting on the assumption that the participants were motivated to follow our instructions to share their RE's, we cannot know if that assumption is true. This is important because assessing whether behavior is adaptive in achieving a valued goal is one of the criteria for classifying the behavior as flexible or not (Kashdan & Rottenberg, 2010).

Additionally, as the current study was meant to be a demonstration, we examined only two cases. Accordingly, its results should be interpreted with caution until confirmed by studies with large samples and several time-points. Third, psychotherapy is (certainly to some extent) an interpersonal process, meaning that assessing the flexibility of one side of an interaction without considering the other may result in conclusions that differ greatly from ones derived by considering both sides in the dyad. In the current study we decided to focus on the patient side of therapy in isolation for the sake of simplifying a complex outlook on human behavior. While that may have provided a clearer demonstration, the results that might have come out of analyzing the flexibility of synchrony of nonverbal behavior between therapist and patient, might have been different. In future studies we intend to use our approach to study the flexibility of synchrony between patient and therapist, in the hopes of shedding light on differences between flexible and inflexible patterns of synchrony and their possible ramifications for therapeutic success.

In conclusion, our study demonstrates a novel approach to measuring flexibility in psychotherapy. The FIP allows for the collection of multimodal data that holds information regarding an individual's repertoire of interpersonal behaviors and the predictability of these behaviors. This measure has the potential to provide a strong operationalization that would complement existing measures and allow the required complexity for understanding this concept. Future studies should assess the replicability and generalizability of this study's findings in large samples of psychotherapy patients that interact with multiple treatment providers over time. Additionally, future studies should further assess whether changes in multimodal behavioral patterns occur during psychotherapy, and whether these changes precede fluctuations in symptom severity. This will serve to further establish the role of flexibility as a mechanism of change in psychotherapy.

Disclosure Statement

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