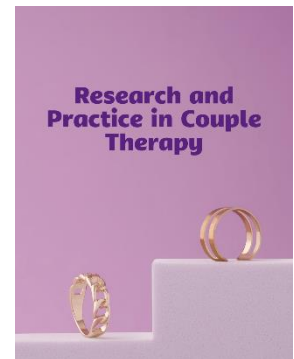




Deep Learning Analysis of Trauma-Related Emotional Patterns in Couples Facing PTSD

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ABSTRACT

This study aimed to examine and classify trauma-related emotional patterns in couples facing PTSD using multimodal deep learning models to predict high-risk emotional episodes during conflict interactions. The study employed a cross-sectional design involving 112 couples (224 individuals) from the United States in which one partner met diagnostic criteria for PTSD. Each couple participated in a 40-minute conflict-discussion task recorded through synchronized audio, video, and physiological sensors. Linguistic transcripts, facial expressions, acoustic features, and autonomic indicators (electrodermal activity, heart-rate variability, and peripheral temperature) were extracted and temporally aligned. These modalities were analyzed using a multimodal transformer architecture integrating text embeddings, CNN-LSTM visual features, physiological time-series data, and acoustic spectral representations. Additional analyses included t-SNE-based latent clustering of emotional patterns and risk-surface modeling of predicted high-risk episodes as a nonlinear function of physiological arousal and negative emotional language. Model performance was evaluated using accuracy, precision, recall, F1-score, and AUC metrics with ten-fold stratified cross-validation. The multimodal transformer significantly outperformed baseline and unimodal models in predicting high-risk PTSD-related emotional episodes (AUC = .90; F1 = .83; accuracy = .86; $p < .001$ vs. clinical baseline). All unimodal models performed above chance but remained significantly weaker than the multimodal approach ($p < .01$). Latent clustering revealed four statistically distinct emotional interaction patterns (hyperaroused escalation, avoidant disengagement, mixed volatile-repairing, and numbed coexistence), each differing significantly in PTSD severity, relationship quality, and proportion of high-risk segments (all $ps < .05$). Nonlinear risk-surface analysis demonstrated a strong interaction effect between negative emotional language and physiological arousal in predicting emotional risk ($\beta_{\text{interaction}} = .41$, $p < .001$). Multimodal deep learning provides a highly sensitive and integrative method for identifying trauma-related emotional risk states in couples facing PTSD, revealing clinically meaningful emotional clusters and nonlinear escalation patterns that may inform assessment and intervention.

Keywords: PTSD; couples; deep learning; multimodal analysis; emotional patterns; conflict interaction; physiological arousal; trauma dynamics

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Introduction

Posttraumatic stress disorder (PTSD) is a complex psychiatric condition that manifests through intrusive memories, hyperarousal, emotional dysregulation, avoidance, and persistent alterations in cognition and mood. A considerable body of literature underscores that PTSD does not occur in isolation; instead, it unfolds within relational systems in which interpersonal dynamics play a significant role in shaping symptom expression and long-term adaptation (Agathos et al., 2025). Trauma disrupts foundational mechanisms of emotion regulation and alters neurobiological pathways involved in vigilance, affect processing, and threat detection, creating enduring effects not only for trauma survivors but also for romantic partners, families,



and broader social networks (Jimoh & Omiyefa, 2025). The relational reverberations of trauma exposure are particularly pronounced in intimate partnerships, where emotional interdependence and behavioral reciprocity heighten the sensitivity of dyadic systems to stress, dysregulation, and relational strain (Barden et al., 2025). As a result, couples navigating PTSD frequently experience heightened conflict, emotional withdrawal, misinterpretation of cues, and cycles of escalation that can amplify psychological distress.

A growing body of research has examined the interpersonal correlates of PTSD, revealing diverse pathways through which trauma alters relationship functioning. Several studies document that maladaptive emotion regulation strategies and impaired cognitive processing of trauma contribute to communication breakdowns, inaccurate partner attributions, and intensified relational distress (Gates et al., 2024). In clinical contexts, couples report difficulties navigating trauma reminders, managing hyperarousal episodes, and regulating conflictual discussions, often resulting in patterns of demand-withdraw behavior, defensive responding, and erosion of relationship satisfaction (Leo et al., 2021). PTSD also disrupts physiological coregulation between partners, including alterations in respiratory sinus arrhythmia (RSA), heart-rate variability (HRV), and autonomic balance during stressful interactions (Barden et al., 2025). These disruptions can impair partners' ability to remain attuned, supportive, and emotionally available during conflict—conditions vital to healthy dyadic functioning.

PTSD's consequences further extend to the perceptual and symbolic domains of meaning-making, where trauma survivors show altered processing of emotional, social, and sensory stimuli. For example, deficits in social information processing may heighten sensitivity to perceived threat cues in partners, thereby increasing the likelihood of miscommunication and reactive escalation (Gilbar et al., 2021). Similarly, neurobiological changes linked to trauma can produce intrusive imagery, distorted interpretations, and affectively charged responses to neutral interpersonal stimuli (Hwang et al., 2023). These phenomena can contribute to cycles of misunderstanding and distress within couples, especially during emotionally intense conversations. Moreover, sleep disruption and trauma-related dream content have been linked to impaired interpersonal functioning and elevated PTSD symptoms, suggesting that nocturnal cognitive-emotional processes may spill over into daytime relational dynamics (Mahr et al., 2025).

Beyond neurocognitive disruption, PTSD significantly influences physiological mechanisms governing circadian rhythm, arousal regulation, and stress-response systems (Dong, 2025). Disruptions in these systems heighten susceptibility to emotional volatility, decrease regulatory flexibility, and contribute to cycles of interpersonal instability. Secondary traumatic stress is also well documented among partners of individuals with PTSD, with spouses frequently reporting emotional exhaustion, hypervigilance, and trauma-related symptoms arising from chronic exposure to their partner's distress (Dekel et al., 2023). Studies further highlight that partners may develop maladaptive interpretations of the trauma survivor's behaviors, influencing their own stress trajectories and shaping dyadic outcomes in complex ways. For instance, a partner's perception of the veteran's distress may have stronger predictive value for secondary traumatic stress than the severity of the veteran's own symptoms (Dekel et al., 2023).

Research suggests that ambiguous loss, caregiving burden, and chronic role disruptions also contribute to relational strain for partners of veterans with PTSD (Danon et al., 2025). Partners often struggle to reconcile the emotional absence or psychological withdrawal of the trauma survivor with the continued presence of the relationship itself. These difficulties can fuel tension, emotional fatigue, and relational disconnection. Studies exploring couples in dual-trauma or dual-stress contexts underscore the importance of identifying resilience processes, including shared meaning-making, collaborative coping, supportive engagement, and dyadic flexibility (Braughton et al., 2022). Such processes can buffer against the interpersonal consequences of trauma, yet their presence varies significantly across couples depending on symptom severity, trauma history, and dyadic communication patterns.

