



Calming the Mind: Spiking Neural Networks Reveal How Havening Touch to Reduce Persistent Distress Attenuates Left Temporal Electroencephalographic Connectivity

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Abstract. Havening is an innovative psychosensory intervention that uses touch to facilitate recovery from psychological trauma. Whilst Havening is commonly employed by practitioners worldwide, only a few empirical studies have investigated efficacy or mechanism. The current study applies explainable machine learning methods to brain data to better understand mechanisms underpinning the role of Havening touch in recovery from trauma. Participants ($n = 27$) who had experienced an event that caused persistent psychological distress underwent a single Havening session that either did (H+, $n = 15$) or did not (H–, $n = 12$) include a touch component. Resting-state electroencephalography (EEG) data was recorded before (T1) and after (T2) the intervention. Two H+ subgroups were formed based on self-reported-response to the intervention. A recently developed brain-inspired machine-learning model, the Spiking Neural Network (SNN) was applied to compare groups and time points on functional connectivity. Results suggest region-specific reductions (left temporal, left frontocentral) in connection weights following Havening touch. Differentiation of H+ and H– was more accurate at T2 than T1; and in H+, brain states at T2 were more accurately classified than at T1, particularly for participants who had a greater response to the intervention. Findings support the SNN in distinguishing brain states associated with response to Havening. Reduction in left temporal connectivity may reflect downregulation of anterior temporal lobe activity, downstream from the amygdala.

AQ1

AQ2

Keywords: Spiking Neural Networks · Machine Learning · Electroencephalography · Connectivity · Havening · Therapy · Touch · Distress · Trauma

1 Background and Introduction

Nurturing affiliative touch is fundamental for healthy psychological, physical, and relational development across the lifespan (Cekaite and Goodwin 2021; Jablonski 2021; Jakubiak and Feeney 2017). It has been associated with a sense of esteem, value and group cohesion, mitigating negative experiences of loneliness and fostering prosocial behaviour (Heatley Tejada et al. 2020). Nurturing touch enhances both psychological (Müller-Oerlinghausen and Eggart 2021) and physical healing (e.g., wound repair; de Souza et al. 2017), and is involved in the development and maintenance of several biological systems, including the oxytocin and stress response systems, immune function, and brain chemistry (Jablonski 2021).

Havening is a form of psychosensory therapy that harnesses the power of touch to reduce emotional distress and promote wellbeing (Ruden 2018). Havening is used globally as a therapeutic intervention to facilitate recovery from psychological trauma. However, only a few studies have empirically evaluated its therapeutic efficacy or implicated mechanism (Thandi et al. 2015; Cizmiciu et al. 2018; Hodgson et al. 2020; Sumich et al. 2022). Recently, for the first time, Sumich et al (2022) empirically demonstrated that the use of Havening touch in a single 20-min therapeutic session was associated with a more rapid and extensive reduction in distress, and that this was paralleled by a reduction in electroencephalographic (EEG) gamma activity (20–50 Hz). This is in line with the idea that Havening helps to downregulate brain regions implicated in the experience of negative emotions (e.g., fear, anxiety, anger), and is relevant to psychopathologies associated with limbic hyperactivity.

Resting-state functional hyperconnectivity, particularly for temporal regions and those involved in the dorsal and ventral (salience) attention networks, is reported in psychopathologies associated with upregulated limbic activity (e.g., schizophrenia Sakakibara et al. 2024; post-traumatic stress disorders; PTSD Li et al. 2022) and in individuals at risk of developing psychosis (Yoon et al. 2015). This may reflect a state of hyperarousal/vigilance, particularly under conditions of threat (Li et al. 2022; Etkin et al. 2019). Evidence-based interventions that help regulate limbic hyperconnectivity in the context of trauma are needed.

