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Research Paper

Hidden Markov model detection of interpersonal interaction dynamics in predicting patient depression improvement in psychotherapy: Proof-of-concept study

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ABSTRACT

Background: Previous human ethology studies have demonstrated that the interpersonal interactions displayed in therapy by both patients and therapists influences a patient's depression improvement. Pairing novel statistical techniques such as the hidden Markov model (HMM), interpersonal interaction dynamics can be uncovered by partitioning time into empirically-derived nonverbal behavioral states. This approach allows for better patient-therapist behavioral dynamics distinctions in predicting depression improvement and, subsequently, for the processes behind depression improvement.
Methods: For the 39 participating patients, the first 15 min of the first or second therapy session was recorded on video to examine the interpersonal interaction behaviors of patients and therapists. The video recordings were encoded for vocalization, looking and leg movement behavior events at a 1 s frequency. A Bayesian multivariate multilevel HMM was fitted on the behavioral event data.
Results: It is demonstrated that patients that show improvement in the depression score are characterized by interpersonal interaction dynamics of hyperfocus when listening to their therapist in psychotherapy when compared to non-improving patients. The data supports evidence for the emergence of differences in interpersonal interaction dynamics through changed durations of the patient hyper focused listening states, but not through changed state-switching dynamics over time.
Limitations: Due to our relatively small sample size we could not fit multilevel HMMs composed of more than three hidden states.
Conclusions: We suggest that applying HMMs will aid human ethological behavior studies in uncovering interpersonal interaction dynamics that occur in therapy and be able to use these dynamics to predict patient depression symptom improvement.

1. Introduction

In order to better understand workings of the psychotherapeutic relationship and its effects on therapy progression, attention has long been given to the examination of interpersonal interaction patterns between the therapist and the patient. Some of the earliest studies in this field have been conducted by human ethologists who, as a discipline, study the biological underpinnings of behavior. Human ethological studies observe and measure nonverbal behaviors; this, in contrast, for example, to the cognitive psychological study of the literal verbal content of an interpersonal interaction. In respect to the psychotherapeutic relationship, human ethologists have conducted some of the earliest observational studies in this field and have demonstrated that the patient's and the therapist's nonverbal behaviors of their interpersonal interactions have been found to influence a patient's depression improvement (e.g., Bouhuys and van den Hoofdakker, 1991; 1993). Subsequent studies using the same human behaviors found similar results for the interpersonal interactions between depressed patients and their partners (e.g., Hale et al., 1997).

This research tradition of nonverbal behavior in the therapeutic setting has received a new impulse with studies on nonverbal patient-therapist synchrony (e.g., Ramseyer and Tschacher, 2014). In one of their studies of nonverbal behavioral interactions in the psychotherapy relationship, Ramseyer and Tschacher (2011) made the following

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observation about patient-therapist synchrony: “Data indicating how nonverbal behavior may affect therapy outcome and therapy relationship are sparse. Nonverbal aspects of relationship formation have only been assessed at either the level of the patient or the therapist, ignoring the system level of the dyad. This restriction must be critically questioned because the therapeutic relationship arises between the therapist and the patient(s) interacting in therapy.” (p. 284).

While there is not yet a complete literature review of the methodology of the nonverbal behavior research of depressed patients and therapist interactions, an examination of the most recent studies on this topic reveals that while most studies still employ the human ethological approach of analyzing the duration and frequency of the patient and therapist nonverbal behaviors in isolation (Akinci et al., 2022; Dowell et al., 2013; Fernandes et al., 2017; Fiquer et al., 2017; 2018), some newer studies have adopted Ramseyer and Tschacher’s patient-therapist synchrony approach (Deres-Cohen et al., 2021; 2022). In terms of the latter, nonverbal synchrony is operationalized as the synchronized movement of global body parts, e.g., the head and upper body, irrespective of the type of nonverbal behavior displayed. While nonverbal synchrony thus allows us to examine patient-therapist nonverbal behavioral interactions as a whole, this comes at the cost of not being able to shed light on specific nonverbal behaviors over time, e.g., patient and therapist looking at each other. Novel developed algorithms (driven by machine learning methods, increased computational power, and open access software) allow us to take the study of patient-therapist interpersonal interaction patterns to the next level: combining the patient-therapist system level approach with dynamics in interaction behavior over time in multiple specific nonverbal behaviors simultaneously, and including other (predictive) variables such as depression symptom reduction.