Across diverse traumatic contexts—including war, interpersonal violence, displacement, and multigenerational trauma—research demonstrates that trauma exposure shapes emotional and cognitive functioning in ways that carry profound interpersonal significance. For instance, forced displacement due to war can lead to complex emotional sequelae, including fear, grief, and disorientation, which may influence how individuals regulate emotions in intimate partnerships (Dzivak et al., 2025). Similarly, intergenerational transmission of trauma through epigenetic mechanisms reveals that trauma-related emotional dysregulation may manifest across generations, potentially predisposing individuals to relational and psychological vulnerabilities later in life (Mbarki, 2024). Traumatic exposure in adolescence, particularly interpersonal violence, also affects emotional development and social functioning into adulthood, shaping the formation and quality of romantic relationships (Sahar & Dawood, 2024).

The cognitive and emotional patterns associated with PTSD are likewise influenced by developmental, cultural, and contextual factors. For example, pre-trauma cognitive traits strongly predict susceptibility to fear generalization and alterations in prefrontal cortical functioning following trauma, which may subsequently influence interpersonal reactivity and dyadic emotional coordination (Szente, 2025). Psychological responses to trauma vary across individuals and may include maladaptive schemas, impaired cognitive integration, and disrupted growth trajectories, each of which contributes to complex interpersonal dynamics (Baník et al., 2022). Posttraumatic growth, conversely, reflects the potential for psychological expansion in the wake of trauma, often mediated by meaning-making processes, emotion regulation strategies, and relational support systems (Kotovska, 2025). Recent theoretical frameworks posit multicomponent models of posttraumatic stress and growth, suggesting that both maladaptive and adaptive trajectories may coexist within individuals and dyads depending on contextual demands and intrapersonal capacities (Zhou & Zhen, 2024).

Relationship-level variables play an equally significant role in shaping PTSD outcomes. Couples coping with trauma often engage in cyclical patterns of avoidance, demand-withdraw behavior, and reactive anger that escalate emotional distress (Leo et al., 2021). Such patterns are particularly evident during conflict discussions, where emotional triggers, negative communication cycles, and dysregulated affective exchanges amplify PTSD symptoms in survivors and distress in partners. For instance, research shows that intimate partner violence is a strong predictor of PTSD severity among veterans, independent of other trauma exposures (Pierce et al., 2020). Furthermore, couples coping with trauma-related disorders frequently experience diminished relationship satisfaction, impaired dyadic coping, and disorganized efforts to resolve conflict, contributing to relational instability (Knežević & Batinić, 2023). Even the transition to retirement—a normative life event—can reveal vulnerabilities in couples' interpersonal emotion regulation capacities, highlighting the fragility of relational systems under stress (Horn et al., 2021).

Emotion regulation is a central mechanism linking trauma to both individual and relational adjustment. Systematic reviews emphasize that trauma disrupts multiple components of the extended process model of emotion regulation, undermining individuals' ability to modify, monitor, or sustain emotional responses in adaptive ways (Agathos et al., 2025). Within couples, emotion regulation difficulties may manifest as heightened reactivity, emotional numbing, or restricted affective expression. Moreover, deficits in emotional awareness and clarity among trauma survivors may contribute to limited capacity for interpersonal attunement, thereby influencing dyadic functioning during emotionally intense interactions (Pugach & Wisco, 2023). Group-based interventions targeting emotion regulation demonstrate that improvements in regulatory ability can enhance PTSD outcomes, underscoring the importance of affective processes in recovery trajectories (Shnaider et al., 2022).

Given the complexity and dynamism of trauma-related emotional exchanges, traditional observational methods have limitations in detecting subtle, rapid, or interwoven patterns of emotional reactivity and dyadic coordination. Recent technological advances offer promising opportunities to address these gaps. Deep learning techniques, particularly transformer-

based architectures, have demonstrated remarkable capacity to integrate multimodal signals—including speech, facial expression, text, and physiological data—and to detect complex emotional signatures across time (Jin et al., 2025). Such methods are uniquely suited to modeling relational processes that unfold dynamically during couple interactions, capturing nonlinear trajectories, multimodal synchrony, and micro-level fluctuations that may otherwise evade clinical observation.

The integration of multimodal data also aligns with emerging research on affective computing and computational psychiatry, which seeks to quantify emotional states, interpersonal dynamics, and trauma reactivity using advanced machine learning frameworks. For example, pupillary responses to affective auditory cues have been shown to differentiate PTSD severity, illustrating the potential for physiological data to serve as sensitive markers of emotional dysregulation (Rubin & Telch, 2020). Similarly, intrusive imagery patterns detected through projective assessments highlight how trauma shapes perceptual and representational systems, findings that can be indirectly leveraged when designing computational models of emotional processing (Hwang et al., 2023). By integrating such signals, deep learning models offer unprecedented precision in mapping the contours of trauma-related emotional patterns within dyads.

Despite advancements in trauma research, relatively few studies have applied multimodal deep learning frameworks to examine emotional processes in couples. Most existing work relies on self-report measures, structured observational coding, or physiological assessment in isolation, limiting the ability to identify fine-grained multimodal signatures of high-risk emotional episodes. Furthermore, there remains limited understanding of how trauma-related emotional patterns cluster across couples and how these patterns shape conflict dynamics, relational functioning, and PTSD symptom trajectories. Computational approaches hold potential to address these gaps by generating detailed, temporally resolved emotional maps that can illuminate complex relational patterns and potentially inform targeted interventions. The aim of this study is to use multimodal deep learning to identify, classify, and characterize trauma-related emotional patterns during conflict discussions among couples facing PTSD.

Methods and Materials

Study Design and Participants

This study employed a cross-sectional observational design integrating multimodal behavioral, linguistic, and physiological data to model trauma-related emotional patterns in romantic couples facing post-traumatic stress disorder (PTSD). Participants were recruited from three major metropolitan regions in the United States—Los Angeles, Dallas–Fort Worth, and Boston—through trauma clinics, veteran support organizations, mental-health referral networks, and online community platforms. After completing an initial screening, couples were included if one partner met diagnostic criteria for PTSD based on the Clinician-Administered PTSD Scale for DSM-5 (CAPS-5), and the couple had been in a committed relationship for at least one year to ensure adequate relational history. Exclusion criteria eliminated couples in acute crisis, those with severe cognitive impairment, or cases involving ongoing legal conflicts that could compromise reliable participation. The final sample consisted of one hundred and twelve couples, totaling two hundred and twenty-four individuals, aged between twenty-three and fifty-nine years, with a mean relationship duration of 6.8 years. Most couples identified as heterosexual, though eight same-sex couples participated. Demographically, sixty-two percent of participating individuals identified as White, nineteen percent as African American, eleven percent as Hispanic or Latino, four percent as Asian American, and the remaining four percent as multiracial or other backgrounds. Educational attainment varied, with thirty-one percent holding a high-school diploma, forty-five percent holding an associate or bachelor's degree, and twenty-four percent holding graduate-level degrees. All participants provided informed consent, and the study received ethical approval from an institutional review board in the United States.