Machine learning techniques are increasingly applied to brain data. A challenge here is in integrating complex, dynamic patterns seen in spatial and temporal data, such as comprises EEG. Often, spatial and temporal information is analysed separately rather than within a unified computational model. The current research applies a computational approach based on spiking neural networks (SNNs), a promising advancement in artificial neural networks (Kasabov 2014). SNNs offer a neurobiologically plausible architecture that integrates both spatial and temporal aspects of data into a single model.

As an explainable method, applicable to spatio-temporal data, SNN have been useful in understanding connectivity and classifying brain states. For example, SNN methods

have been used to generate connection weights, and accurately classify brain states in relation to depressive symptoms and responsiveness to psychological interventions (e.g., mindfulness; Doborjeh et al. 2019; 2020). Other work highlights the application of SNN to cross-sectional electroencephalography (EEG) data to differentiate healthy ageing from early stages of dementia (Crook-Rumsey et al. 2023), and to longitudinal measures of brain structure to accurately predict the onset of dementia 2–4 years in advance (Doborjeh et al. 2021).

The current study applies SNN methods to EEG data recorded immediately prior to, and following, a single Havening session. SNN techniques are used to generate connection weights and classify brain states as a function of *Time*, experimental *Condition* and *Response* to intervention. We predicted greater downregulation of temporal activity following Havening Touch, reflected in a reduction of connection weights.

2 Methods

The study was conducted at Nottingham-Trent University (NTU) and was given a positive opinion by the NTU non-invasive ethics committee. Participants ($n = 24$, 21 female and 3 male, $n = 21$ white, age range 18–47 years mean = 25.21, SD = 7.81), were predominantly staff and students, who had experienced a moderately distressing event (self-rated Subjective units of distress = 5–8 on 0–10 scale) that had persisted for at least a month. Participants were pseudo-randomised into full intervention that included a touch component (H+; $n = 15$) or a partial intervention, where no Havening touch components were applied (H-; $n = 12$). Figure 1 shows study protocol.

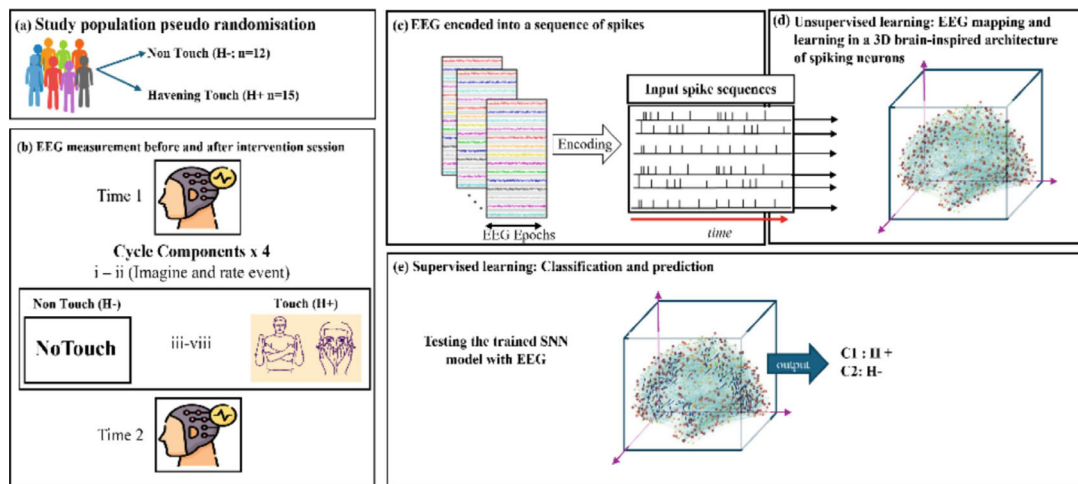


Fig. 1. Electroencephalogram (EEG) data collection and computational spiking neural network modelling. (a) Pseudorandomization into non-touch (H-) and touch (H+) groups; (b) EEG data collection before and after the training; (c) Illustration of the designed methodology, containing EEG encoding into spike sequences; (d) Computational modelling of data into a 3D space of artificial neurons; (e) Pattern classification and prediction.