A powerful tool in temporal pattern recognition that is gaining traction within the behavioral sciences is the hidden Markov model (HMM: Rabiner, 1989; Zucchini et al., 2016; for applications within the behavioral sciences see e.g., Allega et al., 2018; Bueno et al., 2019; Catarino et al., 2022; Vidal Bustamante, 2022), a method first introduced in the field of speech recognition. When pairing longitudinal nonverbal behaviors with the HMM, interpersonal interaction dynamics can be uncovered by partitioning time into empirically-derived nonverbal behavioral states and inferring the likeliness of switching between these states over time. Adopting a multilevel framework (Altman, 2007), we allow for patient-therapist specific behavioral dynamics over time. Utilizing the multilevel HMM to uncover interpersonal interaction dynamics creates many more nuances than the previous conventional human ethological one-dimensional cluster approach or the global nonverbal synchrony approach. Instead of using univariate, static, time-flattened factors or behavior unspecific synchrony over time to predict patient depression improvement, quantified heterogeneity in the dynamics over time based on multivariate nonverbal behaviors itself can be linked to patient depression improvement. The ability to zoom in on the actual dynamics over time provides us with more direct clues on the processes behind depression improvement.

Therefore, the goal of this study is to present a short demonstration of how HMM can be used to discover interpersonal interaction dynamics that occur in therapy and use these dynamics to predict patient depression symptom improvement.

2. Methods

2.1. Sample

For the present study, adolescents and young adults treated for internalizing problems were recruited from the mental health outpatient clinic of the Utrecht University, The Netherlands. Patients were included in the study if they suffered from depressive symptoms, without comorbid externalizing problems, personality disorder or intellectual disabilities. The total sample size was 39 patients, ages of 16 to 26 (61.5% female; $M_{\text{age}} = 21.87$, $SD_{\text{age}} = 2.76$). The two therapists that participated in this study (one male and one female) are both of the same age ($M_{\text{age}} = 51$). At the time of the study, both were 15-year experienced faculty members of the Utrecht University and its mental health outpatient clinic, as well as experienced and registered Dutch mental health care therapists, as well as being the treating therapists of the patients of this outpatient clinic study. The female therapist treated 30.8% of the 39 aforementioned clients (83.3% female; Mage = 19.83, SDage = 3.19). The average therapy duration was 4.69 months ($SD = 2.72$), with an average number of therapy sessions being 10.97 ($SD = 5.42$).

2.2. Procedure

Written informed consent was obtained from all participating patients as well as from the participating therapists. The first 15 min of the first or second therapy session was recorded on video to analyze the interpersonal interaction behaviors of patients and therapists, in agreement with previous human ethological studies (e.g., Bouhuys and van den Hoofdakker, 1991) that used the first or second therapy session since the patient and therapist have not yet adjusted their behavior to each other. Three specific nonverbal behaviors, analyzed in these previous studies, were measured: vocalizations, looking, and leg movements. The 15 min of each recoding was encoded, at a 1 s frequency, by an expert behavioral analyst from Noldus Information Technology B.V., a company specialized in the observation of non-verbal behavior for scientific research, with the use of Noldus’ Observer XT software (Version 14; Zimmerman et al., 2009).

Patients were asked to complete the Dutch version of the Children’s Depression Inventory (CDI; Timbremont and Braet, 2002) after the video recording (pretest), and when therapy was completed (posttest). A composite CDI score (scaled improvement score calculated by $(x_{\text{pretest}} - x_{\text{posttest}}) / SD_{(\text{pretest} - \text{posttest})}$) was obtained to determine depression symptom improvement for all the patients, such that positive values reflect symptom improvement, and negative values reflect symptom deterioration.

This study was approved by the ethics committee of the Faculty of Social and Behavioural Sciences of Utrecht University (The Netherlands).

2.3. Statistical analyses

A Bayesian multilevel hidden Markov model (mHMM; Shirley et al., 2010; de Haan-Rietdijk et al., 2017) was used to identify latent nonverbal behavior states over the recorded therapy sessions. The HMM is a statistical method that is used to infer a sequence of latent or hidden states S_t in $(1, 2, \ldots, M)$ for time points $t = 1, \ldots, T$. The hidden states are defined by the probability to observe an outcome Y_t, and account for the dynamics of the observations in terms of the dynamics of the hidden states. The former is based on the assumption that a given observation Y_t in the sequence is generated by an underlying, latent state S_t. The latter is based on the assumption that the hidden states follow a Markov process. That is, the probability of switching from state i at time point t to state j at $t + 1$ only depends on the current state i at time point t. See the online supplementary materials for a more detailed model specification. As heterogeneity is to be expected between the patient-therapist dyads, we adopt a multilevel framework. Here, observations obtained over the recorded therapy sessions (level 1) are assumed to be nested within patient-therapist dyads (level 2).

