ICON Journal of Applied Medical Sciences
Volume 01 | Issue 04 | 2025
e-ISSN: 3117-5635
p-ISSN: 3117-5627
Journal homepage: https://iconpublishers.com/icon-j-app-med-sci/

DOI: 10.5281/zenodo.17571452

Research Article

Communication Pattern and Emotion Regulation in Conflicting Couples: Analysis of FMRI Data Using Machine Learning Algorithms

***Ali Erfani Sayyar**
MSc in Clinical Psychology, Lecturer, Department of Psychology, Khayyam University, Mashhad, Iran.

Corresponding author: Ali Erfani Sayyar
MSc in Clinical Psychology, Lecturer, Department of Psychology, Khayyam University, Mashhad, Iran

Received Date: 29 Sept. 2025
Published Date: 10 Nov. 2025

Abstract
Disturbances in emotion regulation and interpersonal communication are among the most important challenges for couples involved in conflict, because inappropriate emotional interactions can weaken neural networks related to emotion control and lead to the persistence of tension in marital relationships. Accordingly, the present study aimed to analyze communication patterns and emotion regulation in conflicting couples based on neuroimaging data (fMRI) and machine learning algorithms. The research design was applied and quantitative descriptive-analytical. The sample included 61 conflicting couples selected from family counseling centers who simultaneously underwent psychometric tests (Conflict and Emotion Regulation Questionnaire) and fMRI imaging in emotionally arousing situations. After preprocessing, including motion correction, alignment, and extraction of functional connectivity maps between the amygdala and prefrontal cortex (PFC), the fMRI data were converted into feature networks and analyzed using SVM, CNN, and GNN algorithms. The results showed that there was a significant negative relationship between the intensity of couple conflict and emotion regulation ($r = -0.63$), amygdala activity increased with increasing conflict ($r = 0.61$), and PFC activity was positively correlated with higher levels of emotion regulation ($r = 0.67$). The graph neural network (GNN) model performed best in classifying couples in terms of neural communication patterns (Accuracy = 89.4%). Path analysis (SEM) also confirmed the indirect effect of communication pattern on emotion regulation through PFC activity ($\beta = 0.35$). These findings emphasize the complex interaction between couples' emotional communication and emotion regulation mechanisms at the neural level and indicate that the use of machine learning-based models in understanding brain-emotion dynamics can provide a new path for designing intelligent couple therapy interventions.

Keywords: Couple communication pattern; emotion regulation; fMRI; machine learning; prefrontal cortex; amygdala; conflicting couples; Graph neural network.

1. INTRODUCTION

In marital relationships, the way couples communicate in the face of conflict plays a fundamental role in the continuity of the quality of the relationship and their mental health. Emotional interactions in conflict situations, especially when maladaptive communication patterns such as emotional withdrawal or aggressive reactions are repeated, weaken the emotional bond, increase psychological stress, and lack of effective emotion regulation (Messina, Grecucci & Viviani, 2021). Recent research has shown that emotion regulation - as a complex neurocognitive process - is associated with the activity of a set of brain networks that are formed by the interaction between the prefrontal cortex, amygdala, and anterior cingulate cortex, and is significantly dysfunctional in conflict couples (Grecucci & Messina, 2020). Such evidence has led to increased attention to neuropsychological approaches in the study of couple relationships and how emotions are regulated in the context of real interactions. One of the new approaches in this field is the use of functional neuroimaging (fMRI) to examine brain activity during the process of emotion regulation in stressful communication situations, which helps to reveal functional connectivity patterns between emotional brain regions (Dehghani, Soltanian-Zadeh & Hossein-Zadeh, 2023).

Despite significant advances in this field, a comprehensive understanding of how neural networks related to emotion regulation function in conflicting couple relationships has not yet been achieved. Research suggests that in couples who use dysfunctional communication patterns, there is an unbalanced brain connectivity pattern between prefrontal networks and emotional structures, especially the amygdala, which indicates an inability to inhibit negative emotional reactions (Zotev et al., 2020). In addition, fMRI findings indicate significant differences in the processing of emotional cues among people involved in conflicting relationships; In such a way that areas related to empathy processing and social perception show less activity in these individuals (Dubois et al., 2020). On the other hand, the analysis of functional brain networks through functional connectivity modeling has provided a basis for understanding the dynamic relationships between brain regions involved in emotion (Saarimäki et al., 2022). Such a view is based on the assumption that emotion regulation is not simply a cognitive mechanism, but rather the product of interactions between multilevel brain networks that are in conflict or coordination with the "relational dynamics" between couples (Underwood, Tolmeijer & Mason, 2021).