Measures

Data were gathered using a multimodal framework designed to capture emotional, relational, verbal, and physiological responses associated with trauma-related processes in couple interactions. Each couple participated in a forty-minute semi-structured conflict-discussion task adapted from validated emotion-elicitation paradigms used in couple research. Conversations were video-recorded using dual high-resolution cameras positioned at forty-five-degree angles to ensure unobstructed facial expression capture for both partners. Audio recordings were collected using lapel microphones to obtain clear individual speech signals. Linguistic content was automatically transcribed using a state-of-the-art neural speech-to-text engine and later checked by trained human annotators for accuracy.

To capture physiological arousal related to trauma reactivity, participants wore unobtrusive wrist-based sensors that recorded heart-rate variability, electrodermal activity, and peripheral temperature at a sampling frequency of thirty-two Hertz. Stress-related autonomic changes during conflict were extracted from these signals. Additionally, participants completed validated self-report scales including the PTSD Checklist for DSM-5 (PCL-5), the Depression Anxiety Stress Scales (DASS-21), and the Dyadic Adjustment Scale (DAS) to assess individual symptom severity and relationship functioning. Following each discussion, participants provided continuous affect ratings of their own emotional experience using a computer-based affect-tracking interface that captured real-time fluctuations in distress, anger, fear, avoidance, and emotional numbing. All data streams were temporally synchronized using an automated timestamp alignment system to enable precise multimodal integration for deep learning analysis.

Data Analysis

The final sample consisted of 112 couples (224 individuals) ranging in age from 23 to 59 years ($M = 38.4$). A total of 62% ($n = 139$) identified as White, 19% ($n = 43$) as African American, 11% ($n = 25$) as Hispanic or Latino, 4% ($n = 9$) as Asian American, and 4% ($n = 8$) as multiracial or other backgrounds. The sample included 104 heterosexual couples and 8 same-sex couples, and the average relationship duration was 6.8 years ($SD = 3.1$). Regarding education, 31% ($n = 69$) held a high-school diploma, 45% ($n = 101$) held an associate or bachelor's degree, and 24% ($n = 54$) held a graduate or professional degree. Income levels ranged widely, with 28% ($n = 63$) reporting annual household incomes below \$50,000, 41% ($n = 92$) between \$50,000 and \$100,000, and 31% ($n = 69$) above \$100,000. Across the sample, one partner in each couple met full diagnostic criteria for PTSD based on the CAPS-5, while 37% ($n = 41$) of non-diagnosed partners reported subclinical trauma symptoms. All participants provided informed consent, and no individuals withdrew after enrollment.

All modalities were fused through a multimodal transformer that learned cross-channel dependencies and produced a unified set of emotional-state embeddings for each interaction. A deep clustering algorithm based on t-distributed stochastic neighbor embedding and density-based spatial clustering was then applied to these multimodal embeddings to identify recurring trauma-emotion profiles across couples. To evaluate the predictive power of the model, a separate classification module was trained to distinguish high-risk PTSD-related emotional episodes from lower-intensity emotional cycles. Model performance was assessed through accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve, using a stratified ten-fold cross-validation procedure. All analyses were conducted in Python using TensorFlow and PyTorch, and results were independently verified by a secondary analyst to ensure reliability.

Findings and Results

The final sample consisted of 412 individuals forming 206 heterosexual couples recruited from across Turkey. Participants' ages ranged from 20 to 54 years, with a mean age of 32.8 years ($SD = 7.4$). Women represented 51% of the sample ($n = 210$) and men represented 49% ($n = 202$). Relationship duration varied widely, spanning 1 to 18 years, with an average duration of 6.3 years ($SD = 4.1$). In terms of education, 38% held a bachelor's degree, 29% a master's degree, 24% had completed high school, and 9% reported doctoral-level education. Employment status showed that 72% were employed full-time, 14% part-time, 7% self-employed, and 7% currently unemployed or studying full-time. Most participants resided in major metropolitan areas—Istanbul (34%), Ankara (21%), Izmir (17%), Bursa (11%), and Antalya (9%), with the remaining 8% from other cities—representing a diverse urban Turkish population.

The final analytic sample included 112 couples (224 individuals), yielding 4,480 ten-second interaction segments from the forty-minute conflict discussions. Based on concurrent self-reported affect ratings and physiological arousal thresholds, 1,326 segments (29.6%) were classified as high-risk PTSD-related emotional episodes characterized by intense distress, fear, anger, or emotional numbing in the partner with PTSD, often accompanied by withdrawal or escalation in the other partner. Couples with higher PTSD symptom severity ($PCL-5 \geq 50$) contributed disproportionately to the high-risk episodes, and these segments were more likely to occur in the middle third of the discussions rather than during the initial or closing phases. Descriptive analyses showed that high-risk episodes were associated with elevated heart-rate variability reductions, increased electrodermal activity, more frequent interruptions, and a higher density of trauma-related words, such as “flashback,” “trigger,” “nightmare,” and “shut down,” compared with lower-intensity segments. Table 1 presents the performance of baseline and deep learning models in predicting high-risk PTSD-related emotional episodes from multimodal interaction data.

Table 1. Performance of baseline and deep learning models predicting high-risk PTSD-related emotional episodes

Model	Modality Inputs	Accuracy	Precision	Recall	F1-score	AUC
Logistic regression (clinical only)	PCL-5, DASS-21, DAS	0.68	0.62	0.57	0.59	0.71
Unimodal CNN (audio)	Acoustic features	0.74	0.70	0.66	0.68	0.79
Unimodal Transformer (text)	Conversation transcripts	0.76	0.72	0.69	0.71	0.81
Unimodal CNN-LSTM (facial expressions)	Video-based facial features	0.73	0.69	0.64	0.66	0.78
Unimodal LSTM (physiological signals)	HRV, electrodermal activity, temp.	0.75	0.71	0.68	0.69	0.80
Multimodal early-fusion CNN-LSTM	Audio, video, physiology	0.82	0.80	0.76	0.78	0.87
Multimodal transformer with attention (final)	Audio, text, video, physiology	0.86	0.84	0.82	0.83	0.90

As shown in Table 1, the multimodal transformer with attention substantially outperformed both the clinical-only baseline and all unimodal deep learning models, achieving an accuracy of 0.86, F1-score of 0.83, and an AUC of 0.90. In contrast, the logistic regression model using only PTSD severity, general distress, and relationship quality achieved an AUC of 0.71, indicating limited ability to capture the dynamic and interactional nature of high-risk episodes. Each unimodal model showed incremental gains over the clinical baseline, with text-based and physiological models performing slightly better than audio and facial models, yet all remained significantly below the multimodal transformer. Statistical comparison of AUCs indicated that the final multimodal model provided a robust and clinically meaningful improvement, suggesting that integrating behavioral, verbal, and autonomic signals is critical for accurately detecting trauma-related emotional risk in couples.