Within this framework, the overall temporal dynamics are reflected by a set of group-level parameters, and variability between dyads is accommodated by the inclusion of dyad level random effects. Hence, the multilevel approach used ensures that although patient-therapist dyad parameters are allowed to vary, hidden state composition and interpretation is similar over patient-therapist dyads, in contrast to for example fitting a separate HMM to each patient-therapist dyad.

Analysis code is publicly available at Hale and Aarts, 2023. All

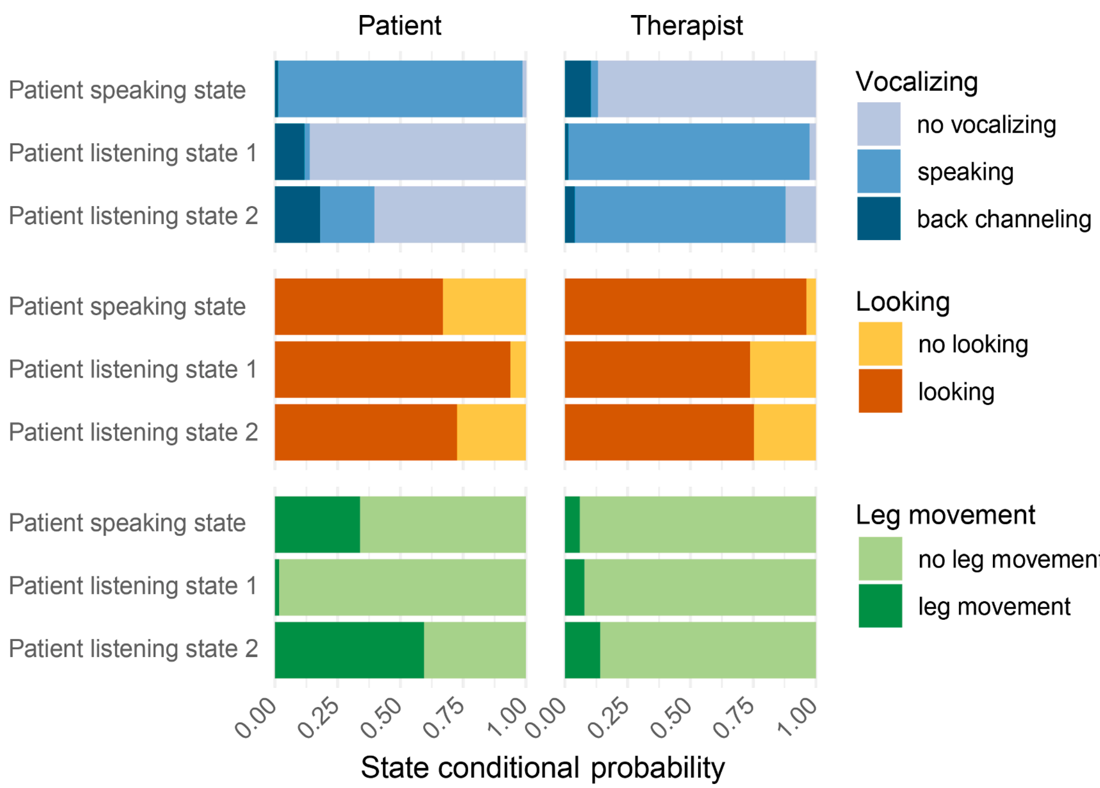

Fig. 1. Group-level composition of the three behavior states based on the indicators vocalizing, looking and leg movement for the patient-therapist dyads.

analyses were performed in the statistical computing software R (R Core Team, 2021). The R *mHMMbayes* package (v0.2.0; Aarts, 2022) fitted a multivariate mHMM over the patient-therapist specific recordings of six variables (patients' and therapists' vocalization, looking and leg behaviors). Models with two to four state solutions were fitted, model selection was performed on lowest Akaike Information Criterion (AIC), model convergence, and interpretability. The relationship between state dynamics and depression improvement score was accommodated in the model by modeling each row of the state transition matrix using a (multilevel) multinomial logit model. Three depression improvement scores (which were distant from the centroid of the predictor scale) were found to have high leverage values (i.e., x-outliers that potentially unduly influence the analysis results) and were therefore omitted from the analysis.