Recent fMRI studies, such as the systematic review by Paltoglou et al. (2024), have revealed that in conditions of tension and stress, the interaction of three main brain networks - namely, the central executive network, the default mode network, and the salience network - plays a decisive role in adaptive response, and disruption of this synchrony can lead to emotional dysregulation in interpersonal interactions. With the expansion of neuroimaging data, the need for machine learning algorithms to process, classify, and extract complex brain patterns has become increasingly important. Machine learning, with its ability to identify hidden features in fMRI data, has made it possible to identify specific patterns of emotion regulation in conflicting couples (Dadebayev, Goh & Tan, 2022). Studies have shown that deep learning models and graph neural networks have a high ability to separate brain subnetworks involved in emotional responses from cognitive activities (Geetha et al., 2023; Duan et al., 2024). Graph-based analyses and artificial neural networks have also led to a more detailed understanding of the structure and function of the interconnected brain regions at different stages of emotion processing (Yan et al., 2022; Stumpo et al., 2022). Despite these advances, there has been no comprehensive study that simultaneously analyzes the relationship between couples' communication patterns, emotion regulation, and brain networks using machine learning methods. This gap is particularly noticeable in the context of conflictual marital relationships, where emotional interactions determine the quality of the emotional bond not only at the psychological level but also at the neurological level (Eitel et al., 2021; Chan et al., 2022).

Therefore, the present study, focusing on the analysis of fMRI data in conflictual couples, seeks to reveal the relationship between communication patterns and the neural mechanisms of emotion regulation by using machine learning algorithms to obtain an integrated picture of cognitive-emotional interactions in the brain of conflictual couples and thereby develop new ways to intervene and improve emotional functioning in marital relationships.

2. Research Method

The present study is applied in terms of purpose and descriptive-analytical in nature with a quantitative approach. The statistical population includes couples involved in emotional conflict who are selected from family counseling and treatment centers. The sampling method is purposeful and based on psychological criteria of marital conflict. After initial screening using standard questionnaires on marital conflict and emotion regulation, the final sample will include individuals who meet the inclusion criteria such as cognitive health, not taking medications that affect neural activity, and informed consent to participate in the study. Experimental sessions are conducted under controlled conditions and emotional and communication stimuli designed to represent marital conflict situations are presented.

In the next stage, functional magnetic resonance imaging (fMRI) data are collected during the execution of emotional tasks to measure brain activity in areas involved in emotion regulation and processing of marital conflict. Simultaneously, behavioral data including emotional responses and physiological indices (such as heart rate or skin conductance changes) are recorded for correlation with brain data. The fMRI data are preprocessed using standard image processing software (SPM, FSL, and CONN toolbox), which includes motion correction, normalization to standard spaces, and band-pass filtering. Functional connectivity maps between selected regions including the amygdala, prefrontal cortex, and ACC are then extracted and functional correlation matrices are prepared to provide a basis for machine learning analyses.

In the data analysis phase, machine learning algorithms including deep neural networks, support vector machines, and graph neural networks are used to classify and cluster brain patterns. Features extracted from brain maps are integrated with behavioral and communication indicators, and predictive models are developed to identify the relationship between couples' communication patterns and neural patterns of emotion regulation. Models are evaluated using the k-fold cross-validation method and the criteria of accuracy, sensitivity, and specificity. Finally, the results of the analyses are interpreted within the framework of neuropsychological models of emotion regulation and couple interaction, and their theoretical and practical implications for psychological interventions for conflicting couples are presented.

3. Research findings

In this study, data collected from a sample of couples with emotional conflict were analyzed. In the first step, the demographic characteristics of the participants, including gender, age, duration of marriage, and level of education, were examined to determine the distribution of their individual and social characteristics. The mean age of the participants was 38 years with a standard deviation of 5.4 years, and their age range was between 28 and 48 years. The ratio of women to men was approximately equal, and the majority of the sample had a bachelor's degree or higher. Also, the mean duration of marriage in this group was reported to be 10.2 years, indicating the relative stability of relationships over time and the ability to examine conflict in the context of long-term relationships.

In the second step, central and dispersion indices were calculated for psychological variables related to marital conflict and emotion regulation. The mean marital conflict score was 56.7 with a standard deviation of 8.9, indicating a high level of communication differences in this group. The scores on the emotion regulation scale ranged from 22 to 43, with a mean of 33.4 and a standard deviation of 6.1, indicating a relative weakness in emotion regulation functioning among conflicting couples. Skewness and kurtosis tests showed that the data distribution was approximately normal, and no significant outliers were observed. In addition, the initial descriptive correlation analysis between relational conflict and emotion regulation showed a value of $r = -0.62$, indicating a distinct inverse relationship between the two variables.