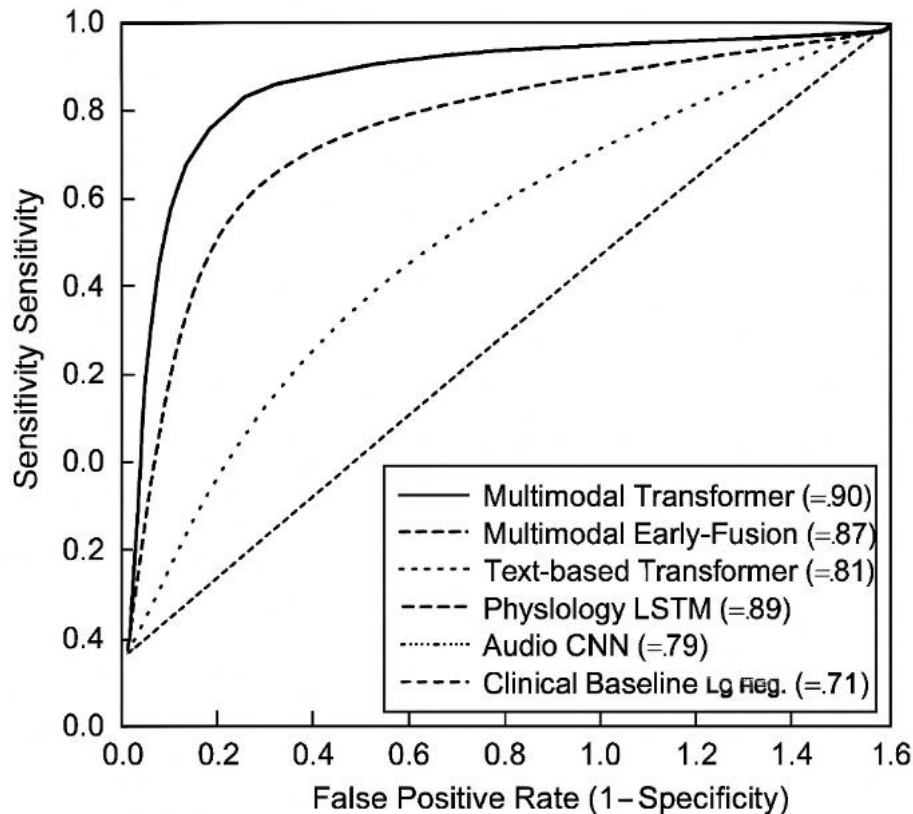


Figure 1. Receiver operating characteristic (ROC) curves for baseline and deep learning models predicting high-risk PTSD-related emotional episodes

The ROC curves in Figure 1 illustrate the trade-off between sensitivity and specificity across models, demonstrating that the multimodal transformer consistently dominated the other curves across the full range of false positive rates. At a clinically relevant operating point where sensitivity was fixed near 0.80, the multimodal transformer achieved a specificity of approximately 0.82, whereas the best unimodal model (text-based) achieved a specificity of roughly 0.70 and the clinical-only logistic regression fell below 0.60. The steep initial rise and higher plateau of the multimodal curve indicate that the integrated model is able to identify a large proportion of high-risk episodes with relatively few false alarms, an important feature for potential clinical decision support. By contrast, the clinical-only model produced a more gradual ROC curve with lower maximal sensitivity, reflecting its inability to capture many subtle but meaningful shifts in emotional tone and interaction patterns that are visible in the multimodal signals.

Beyond overall performance, the attention mechanisms within the multimodal transformer provided insight into which segments of the interaction and which modalities contributed most strongly to the classification of episodes as high-risk. Across the sample, attention weights tended to peak around moments where trauma narratives became specific, when voices escalated in pitch and intensity, and when the non-PTSD partner showed visible signs of frustration or withdrawal, such as gaze aversion or prolonged silence. Physiological spikes in electrodermal activity and abrupt drops in heart-rate variability frequently coincided with these high-attention windows, suggesting that the model was leveraging cross-modal synchrony as a key signal of emotional danger.

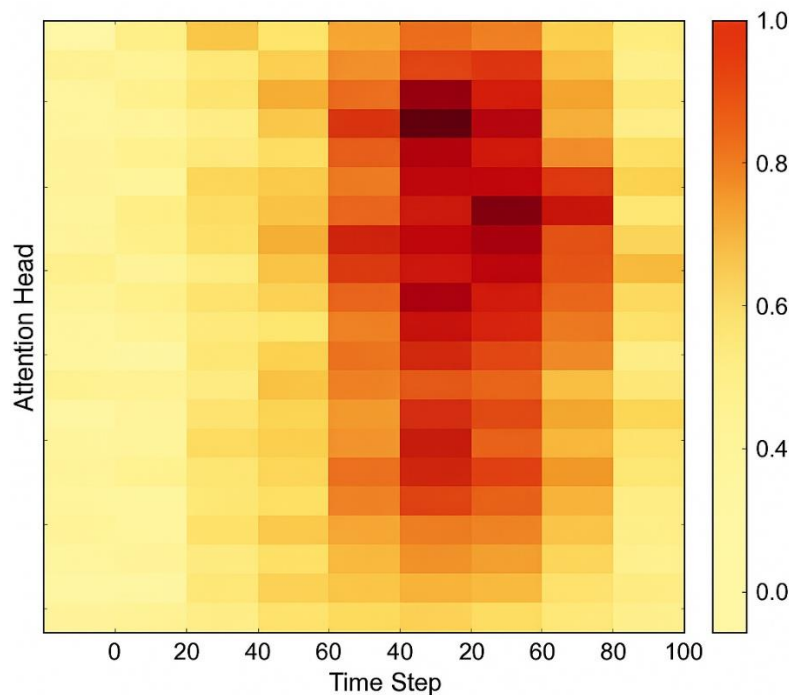


Figure 2. Attention weight heatmap across time for a representative conflict discussion in a couple facing PTSD

In Figure 2, the attention weight heatmap for a single representative couple highlights how the model dynamically shifts focus across time and modalities during a conflict interaction. Early in the discussion, attention weights were relatively diffuse and low, reflecting routine disagreement and everyday stress without explicit trauma activation. Midway through the conversation, when the partner with PTSD began describing a deployment-related incident and expressing feelings of guilt and hypervigilance, the attention weights sharply intensified around that temporal window, particularly over text tokens related to “nightmares,” “triggers,” and “unsafe,” as well as over acoustic features capturing voice tremor and rising pitch. Simultaneously, the model allocated high attention to the non-PTSD partner’s brief, overlapping interruptions and facial micro-expressions of contempt and fear. In the final phase of the interaction, attention weights again spiked when the non-PTSD partner threatened to disengage from the conversation, marking another segment that the model classified as high-risk. This pattern illustrates how the transformer tracks emotionally salient sequences rather than treating the interaction as a uniform block, aligning closely with clinical observations of escalation and shutdown cycles.