The Bayesian mHMM requires initial values for the state composition and state dynamics, which were based on estimation results of a conventional HMM trained on the pooled recordings (depmixS4; Visser and Speekenbrink 2010). The model was run with 20,000 iterations and a 5000 burn-in period and weakly informative priors. Convergence of all group-level parameters was checked with the potential scale reduction factor R-hat (Brooks and Gelman, 1998) for two additional chains with varying starting values. R-hat measures whether the chains have converged to the same parameter value by testing for equality of means: R-hat measures the degree to which variance (of the means) between chains exceeds what one would expect if the chains were identically distributed. Generally, a value of R-hat below 1.2 is used to indicate convergence. The Viterbi algorithm (Viterbi, 1967) was used to uncover the sequence of behavioral states for each patient-therapist dyad.

3. Results

3.1. Composition of the nonverbal behavior states

The three-state multilevel HMM showed the best fit indicated by a combination of AIC and model stability (Table S1, Supplementary Materials). The three nonverbal behavior states were classified as a patient speaking state, a patient hyper focused listening state and a patient unfocused listening state, which are visualized in Fig. 1 at the group-level. The patient speaking state was characterized by the patient almost exclusively speaking and the therapist predominantly listening. Looking toward the face of the other was higher in the therapist compared to the patient, in line with the general pattern that looking was highest when listening. Both patient listening states were characterized by the patient predominantly listening and the therapist speaking, in addition to some backchanneling by the patient. Differentiation of the two states was primarily by the amount of patient's looking toward the face of the therapist and patient's leg movement. In the hyper focused listening state, the patient was almost exclusively looking toward the face of the therapist, and virtually no leg movement was observed. In the patient unfocused listening state, the amount of looking toward the face of the therapist was reduced to the level of the patient speaking state and leg movement was observed over half of the time. The therapists' behaviors were similar across the two patient listening states.

3.2. Dynamics over time in the behavior states

Overall, patient-therapist dyads spent most time in the patient speaking and hyper focused listening states (41% and 39%, respectively), followed by the patient unfocussed listening state (20%). Staying within the same nonverbal behavior state from one second to the next was highest for the patient speaking state (probability of 0.94) and lowest for the patient unfocused listening state (probability of 0.82; Figure S2, Supplementary Materials). Over the 15-minute recorded therapy session, patient-therapist dyads moved on average 90.58 (SD = 24.07) times from one behavioural state to another, corresponding to ~6 switches per minute. No clear pattern in the likeliness to switch from one state to either one of the two remaining states was observed for the nonverbal behavior states, although clear interpretations of the between state switching probabilities is hindered by the large probabilities to remain within the current state. Large heterogeneity was observed in the