In both conditions, the protocol comprised a series of components that required participants to: i) close their eyes for 15 s and think about the distressing event/memory;

ii) rate their subjective feelings of distress in relation to the event/memory; iii) name animals beginning with specific letters; iv) imagine photos of happy images; v) hum a childhood song; vi) count their steps as they imagine walking through a beautiful landscape; vii) count the racquet strokes as they imagine watching a tennis match; and viii). State the months of the year in backwards order from December to January. There were 4 cycles of these 8 components in an intervention session. During the H+ condition only, the therapist incorporated Havening Touch during components iii–viii. SUDs were assessed at baseline and as component ii in each of the repeated cycles.

Resting-state EEG (64 channels, Biosemi; sampling rate = 2048 Hz) was recorded for two minutes (eyes closed) prior to (T1) and following (T2) the therapeutic session (which lasted approximately 20 min). Signal processing was performed using Curry 7.12 software (with bug fixes). For further details on Havening and EEG protocols see Sumich et al. (2022). Following cleaning EEG data were downsampled to 256 Hz.

2.1 EEG Modelling and Analysis Using SNN Architecture

NeuCube (Kasabov 2014) was used to apply SNN to EEG data to generate connection weights and classify brain states as a function of *Time* (T1, T2), *Condition* (H–, H+) and *Response* to intervention (H+R–, H+R+). The criterion for response was change in Subject Units of distress (SUDs) greater than the mean change of 3 for the H+ group. In the H+ group, 8 participants were responders (change in SUD mean = 4.75). Seven participants were nonresponders (change in SUD < 3; change in SUD mean = 1.38). The EEG data was pre-processed and encoded into spike trains, retaining only significant changes in activity, which were then trained using the unsupervised learning algorithm which learns from the spatiotemporal relationships from input spikes, Spike Time-Dependent Plasticity, in NeuCube software (Kasabov 2014). Talairach atlas-based 3-dimensional space of spiking artificial neurons was constructed using NeuCube to create a brain template. SNN models were trained on EEG data as a function of *Time*, *Condition* and *Response*. Traditional statistical analysis, Analysis of Variance (ANOVA), tested for the effects of *Time* and *Condition* on connection weights. An output layer classifier was trained in a supervised mode to learn the association between the trained SNN connectivity and the class label information. The dynamic evolving Spiking Neural Network (deSNN) classifier was used to perform the classification task to compare classes based on *Time* for each *Condition*, and classes based on *Condition* for each timepoint. Similar analysis was performed comparing Responders (H+R+) to Nonresponders (H+R–).

3 Results

3.1 Data Analysis

The research outcomes are organised in a three-phase analysis as follows:

- (1) Pattern Visualization: EEG data were modelled using the SNN architecture and are present as functional connection weights, as a function of Condition, Time and Response (see Fig. 2.).

- (2) Inferential Statistics were used to test differences in connection weights as a function Condition and Time.
- (3) Pattern classification: functional connection weight maps were used to classify brain states as a function of Condition, Time and Response.