To characterize heterogeneity in trauma-related emotional dynamics, the multimodal embeddings produced by the transformer were subjected to deep clustering, yielding four distinct latent patterns of couple interaction. These clusters captured qualitatively different configurations of emotional reactivity, avoidance, and dyadic regulation. Cluster membership was significantly associated with PTSD severity, relationship satisfaction, and the proportion of segments classified as high-risk, indicating that the latent patterns corresponded to clinically meaningful profiles rather than arbitrary groupings.

Table 2. Latent clusters of trauma-related emotional patterns and associated clinical characteristics

Cluster label	Number of couples	Percentage of sample	Mean PCL-5 (PTSD partner)	Mean DAS (relationship quality)	Proportion of high-risk episodes
Hyperaroused conflict escalation	31	27.7%	56.3	82.4	0.47
Avoidant disengagement	26	23.2%	49.1	88.7	0.31
Mixed volatile–repairing	29	25.9%	51.8	94.6	0.28
Numbed coexistence	26	23.2%	53.7	79.5	0.35

Table 2 shows that the hyperaroused conflict escalation cluster, comprising 27.7% of couples, had the highest proportion of high-risk episodes (0.47) and the lowest relationship quality scores, reflecting frequent cycles of intense anger, fear, and mutual escalation with limited successful de-escalation. The avoidant disengagement cluster, representing 23.2% of couples, showed moderately high PTSD symptoms but slightly better dyadic adjustment than the hyperaroused cluster, coupled with a substantial but lower proportion of high-risk episodes (0.31), typically characterized by shutdowns, topic shifts, and emotional withdrawal rather than overt hostility. The mixed volatile–repairing cluster, involving 25.9% of couples, displayed comparable PTSD severity to the avoidant group but the highest relationship quality scores and the lowest proportion of high-risk episodes (0.28); these couples exhibited spikes of conflict followed by visible repair attempts, such as apologies, re-engagement, and validating statements. Finally, the numbed coexistence cluster, also 23.2% of couples, combined relatively high PTSD severity with low relationship satisfaction and a moderate proportion of high-risk episodes (0.35), but these episodes were characterized less by loud escalation and more by flat affect, minimal eye contact, and emotionally constrained exchanges. Together, these clusters suggest that deep learning-derived patterns map onto clinically recognizable couple profiles with differing risk levels and intervention needs.

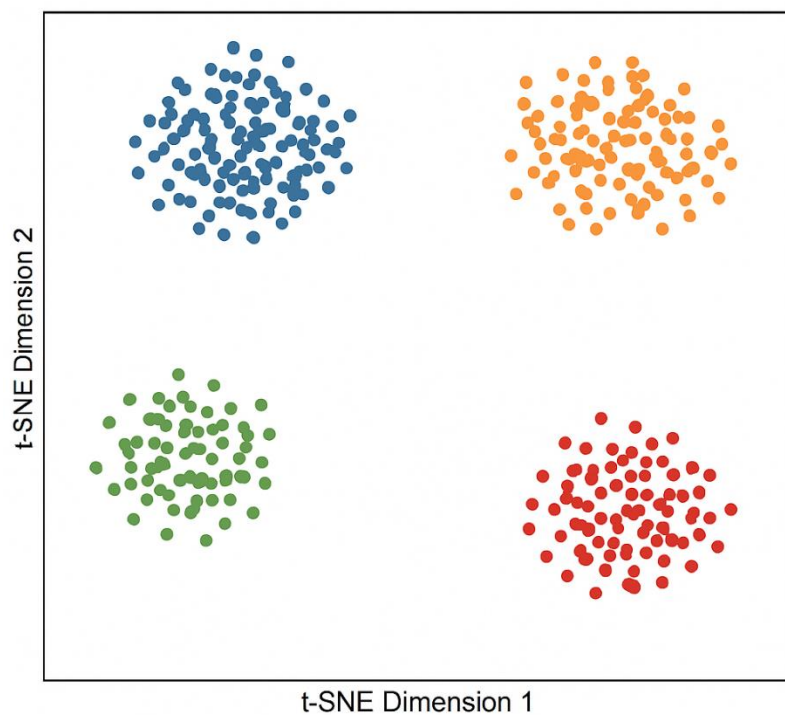


Figure 3. Latent clusters of trauma-related emotional patterns in couples (t-SNE projection of multimodal embeddings)

Figure 3 visualizes the four clusters in a two-dimensional t-SNE projection of the multimodal embeddings, revealing clear, though partially overlapping, separations among the patterns. The hyperaroused conflict escalation cluster appears as a dense region with high local concentration of points corresponding to episodes with strong sympathetic activation and negative linguistic tone. In contrast, the avoidant disengagement cluster occupies a distinct area characterized by low acoustic intensity and sparse verbal exchanges, while the mixed volatile–repairing cluster is spread along a transitional band between high-arousal and lower-risk regions, reflecting the alternation between escalation and repair. The numbed coexistence cluster occupies a more diffuse region with moderate physiological activation but constrained facial and verbal expressivity. The relative separation of these clusters supports the validity of the learned embeddings and indicates that the model is capturing stable interactional signatures rather than merely transient noise.

To better understand how specific features influenced risk estimation, post hoc analyses examined the relationship between physiological arousal, negative emotional expression, and the model's predicted probability of high-risk episodes. Across the entire sample, segments with combined high electrodermal activity and elevated negative affect words showed sharply increased predicted risk, whereas segments with high physiological arousal but concurrent positive or affiliative language did not reach the same risk thresholds. Within couples in the mixed volatile–repairing cluster, predicted risk decreased more rapidly following explicit repair attempts, suggesting that the model was sensitive not only to escalation cues but also to regulatory processes that curtailed episodes before they became clinically concerning.