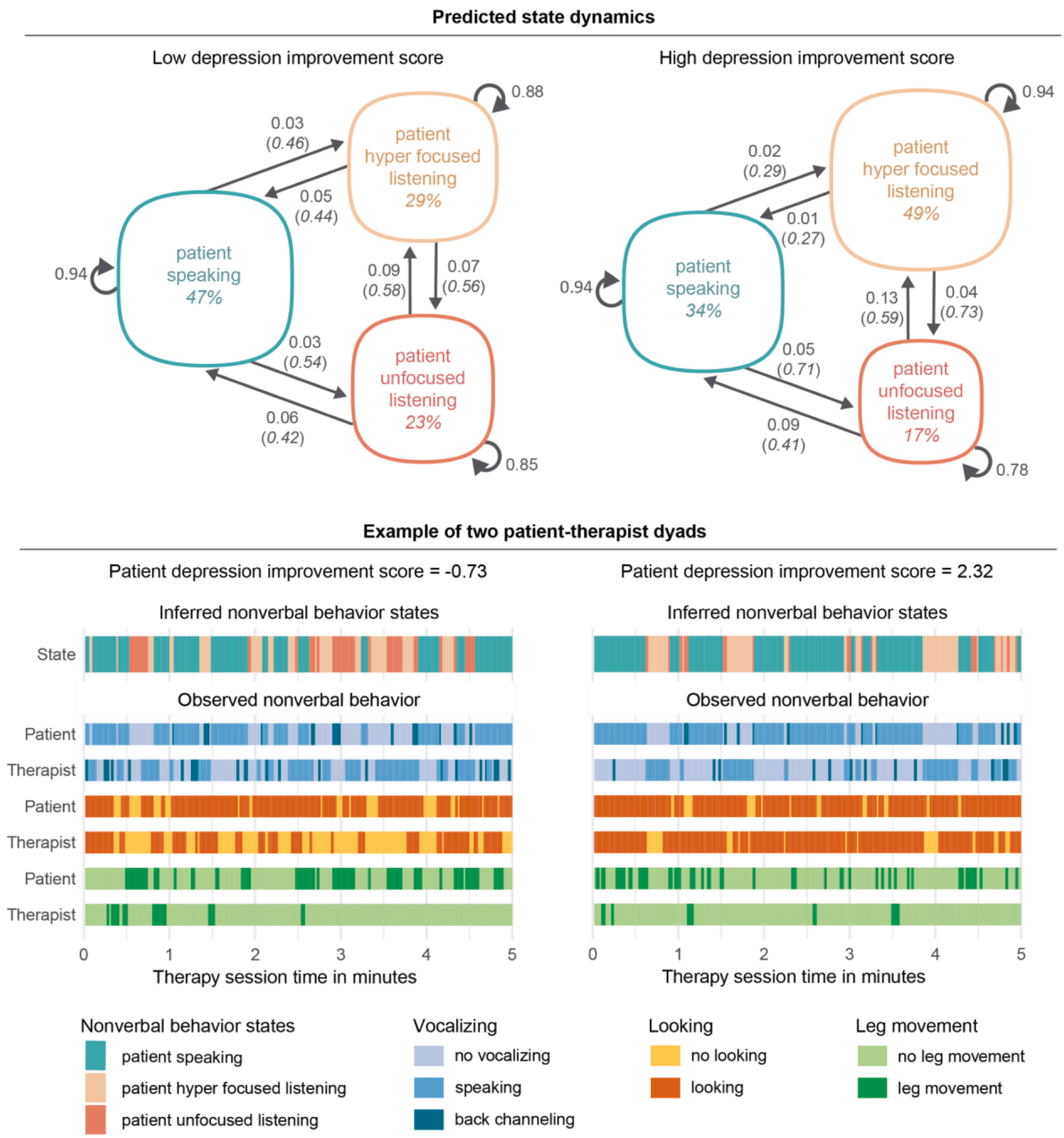

Fig. 2. Graphic representation of the predicted interpersonal interaction dynamics (top) and example observed nonverbal behavior and inferred dyad specific state trajectories (bottom) for patients with low and high depression improvement scores.
Top: Low and High Depression Improvement Scores were used to obtain the predicted state dynamics for hypothetical patients which show low or high depression improvement according to the Children's Depression Inventory. Low and High Depression Improvement Scores were taken as −1.07 and 2.93, corresponding to two standard deviations below and above the average scaled improvement score of 0.93, respectively. Interpersonal interaction dynamics are depicted in squircles, with the percentage of nonverbal behavioral state frequency indicated inside the squircle in italics. The area of each squircle is proportional to state frequency. Arrows that loop back to the departing state represent self-transition probabilities, arrows pointing towards another state represent transition probabilities between the states. Absolute self-transition and between state transition probabilities are indicated next to the arrows. Standardized transition probabilities (i.e., discounting self-transition probabilities to allow for the comparison of between state transition probabilities over models and over transitions departing from different states) are indicated in italics in between brackets. Bottom: Two examples of observed nonverbal behavior and inferred dyad specific state trajectory for a patient showing a low (−0.73) and a high (2.32) depression improvement score for the first 5 min of the recorded therapy session.

state dynamics over patient-therapist dyads (Figure S3, Supplementary Materials), primarily in the likeliness to remain within the two patient listening states, with probabilities ranging from 0.81 to 0.97 and 0.62 to 0.96, respectively.

3.3. *Prediction of patient depression improvement from the interpersonal interaction dynamics*

In Fig. 2, the predicted interpersonal interaction dynamics for patients that show a low and high depression improvement score is provided (top), together with two snippets of observed patient-therapist nonverbal behavior over time with dyad specific state trajectories (bottom). Here it can be seen that patients that showed high depression improvement demonstrated interpersonal interaction dynamics of hyperfocus when listening to their therapist in psychotherapy when compared to low improving patients; the predicted frequency of the patient hyper focused listening increased (39 % vs 49%), while the frequency of the patient unfocussed listening and patient speaking decreased (23 % vs 17% and 47 % vs 34%, respectively).