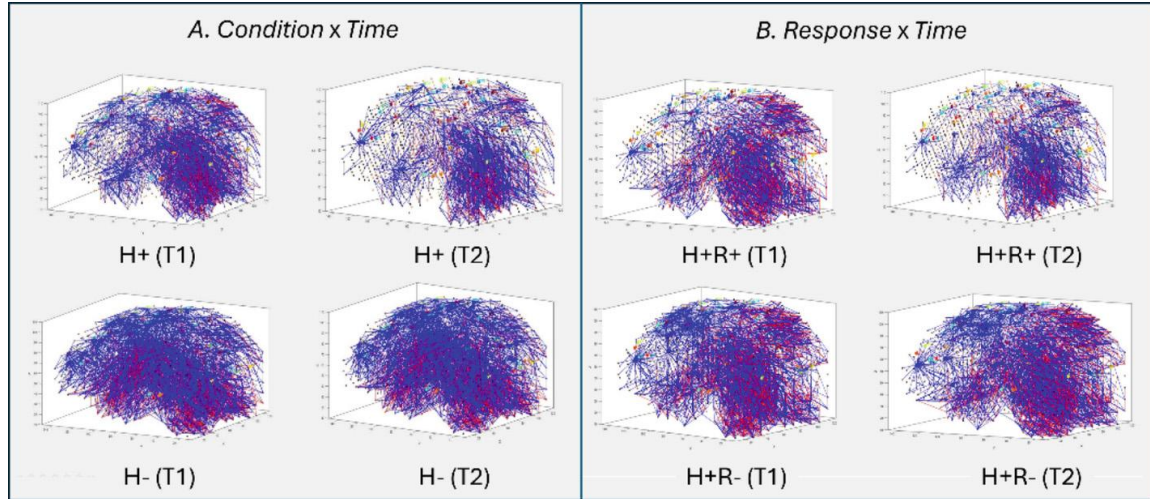


Fig. 2. SNN connectivity trained on EEG samples, as a function of *Condition* and *Time*.

3.2 Pattern Visualization: EEG Data Modelling Using SNN

Figure 1 shows spatio-temporal connections in the SNN models as a function of *Time* (T1, T2), *Condition* (H−, H+) and *Response* (H+R+, H+R−). Grand average connection weights at T1 were: H− = 1.53, H+ = 1.49, H+ R− = 1.43, H+R+ = 1.54; and at T2 were H− = 1.52, H+ = 1.45, H+R− = 1.42, H+R+ = 1.49. In panel A, a reduction in connection weights is apparent over the temporal cortex in H+ at T2, whilst little change is seen for H−. Similarly, responders show greater reduction in temporal cortex connectivity than nonresponders. In order to perform inferential statistics, connection weight data were grouped across five regions for each hemisphere: frontal (Fp1/2, AF7/8, AF3/4, F1/2, F3/4, F5/6), frontocentral (FC5/6, FC3/4, FC1/2, C1/2, C3/4, C5/6), temporal (F7/8, FT7/8, T7/8, TP7/8), centroparietal (CP7/6, CP3/4, CP1/2, P1/2, P3/4, P5/6, P7/8, P9/10), and occipitoparietal (PO7/8, PO3/4, O1/2; please see Fig. 3.).

3.3 Inferential Statistics

Repeated-measures ANOVA tested for differences in connection weights as a function of *Hemisphere* (left, right), *Site* (frontal, frontocentral, temporal, centroparietal and occipitoparietal), *Time* (T1, T2) and *Condition* (H+, H−).

There was a significant effect of *Hemisphere* [$F = 471.57$, $df = 1, 23$, $p < 0.001$, $\eta^2 = 0.95$; $R > L$] and *Site* [$F = 107.08$, $df = 1.75, 40.18$, $p < 0.001$, $\eta^2 = 0.82$; Frontocentral < Frontal < Temporal = Centroparietal < Occipitoparietal], as well as a *Hemisphere*Site* interaction ($F = 30.70$, $df = 2.06, 47.38$, $p < 0.001$, $\eta^2 = 0.57$). The

*Hemisphere*Site* interaction was due to higher scores at centroparietal than temporal sites in the left ($p < .001$), but not right ($p = .176$) hemisphere. Significant *Hemisphere* effects were seen as all sites: temporal [$F = 202.12$, $df = 1, 23$, $p < 0.001$, $\eta^2 = 0.90$], frontocentral ($F = 216.40$, $df = 1, 23$, $p < 0.001$, $\eta^2 = 0.90$), frontal [$F = 304.49$, $df = 1, 23$, $p < 0.001$, $\eta^2 = 0.93$], centroparietal [$F = 131.88$, $df = 1, 23$, $p < 0.001$, $\eta^2 = 0.85$], and occipitoparietal [$F = 7.14$, $df = 1, 23$, $p = 0.014$, $\eta^2 = 0.24$].