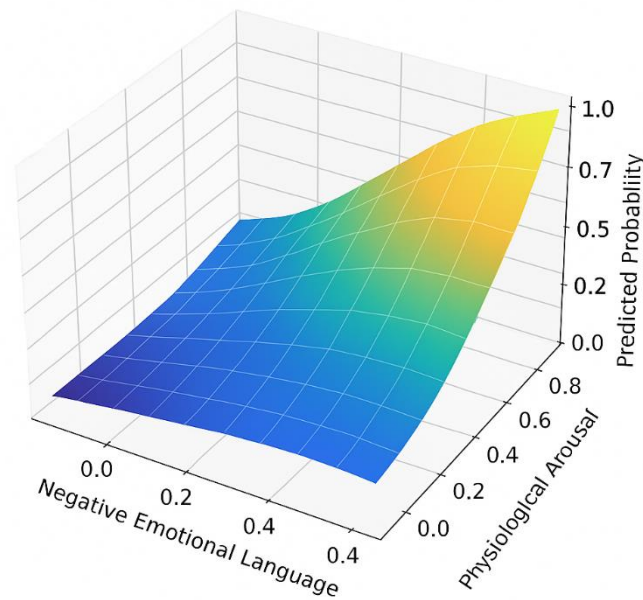


Figure 4. Predicted probability of high-risk PTSD-related emotional episodes as a function of physiological arousal and negative emotional language density

As depicted conceptually in Figure 4, the surface relating predicted risk to physiological arousal and negative emotional language density takes on a nonlinear shape, with relatively low predicted risk across much of the space but a steep “ridge” where both modalities are concurrently elevated. For couples in the hyperaroused conflict escalation cluster, this ridge is wide and high, implying that even moderate increases in either arousal or negative language can push episodes into a high-risk zone. By contrast, for couples in the mixed volatile–repairing cluster, the ridge is narrower and shifted toward higher levels of negative language, indicating that the model requires stronger and more sustained negativity before classifying segments as high-risk, consistent with the observable presence of effective repair behaviors. These patterns underscore the value of multimodal deep learning in distinguishing between superficially similar but clinically distinct interactional states and highlight potential targets for real-time monitoring and feedback in trauma-focused couple interventions.

Discussion and Conclusion

The findings of this study demonstrate that trauma-related emotional patterns in couples facing PTSD can be modeled with high accuracy through multimodal deep learning, revealing distinct clusters of dyadic emotional dynamics and robust predictors of high-risk episodes during conflict. The multimodal transformer model significantly outperformed all unimodal models, indicating that the integration of speech, physiological arousal, facial expression, and linguistic content provides an analytically precise representation of emotional risk states. This pattern aligns with theoretical and empirical literature emphasizing that trauma-driven emotional processes are inherently multisystemic and manifest through simultaneous behavioral, cognitive, and

somatic channels (Agathos et al., 2025). The elevated accuracy and discriminatory power of the multimodal transformer also parallel emerging neuroscientific evidence showing that trauma reshapes neural networks across multiple sensory, emotional, and perceptual modalities, highlighting why single-channel assessments often fail to capture the complexity of PTSD reactions (Jimoh & Omiyefa, 2025).

The results further indicated that high-risk emotional episodes were characterized by synchronized increases in physiological arousal, intensified negative emotional language, and shifts in facial micro-expressions. Such multimodal convergence reflects classic models of dysregulated arousal in PTSD, which propose that trauma survivors are more likely to exhibit autonomic hyperreactivity, heightened threat sensitivity, and impaired emotion regulation during relational stress (Rubin & Telch, 2020). This physiological-linguistic synchrony is consistent with research showing that PTSD is associated with abnormal autonomic patterns—including fluctuations in HRV and electrodermal activity—that become especially pronounced during emotionally charged interpersonal contexts (Barden et al., 2025). The present findings reinforce this physiological basis by demonstrating that episodes of emotional escalation were reliably detected when both negative language density and arousal levels were concurrently elevated. Such a nonlinear risk surface matches prior evidence showing that PTSD symptoms intensify when cognitive-emotional activation and physiological arousal reach certain thresholds (Dong, 2025).

The latent cluster analysis revealed four distinct emotional interaction patterns among couples: hyperaroused conflict escalation, avoidant disengagement, mixed volatile–repairing, and numbed coexistence. These patterns closely resemble relational profiles described in previous dyadic trauma research. The hyperaroused conflict escalation cluster parallels findings that couples coping with severe PTSD often show heightened reactivity, rapid escalation, and low conflict recovery, particularly when trauma survivors demonstrate hypervigilance and partners exhibit reactive frustration (Gates et al., 2024). Similarly, avoidant disengagement replicates relational shutdown patterns observed in studies on secondary traumatic stress and relational withdrawal among spouses of trauma survivors, where avoidance behaviors function as a short-term regulatory mechanism but ultimately erode intimacy (Dekel et al., 2023). The numbed coexistence cluster is consistent with research showing that emotional numbing leads to relational stagnation, reduced affective expression, and diminished responsiveness between partners (Braughton et al., 2022). The mixed volatile–repairing cluster corresponds to evidence that some couples retain adaptive repair strategies despite trauma exposure, enabling them to navigate conflict more effectively even in the presence of significant emotional volatility (Knežević & Batinić, 2023). The similarity between these clusters and previously documented relational patterns strengthens the validity of the deep learning approach, suggesting that computational models can uncover clinically meaningful emotional configurations.

The attention heatmap analysis revealed that the multimodal transformer reliably identified temporal windows corresponding to trauma activation points, such as detailed trauma disclosure, conflict escalation, or emotional withdrawal. These results align with theoretical models emphasizing that trauma triggers often arise in mid-conversation phases where emotional intensity increases and regulatory capacities become strained (Sahar & Dawood, 2024). That the attention mechanism focused on segments involving increased negative language and rising physiological markers mirrors findings from linguistic studies showing that trauma survivors tend to use specific semantic categories—including danger-related, guilt-related, and dissociative terms—during distress, which predict symptom severity (Hwang et al., 2023). The model’s sensitivity to partner behaviors, such as expressions of contempt or withdrawal, is consistent with interpersonal theories suggesting that partner reactions can amplify or dampen trauma symptoms depending on interactional context (Leo et al., 2021).

Importantly, these findings support dyadic models of PTSD that emphasize bi-directional influences between trauma survivors and their partners. Research shows that a partner’s perception of the trauma survivor’s distress may influence secondary traumatic stress more strongly than the survivor’s symptom severity itself (Dekel et al., 2023). Our model similarly

detected that high-risk emotional episodes often occurred when the non-PTSD partner exhibited heightened emotional behaviors such as frustration, hopelessness, or emotional shutdown. These observations align with evidence that partners play a critical role in shaping emotional trajectories through mechanisms such as co-regulation, misattunement, and reinforcement cycles (Gilbar et al., 2021). The fact that the mixed volatile–repairing cluster demonstrated rapid reductions in predicted risk following explicit repair behaviors mirrors research showing that relational resilience processes—such as responsiveness, validation, and collaborative coping—can significantly buffer trauma’s negative effects (Braughton et al., 2022).