Inspecting the dynamics over time in the behavior states sheds light on the emergence of these differences in the interpersonal interaction dynamics. The patients who showed higher depression improvement demonstrated a significantly increased probability to remain within the patient hyper focused listening state, relative to lower improvement patients (probability of 0.94 versus 0.88, respectively, multinomial logistic $\beta = 0.32$, $CI_{95} = [0.02, 0.63]$). The probability to remain within the patient pattern of speaking is similar across the patients (probability 0.94). The between interpersonal interaction state transition probabilities do not show significant differences (Figure S3, Supplementary Materials), and standardized values of the between transition probabilities reveal increased standardized probabilities of switching towards the patient unfocused listening and decreased standardized probabilities of switching towards the patient hyper focused listening in the high improving patients. Hence, the data supports evidence for the emergence of differences in interpersonal interaction dynamics through changed duration of the patient hyper focused listening state, but not through changed between state-switching dynamics over time.

4. Discussion

In this proof-of-concept study we have briefly demonstrated how the multilevel HMM algorithm can be used to discover the interpersonal interaction patterns that occur in therapy, how these patterns vary over patient-therapist dyads, and can be used to predict depression improvement.

One of the striking findings of this study is the importance of interpersonal interactions in psychotherapy play in patient symptom reduction. It is demonstrated that higher depression improvement occurred for patients that displayed intensely focused listening behaviors (to their therapist in psychotherapy) when compared to patients that displayed less focused listening behaviors.

Due to the rise of psychotherapy at a distance that gained strong prominence during the corona lockdowns (e.g., Konieczny, 2022), one could be excused for believing that interpersonal interactions are of little to no consequence in modern psychotherapy. However, this has been shown not to be the case. For example, in a study of video-based online therapy during the corona lockdowns (Notermans and Philippot, 2022), psychotherapists indicated that compared to face-to-face contact, that the therapeutic alliance, which is composed of interpersonal interactions, was found to significantly deteriorate in online therapy sessions. The question then arises, of what importance do these interpersonal interactions have in the therapy (for example, the length of the therapy) and what role does it play in both short and long-term patient improvement. Researchers such as Koole and Tschacher (2016) have suggested that the therapeutic alliance can be best studied by means of nonverbal patient-therapist synchrony. It is conceivable that future studies that employ the methodology of human ethology (e.g., Hale et al., 1997) and nonverbal patient-therapist synchrony (e.g., Cohen et al., 2021), combined with multilevel HMM algorithm behavioral analyses, may lead to better insights into the relative importance of interpersonal interactions in psychotherapy, both in person and online.

A limitation of this study that should be pointed out is that due to our relatively small sample size we could not fit multilevel HMMs with more than three nonverbal behavior states, as indicated by the obtained model convergence metrics. A recent large scale simulation study showed that with (multivariate) categorical data and complex state composition (states that show a large degree of overlap and noise in the emission distribution) a minimum of 800 observations for four dependent variables on five individuals is required - which we exceed - when fitting a three-state model (Mildiner Moraga and Aarts, 2023). However, more data is needed when fitting a model composed of a higher number of hidden states, but benchmarks on minimal required sample sizes for these scenarios are currently still lacking in literature. In addition, in this proof-of-concept study, the multilevel HMM predicting depression improvement was not controlled for the potential influence of treating therapist or patient background covariates for the sake of conciseness and simplicity, and sample size limitations. Future studies aiming to explain observed heterogeneity in multilevel HMMs by predictors such as depression improvement are advised to accommodate possible effects of extraneous variables.

In summary, we believe the findings of this proof-of-concept study of nonverbal behavior in psychotherapy, which takes its inspiration from patient-therapist synchrony studies, are much fuller and nuanced than the one-dimensional cluster approach of previous human ethological studies. We believe that the multilevel HMM algorithm will strongly contribute to the continuing discovery of patient-therapist interpersonal interaction patterns that occur in therapy. These discoveries will help to guide potential adjustments to improve the therapy, and, ultimately, to contribute to patient depression symptom improvement.

Ethical standards

The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

CRediT authorship contribution statement

William W. Hale: Conceptualization, Funding acquisition, Writing – original draft, Writing – review & editing. **Emmeke Aarts:** Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

Both authors declare that they have no conflicts of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jadr.2023.100635.

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