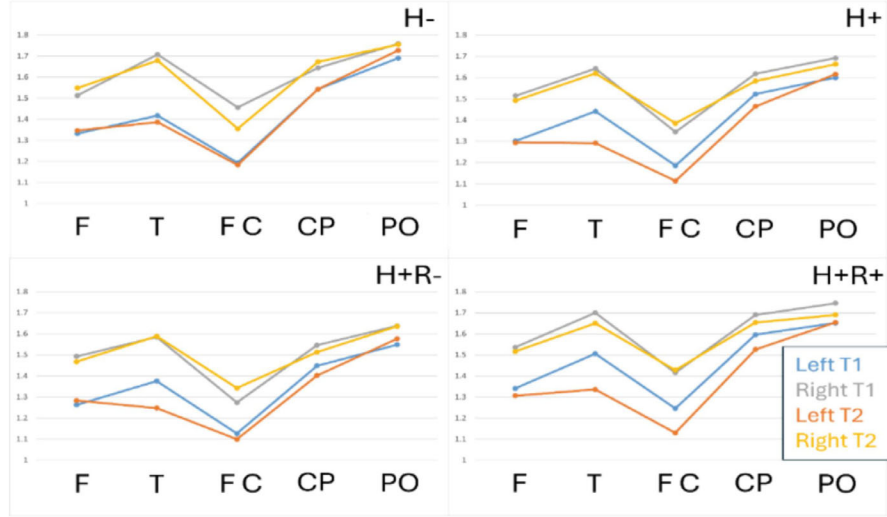


Fig. 3. Mean SNN connection weights as a function of Condition, Time Point and Scalp region (F = Frontal, T = Temporal, FC = Frontocentral, CP = Centroparietal, PO Occipitoparietal).

There were also significant *Time*Site* ($F = 3.65$, $df = 2.69, 61.77$, $p = 0.021$, $\eta^2 = 0.137$), *Hemisphere*Time*Site* ($F = 3.66$, $df = 2.89, 66.56$, $p = 0.018$, $\eta^2 = 0.14$) and *Hemisphere*Time*Site*Condition* ($F = 6.43$, $df = 2.894$, $p < 0.001$, $\eta^2 = 0.22$) interactions. These were partially driven by higher values at T1 than T2 at left temporal sites in H+, but not H- (significant *Hemisphere*Time*Condition* interaction at temporal sites; $F = 4.96$, $df = 1, 23$, $p = .036$, $\eta^2 = 0.17$). At temporal sites in H+, there was a significant *Time*Hemisphere* interaction ($F = 12.57$, $df = 1, 13$, $p = 0.004$, $\eta^2 = 0.49$), due to a significant effect of *Time* in the left hemisphere ($F = 13.28$, $df = 1, 13$, $p = 0.003$, $\eta^2 = 0.51$), but not in the right hemisphere ($F = .348$, $df = 1, 13$, $p = 0.565$, $\eta^2 = 0.026$). There was no effect of *Time* at either temporal sites in H-. In addition, there was a significant *Hemisphere*Time*Condition* interaction at frontocentral sites ($F = 33.19$, $df = 1, 23$, $p < .001$, $\eta^2 = 0.59$). This was partly due to an effect of *Time* in the left hemisphere in H+ (T1 > T2; $F = 6.92$, $df = 1, 13$, $p = .021$, $\eta^2 = 0.35$), but not in H- ($F = .073$, $df = 1, 13$, $p = .79$, $\eta^2 = 0.007$). There was no effect of *Time* in either H+ or H- at right frontocentral sites.

3.4 Pattern Classification of EEG Data Measuring Brain States Before and After Havening in the Designed SNN Model

Table 1 shows results of output classifiers trained to classify A) T1 vs T2 in H+; B) T1 vs T2 in H-; C) H- vs H+ at T1; D) H- vs H+ at T2; E) H+R- vs H+R+ and T1; and

Table 1. Confusion tables showing classification with per class and total accuracy.