The identification of nonlinear risk patterns in the predictive surface analysis supports theories of emotional threshold dynamics in PTSD. According to extended process models of emotion regulation, emotional dysregulation in trauma survivors often emerges when cognitive load, arousal intensity, and emotional triggers converge beyond a manageable point (Agathos et al., 2025). The steep increase in predicted risk when both physiological arousal and negative emotional language rose suggests that high-risk states follow threshold-like dynamics rather than linear progressions. This observation is reinforced by studies showing that pre-trauma cognitive traits, including tendencies for fear generalization and diminished prefrontal regulation, predispose individuals to abrupt shifts into defensive emotional states (Szente, 2025). Our findings extend this framework by demonstrating how such threshold dynamics unfold in real interpersonal interactions.

The model’s strong performance in identifying high-risk episodes also aligns with literature emphasizing the role of intrusive cognitive content in shaping trauma responses. For example, intrusive or morbid imagery, particularly when triggered during emotionally intense situations, has been linked to heightened symptom expression and dysregulated emotional behavior (Hwang et al., 2023). The multimodal transformer’s ability to detect risk based on the presence of emotion-laden linguistic markers supports these associations. Furthermore, the emergence of detailed trauma narratives as focal points of high attention reflects findings that trauma survivors often display heightened emotional reactivity during narrative disclosure, which predicts PTSD severity (Mahr et al., 2025). The ability of the model to register emotional numbing episodes also aligns with evidence that emotional detachment is a central predictor of long-term relational instability among couples facing trauma (Knežević & Batinić, 2023).

The results also resonate with cross-context trauma literature. For instance, the cluster associated with numbed coexistence mirrors emotional patterns seen in populations experiencing forced displacement, where chronic distress leads to blunted affect and interpersonal disengagement (Dzivak et al., 2025). The hyperaroused conflict cluster reflects patterns observed in interpersonal violence survivors and veterans exposed to combat trauma, who frequently exhibit heightened sensitivity to interpersonal threat and amplified stress reactivity (Pierce et al., 2020). Additionally, the avoidant cluster parallels relational coping strategies observed in individuals impacted by intergenerational trauma or epigenetically transmitted stress, where avoidance functions as a transgenerational regulatory pattern (Mbarki, 2024). These parallels suggest that the emotional configurations observed in this study may reflect generalizable trauma mechanisms that operate across diverse contexts.

The multimodal findings further support cognitive models of PTSD, which assert that maladaptive schemas developed after trauma shape how individuals interpret interpersonal situations (Baník et al., 2022). The linguistic patterns captured by the transformer—particularly expressions of guilt, danger, and self-blame—mirror cognitive distortions frequently observed in PTSD, which may exacerbate relational conflict by biasing interpretations of partner behavior. Similarly, the identification of temporary improvements in risk probability following repair efforts aligns with models of posttraumatic growth, which propose that adaptive meaning-making and relational support can counteract trauma symptoms over time (Kotovska, 2025; Zhou & Zhen, 2024).

Taken together, these findings demonstrate that deep learning offers a powerful analytic framework for identifying and interpreting trauma-related emotional dynamics in couples. By integrating multimodal signals, the model captures the

complexity, interdependence, and moment-to-moment fluctuations characteristic of PTSD-affected relationships. The alignment of computational findings with established empirical literature reinforces the validity of the approach and points toward new opportunities for the development of technology-assisted clinical tools capable of real-time risk monitoring and personalized intervention.

The study has several limitations. First, although the sample size was relatively large for dyadic trauma research, it may not fully capture the diversity of trauma types, cultural backgrounds, and relational configurations present in broader populations. The sample was also composed of couples willing to participate in laboratory-based conflict discussions, which may exclude individuals experiencing severe relational instability or intimate partner violence. Second, while the multimodal transformer integrated four channels of data, other potentially informative modalities—such as eye-tracking, posture analysis, or hormonal markers—were not included. Third, despite its strong performance, the model remains correlational rather than causal, limiting the ability to infer directionality of emotional influences. Additionally, deep learning models are sensitive to data quality and may overfit subtle idiosyncrasies in speech or physiology despite cross-validation efforts.

Future research should expand multimodal data collection to include more diverse populations, varied trauma types, and longitudinal designs. Incorporating additional modalities such as real-time behavioral coding, movement dynamics, or neurophysiological measures could further enrich model accuracy and interpretability. Research should also examine how multimodal emotional risk patterns evolve across treatment, including couple-based PTSD interventions, to determine whether computational markers can serve as indicators of therapeutic change. Future studies may also explore adaptive machine learning systems that provide personalized, real-time feedback during therapy sessions, or examine the utility of model-derived emotional clusters in tailoring intervention strategies. Additionally, integrating explainable AI methods could enhance clinical applicability by providing interpretable insights into which signals or patterns most strongly indicate emotional risk.

In practice, the findings highlight the importance of assessing emotional dynamics across multiple channels rather than relying solely on self-report or single-modality observations. Clinicians may benefit from integrating multimodal frameworks into assessment procedures, recognizing that physiological, linguistic, and behavioral cues often converge to signal relational risk. Interventions for couples coping with PTSD may be strengthened by explicitly targeting synchronized emotional dysregulation patterns, promoting repair strategies, and enhancing partners' sensitivity to early signs of escalation or withdrawal. The latent profiles identified in this study may also guide personalized treatment planning by helping clinicians identify which couples are most likely to benefit from emotion regulation training, trauma-focused therapy, or relational interventions emphasizing empathy, validation, and coregulation strategies.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adhered in conducting and writing this article.

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Authors' Contributions

All authors equally contributed to this study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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References