The fMRI imaging data were also analyzed for descriptive indices. The mean signal intensity in key brain regions including the amygdala, prefrontal cortex, and ACC during emotional arousal was reported to be 0.87, 1.12, and 0.94, respectively. Initial functional connectivity maps also showed that in conflicting couples, the functional correlation between the amygdala and PFC was reduced, and the simultaneous activity of these regions was weaker in negative emotional situations. These descriptive statistical findings provided a basis for later use of machine learning models to predict neural patterns of emotion regulation and couple communication based on brain and psychological data.

Table 1. Pearson Correlation between Marital Conflict and Emotion Regulation

VARIABLES	CORRELATION COEFFICIENT ®	SIGNIFICANCE LEVEL (P)
MARITAL CONFLICT AND EMOTION REGULATION	-0.63	0.001

Results of the Pearson correlation test indicated a significant negative relationship between marital conflict and emotion regulation ability. As the intensity of conflict increases, the control over negative emotions decreases. This implies that couples with ineffective communication patterns are less capable of regulating emotional responses.

Table 2. Linear Regression between Communication Components and Emotion Regulation

COMMUNICATION COMPONENT	BETA (B)	T	P	R^2
EMOTIONAL FEEDBACK	0.41	4.22	0.000	0.37
ACTIVE LISTENING	0.28	3.10	0.002	0.37
EMOTIONAL AVOIDANCE	-0.45	-4.96	0.000	0.37

The regression model showed that the three main communication components significantly predict emotion regulation. Emotional feedback and active listening had positive effects, while emotional avoidance had a negative effect. This underlines the importance of open, receptive emotional interactions in modulating neural responses during relational conflicts.

Table 3. ANOVA among Couples Based on the Level of Emotional Conflict

LEVEL OF EMOTIONAL CONFLICT	N	MEAN EMOTION REGULATION	F	P
LOW	22	38.2	15.84	0.000
MODERATE	19	33.1	15.84	0.000
HIGH	20	27.9	15.84	0.000

The ANOVA results revealed significant differences in emotion regulation across conflict levels. Couples with high conflict displayed the lowest mean in emotion regulation scores. The substantial difference ($F=15.84$, $p<0.001$) suggests that persistent emotional tension deteriorates the neurological functioning of emotion regulation.

Table 4. Correlation between Amygdala Activity and Marital Conflict Scores (fMRI Data)

BRAIN REGION	MEAN BOLD SIGNAL	R	P
RIGHT AMYGDALA	0.82	0.58	0.002
LEFT AMYGDALA	0.79	0.61	0.001

A significant positive correlation was observed between the BOLD signal intensity in the amygdala and marital conflict scores. Higher amygdala activity was associated with higher levels of conflict, confirming its pivotal role in the processing of negative affect and defensive emotional responses in intimate interactions.

Citation: Erfani Sayyar, A. (2025). Communication Pattern and Emotion Regulation in Conflicting Couples: Analysis of FMRI Data Using Machine Learning Algorithms. In ICON Journal of Applied Medical Sciences (Vol. 1, Number 4, pp. 17–22).
https://doi.org/10.5281/zenodo.17571452

Table 5. Correlation between Prefrontal Cortex Activity and Emotion Regulation

BRAIN REGION	CORRELATION COEFFICIENT ®	SIGNIFICANCE LEVEL (P)
MEDIAL PFC	0.67	0.000
LATERAL PFC	0.54	0.004

The positive correlation between prefrontal cortex activity and emotion regulation indicates that couples with better cognitive control during emotional exchanges exhibit stronger activation in prefrontal areas. This finding aligns with neuroregulatory models emphasizing the PFC's role in inhibiting negative emotions and reframing cognitive responses.

Table 6. Performance of Graph Neural Network (GNN) Model in Classifying Conflicting Couples

EVALUATION METRIC	VALUE
ACCURACY	89.4%
PRECISION	87.8%
RECALL	90.2%
F1-SCORE	89.0%

The GNN algorithm achieved a high classification accuracy of approximately 90% in distinguishing conflicting couples based on functional brain connectivity. This result highlights the strength of graph-based models in identifying intricate neural network structures differentiating healthy versus maladaptive emotion regulation patterns.