	Predicted		Accuracy	
	H+(T1)	H+(T2)	Per Class	Total
A. Real				
H+(T1) (n = 12)	4	2	71.43	76.63
H+(T2) (n = 12)	1	5	81.82	
	H– (T1)	H– (T2)		
B. Real				
H– (T1) (n = 11)	4	2	71.43	71.43
H– (T2) (n = 11)	2	4	71.43	
	H– (T1)	H+ (T1)		
C. Real				
H– (T1) (n = 6)	3	3	0.45	0.56
H+ (T1) (n = 6)	2	4	0.67	
	H– (T2)	H+ (T2)		
D. Real				
H– (T2) (n = 6)	4	2	0.67	0.72
H+ (T2) (n = 6)	1	5	0.77	
	H+R+ (T1)	H+R+ (T2)		
E. Real				
H+R+ (T1) (n = 7)	2	5	0.39	0.63
H+R+ (T2) (n = 7)	1	6	0.87	
	H+ R– (T1)	H+R– (T2)		
F. Real				
H+R– (T1) (n = 7)	4	3	0.57	0.57
H+R– (T2) (n = 7)	3	4	0.57	

F) H+R– vs H+R+ at T2. We extracted 30 s (10 s from beginning, middle and end) of data from each participant at each time point (7680 samples 30×256 hz). Classification was based on random 50/50 training/testing. H+ showed higher accuracy at T2 than T1. However, T1 and T2 accuracy for H– were identical. Similar findings were seen for responders vs nonresponders. At T1, classification of H+ vs H– was low (56%), whilst this increased for T2 (72%).

4 Discussion

The current study is the first to investigate change in EEG connectivity following a single Havening therapy session for a persistently distressing event. Resting-state EEG data were collected prior to and following the intervention in two conditions: those who received Havening touch and those who did not. Analysis methods benefitted from the synthesis of innovative, brain-inspired, explainable machine learning – spiking neural networks – and inferential statistical methods. In line with the hypotheses, people who received the Havening touch showed significant reduction in connection weights over left temporal regions, compared to those in the nontouch condition. However, unexpectedly, significant reductions in connection weights with Havening touch extended to left frontocentral regions. Classification accuracy was higher for T2 than T1 in the touch condition only. Moreover, accuracy in differentiating touch vs nontouch was little over chance at T1, but increased following the intervention, supporting a divergence of brain states between conditions.

The development of the Havening technique is based on theory that it “calms” limbic hyperactivity. By using innovative interpretable machine learning methods to examine connection weights across brain regions, the current study is the first to lend empirical support to this theory. The reduction in connection weights parallels greater reduction in SUDs with Havening touch previously reported in this cohort (Sumich et al. 2022).

The amygdala, situated in the medial temporal cortex, is central to the experience of emotions that carry negative valence (e.g., anger, fear, sadness), and has strong connections with anterior lateral temporal and frontal regions. Reduction in amygdala activity has been implicated in the therapeutic effect of Havening touch, and oxytocin administration reduces amygdaloid gamma activity in rodents (Sobota et al. 2015). Whilst scalp-recorded EEG activity is unlikely to directly reflect amygdala activity, it may well represent downstream temporal and frontal regions. Future approaches should therefore further investigate the current findings using other neuroimaging methods with greater precision in assessing amygdala function, such as functional magnetic resonance imaging.

Havening is commonly used to treat psychological trauma-based problems. Hyperconnectivity has been reported in PTSD using several measures of brain function. For example, using magnetoencephalography, Dunkley et al. (2018) show hypersynchrony in thalamus, ventromedial prefrontal cortex, cingulum gyri, inferior temporal and parietal regions, under conditions of threat. However, heterogeneity in connectivity has been reported in PTSD, and hyperconnectivity may be more evident in specific illness subtypes and under threatening conditions (Etkin et al. 2019). For example, Li et al. (2022) applied unsupervised sparse K-means clustering to EEG data to identify two subtypes of patients with PTSD, one of which was associated with hyperconnectivity, particularly in ventral and dorsal attention networks.