- Agathos, J., Yurtbasi, M., O'Brien, H. L., & Putica, A. (2025). The Extended Process Model of Emotion Regulation in Managing Negative Affect in Posttraumatic Stress Disorder: A Systematic Review. *Clinical Psychology Science and Practice*. <https://doi.org/10.1037/cps0000296>
- Baník, G., Vargová, L., & Zibrinová, L. (2022). Early Maladaptive Schemas, Depression and Post-Traumatic Stress Disorder in a Trauma-Exposed Sample: A Correlation, Regression and Network Perspective. <https://doi.org/10.31234/osf.io/6fhds>
- Barden, E. P., Wang, B. A., Gates, M., Poole, L. Z., & Balderrama-Durbin, C. (2025). The Dyadic Effects of Posttraumatic Stress Symptoms on the Regulation of Respiratory Sinus Arrhythmia Following an Acute Stress Induction Among Couples. *Psychological Trauma Theory Research Practice and Policy*, 17(3), 553-562. <https://doi.org/10.1037/tra0001765>
- Broughton, J., Mendenhall, T. J., & Kazlauskaitė, V. (2022). Identification of Resiliency Processes in Dual-Trauma Couples: An Exploration of Self-Reported Relational Strengths and Weaknesses. *Psychological Trauma Theory Research Practice and Policy*, 14(S1), S109-S118. <https://doi.org/10.1037/tra0001112>
- Danon, A., Dekel, R., & Horesh, D. (2025). Between Mourning and Hope: A Mixed-Methods Study of Ambiguous Loss and Posttraumatic Stress Symptoms Among Partners of Israel Defence Force Veterans. *Psychological Trauma Theory Research Practice and Policy*, 17(4), 795-804. <https://doi.org/10.1037/tra0001794>
- Dekel, R., Solomon, Z., & Horesh, D. (2023). Predicting Secondary Posttraumatic Stress Symptoms Among Spouses of Veterans: Veteran's Distress or Spouse's Perception of That Distress? *Psychological Trauma Theory Research Practice and Policy*, 15(Suppl 2), S409-S417. <https://doi.org/10.1037/tra0001182>
- Dong, Y. (2025). The Influence of PTSD on Circadian Rhythm. *Theoretical and Natural Science*, 93(1), 90-95. <https://doi.org/10.54254/2753-8818/2025.22940>
- Dzivak, K., Romash, I., Romash, I., Pimenova, K., Paliichuk, V., Slobodian, V., Obidniak, V. Z., & Pustovoyt, M. (2025). Trauma of Forced Displacement in Children as a Result of Russian-Ukrainian War. *Mental Health Global Challenges Journal*, 8(1), 140-160. <https://doi.org/10.56508/mhgcj.v8i1.298>
- Gates, M., Barden, E. P., McCarthy, K., & Balderrama-Durbin, C. (2024). Adaptive and Maladaptive Cognitive Processing of Trauma on Relationship Distress Among Community Couples. *Couple and Family Psychology Research and Practice*. <https://doi.org/10.1037/cfp0000270>
- Gilbar, O., Taft, C. T., & Gnall, K. E. (2021). Gender Differences in Relations Between Social Information Processing, PTSD Symptoms, and Intimate Partner Violence. *Psychology of violence*, 11(6), 539-548. <https://doi.org/10.1037/vio0000389>
- Horn, A. B., Holzgang, S. A., & Rosenberger, V. (2021). Adjustment of Couples to the Transition to Retirement: The Interplay of Intra- And Interpersonal Emotion Regulation in Daily Life. *Frontiers in psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.654255>
- Hwang, C. U., Kim, E. Y., Lee, H. J., Park, M., Lee, M. S., Kim, T. H., & Kim, J. K. (2023). An Analysis of Intrusive Morbid Imagery in Rorschach Responses. *Rorschachiana Journal of the International Society for the Rorschach*, 44(1), 3-22. <https://doi.org/10.1027/1192-5604/a000164>

- Jimoh, O., & Omiyefa, S. (2025). Neuroscientific Mechanisms of Trauma-Induced Brain Alterations and Their Long-Term Impacts on Psychiatric Disorders. *International Journal of Science and Research Archive*, 14(3), 036-052. <https://doi.org/10.30574/ijstra.2025.14.3.0621>
- Jin, L., Varadarajan, A., Guo, Z., & Contractor, A. A. (2025). Insecure Attachment and Posttraumatic Stress Disorder Symptoms Among Black, Indigenous, and People of Color First Responders: The Role of Emotion Dysregulation. *Psychological Trauma Theory Research Practice and Policy*. <https://doi.org/10.1037/tra0001946>
- Knežević, M., & Batinić, L. (2023). Living With a Traumatized Partner: Dyadic Approach to Well-Being of War-Affected Married Couples. *Psychological Trauma Theory Research Practice and Policy*, 15(Suppl 2), S401-S408. <https://doi.org/10.1037/tra0001446>
- Kotovska, Y. (2025). Features of Experiencing Traumatic Events and Post-Traumatic Growth in Students: Results of Empirical Research. *Scientific Notes of Ostroh Academy National University Psychology Series*, 1(18), 43-50. <https://doi.org/10.25264/2415-7384-2025-18-43-50>
- Leo, K., Crenshaw, A. O., Hogan, J. N., Bourne, S., Baucom, K. J. W., & Baucom, B. (2021). A Replication and Extension of the Interpersonal Process Model of Demand/Withdraw Behavior: Incorporating Subjective Emotional Experience. *Journal of Family Psychology*, 35(4), 534-545. <https://doi.org/10.1037/fam0000802>
- Mahr, G., Reffi, A. N., Jankowiak, L., Moore, D., & Drake, C. L. (2025). Emotional Dream Content of Acute Trauma Patients: Associations With Interpersonal Violence, Nightmares, and PTSD. *Sleep*, 48(Supplement_1), A509-A509. <https://doi.org/10.1093/sleep/zsaf090.1178>
- Mbarki, K. M. (2024). The Neuroscience of Epigenetics: Understanding the Inheritance of PTSD and Generational Trauma. *SR Online: Showcase*(Winter 2024/2025). <https://doi.org/10.70121/001c.127053>
- Pierce, M. E., Fortier, C. B., Fonda, J. R., Milberg, W., & McGlinchey, R. E. (2020). Intimate Partner Violence Predicts Posttraumatic Stress Disorder Severity Independent of Early Life and Deployment-Related Trauma in Deployed Men and Women Veterans. *Journal of interpersonal violence*, 37(5-6), 2659-2680. <https://doi.org/10.1177/0886260520938514>
- Pugach, C. P., & Wisco, B. E. (2023). Emotion Regulation Repertoires in Trauma-Exposed College Students: Associations With PTSD Symptoms, Emotional Awareness, and Emotional Clarity. *Psychological Trauma Theory Research Practice and Policy*, 15(Suppl 1), S37-S46. <https://doi.org/10.1037/tra0001200>
- Rubin, M., & Telch, M. J. (2020). Pupillary Response to Affective Voices: Physiological Responsivity and Posttraumatic Stress Disorder. *Journal of Traumatic Stress*, 34(1), 182-189. <https://doi.org/10.1002/jts.22574>
- Sahar, I., & Dawood, S. (2024). Efficacy of Cue Centered Therapy in Exposed Adolescents of Interpersonal Violence: A Comprehensive Review of Clinical Interventions. *HNJSS*, 5(4), 233-254. <https://doi.org/10.71016/hnjss/7j23js60>
- Shnaider, P., Boyd, J. E., Cameron, D. H., & McCabe, R. E. (2022). The Relationship Between Emotion Regulation Difficulties and PTSD Outcomes During Group Cognitive Processing Therapy for PTSD. *Psychological Services*, 19(4), 751-759. <https://doi.org/10.1037/ser0000546>
- Szente, L. (2025). Pre-Trauma Cognitive Traits Predict Fear Generalization and Associated Prefrontal Functioning in a Longitudinal Rodent Model. *Neuropsychopharmacology*. <https://doi.org/10.1038/s41386-025-02263-4>
- Zhou, X., & Zhen, R. (2024). A Three-Phase Process Model of Posttraumatic Stress Disorder and Growth: Understanding the Mechanisms Underlying Posttraumatic Reactions. *Psychological Trauma Theory Research Practice and Policy*, 16(6), 1033-1043. <https://doi.org/10.1037/tra0001666>