Lower connectivity in PTSD predicts poorer treatment response to prolonged exposure psychotherapy in PTSD (Etkin et al. 2019). In contrast, however, based on the connection weights in the current study, poorer treatment responders to Havening touch appeared to have higher connection weights than responders. However, given small sample size this was not tested using inferential statistics. Nevertheless, comparison across studies raises the possibility of distinct mechanisms of action for Havening compared

to prolonged exposure psychotherapy. Also, mindfulness training (which builds awareness of experience) in people with raised depression symptoms was associated with an increase in connection weights across several regions (Doborjeh et al. 2019). Thus, future studies should use SNN to directly compare brain states that track and predict response to distinct interventions. Implications for such work would be in supporting synergistic effects of multi-modal interventions and more personalized therapies.

Whilst Li et al. (2022) highlight importance of theta, alpha and beta frequency bands, a magnetoencephalography study used graph analysis to associate left hippocampal hyperconnectivity in the high-gamma band with severity of PTSD (Dunkley et al. 2014). Reduction in EEG gamma activity has been reported following Havening (Sumich et al. 2021). Thus, future studies should investigate connection weights for specific frequency bands. Such work would also provide further understanding of the underpinning mechanisms and functional significance of the reduction in connection weights following Havening touch.

IAQ3

Prolonged psychological distress (trauma) is a risk factor for several psychopathologies, such as psychosis and major depressive disorders. Hyperconnectivity has been observed in individuals at ultra-high risk for psychosis (UHR), in first episode psychosis (FE), and schizophrenia (Yoon et al. 2015; Sakakibara et al. 2024). In UHR and FE, increased connectivity was noted between left planum temporal and bilateral dorsolateral prefrontal cortex (Yoon et al. 2015). Such findings mirror the topography of the current results that show the effects of Havening touch at left temporal and frontocentral regions. Thus, Havening should be investigated as an early intervention to reduce risk of illness progression in UHR and FE. In comparison, however, hyperactivity of the right temporal cortex, along with bilateral orbitofrontal cortex is reported in schizophrenia using whole-head near-infrared spectroscopy (Sakakibara et al. 2024). Higher left temporal connection weights were observed in relation to cognitive depression (Doborjeh et al., in press). However, comparison of connection weight maps to current findings suggests differences in topography (more anterior in cognitive depression), suggesting distinct underpinning mechanisms.

SNN methods are emerging as an innovative, interpretable tool for understanding and classifying brain states and have been applied to various types of spatio-temporal brain data with relatively good accuracy compared to some other methods. SNN did not differentiate groups at baseline. This makes sense as high accuracy prior to the interventions would not be expected for the H+ vs H− comparison if the groups were drawn from a similar cohort. However, higher accuracy following the distinct interventions supports the efficacy of Havening Touch in affecting brain states. Future studies should consider using SNN to investigate other types of intervention for trauma and in general for psychopathology. Direct comparison should be made with other interpretable machine learning classification methods.

Whilst the relatively small, nonclinical and predominantly female sample used in the current study restricts generalizability, as noted above, findings are in line with several clinical studies of PTSD. Nevertheless, future work should apply similar methods to clinical cohorts. Larger studies will enable investigation of heterogeneous groups observed in other studies (Etkin et al. 2019), and inferential evaluation of predictors of

response. Future work might also compare other types of touch, including other types of therapeutic touch in order to test unique properties of Havening touch.

4.1 Summary and Conclusion

The synthesis of explainable SNN, visualization and inferential statistical methods currently support the importance of the touch component of Havening in lowering activity over left temporal and frontocentral regions. Such findings contribute to understanding how Havening helps with several trauma-based psychopathologies, by lowering hyper-connectivity. Moreover, the utility of using SNN to study spatio-temporal brain dated is supported.

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Disclosure of Interests. Kasabov, N. has developed NeuCube software. Burgess T. and French J. are wellbeing practitioners who employ Havening methods. The authors have no other competing interests to declare that are relevant to the content of this article.

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