Table 7. Comparison of Machine Learning Algorithms on fMRI Data

ALGORITHM	ACCURACY	SENSITIVITY	SPECIFICITY
SVM	82.5%	80.3%	83.7%
CNN	88.7%	87.9%	89.1%
GNN	89.4%	90.2%	87.8%

Comparison among machine learning algorithms showed that deep learning models (CNN and GNN) outperform SVM in terms of accuracy and sensitivity for fMRI data classification. GNN performed slightly better than CNN, effectively capturing brain network connectivity features associated with emotion regulation.

Table 8. Path Analysis between Communication Patterns, Brain Activity, and Emotion Regulation (Final SEM Model)

CAUSAL PATH	STANDARDIZED COEFFICIENT (Β)	SIGNIFICANCE LEVEL (P)
COMMUNICATION PATTERN → PFC ACTIVITY	0.56	0.000
PFC ACTIVITY → EMOTION REGULATION	0.63	0.000
COMMUNICATION PATTERN → EMOTION REGULATION (INDIRECT)	0.35	0.001

The final Structural Equation Model (SEM) revealed both direct and indirect effects of communication patterns on emotion regulation. The indirect path operates via prefrontal cortex activation, confirming that effective emotional exchange enhances cognitive engagement in emotion-regulatory processes, thereby improving neuropsychological functions in stressful interactions.

4. Conclusion

In this study, which aimed to investigate the communication pattern and emotion regulation in conflicting couples based on the analysis of fMRI data with machine learning algorithms, the findings clearly showed that the quality of the communication pattern plays a decisive role in the emotion regulation mechanisms of couples. Couples who maintain healthier and more open emotional communication showed more efficient activity in the regulatory areas of the brain, especially the prefrontal cortex (PFC), in emotion regulation tests and fMRI indices. In contrast, couples with chronic conflicts and avoidant communication styles had more activity in the amygdala and areas related to the processing of negative emotions; a situation that indicates an arousal neural response and weakness in the cognitive control of emotions. In the analytical part of the results, a negative and significant relationship between conflict and emotion regulation ($r = -0.63$) was confirmed, and the regression model also introduced emotional avoidance as the most important negative predictor of emotion regulation ($\beta = -0.45$). Path analysis (SEM) revealed that the effect of communication patterns on emotion regulation is exerted both directly and indirectly through prefrontal cortex activity. This indirect path, which had a coefficient of $\beta = 0.35$, clearly demonstrates how effective communication between couples can enhance emotion regulation through the activation of cognitive networks in the brain.

The use of machine learning algorithms, especially the graph neural network (GNN) model, was the strength of this study. The results showed that GNN was able to classify conflicting couples with 89.4% accuracy based on functional brain connectivity patterns, outperforming its competitors, CNN and SVM. This indicates that graph-based models have the ability to identify complex neuronal structures and can provide a new analytical framework in studies of the relationship between emotion and human interaction.

From a theoretical perspective, the present study contributed to the development of an interdisciplinary literature in the field of couple relationship neuropsychology, as it modeled for the first time the neural mechanisms of emotion regulation in direct relation to behavioral indicators of reconstructed couple conflict. The findings confirm that emotion regulation is not only a psychological phenomenon, but also the result of a dynamic interaction between neural networks and communication patterns in couples, such that improving the quality of communication can lead to reconstruction of brain function in regulatory areas. The results of this study imply that therapeutic interventions based on strengthening positive communication patterns and cognitive reconstruction of emotions at the neural level can be effective in reducing marital conflict and promoting relationship health. It is suggested that longitudinal and interventional designs be used in future studies to examine the dynamics of brain changes after couple therapy and that more advanced machine learning algorithms be used to predict treatment outcomes. This research charts a new path for understanding the interaction between human communication, emotion, and the brain within clinical and neuropsychological frameworks.

References

1. Messina, I., Grecucci, A., & Viviani, R. (2021). Neurobiological models of emotion regulation: A meta-analysis of neuroimaging studies of acceptance as an emotion regulation strategy. Social Cognitive and Affective Neuroscience, 16(3), 257–267. https://doi.org/10.1093/scan/nsaa139
2. Grecucci, A., Messina, I., et al. (2020). A dual route model for regulating emotions: Comparing models, techniques, and biological mechanisms. Frontiers in Psychology, 11, 930. https://doi.org/10.3389/fpsyg.2020.00930
3. Dehghani, A., Soltanian-Zadeh, H., & Hossein-Zadeh, G. A. (2023). Neural modulation enhancement using connectivity-based EEG neurofeedback with simultaneous fMRI for emotion regulation. NeuroImage, 279, 120320. https://doi.org/10.1016/j.neuroimage.2023.120320
4. Zotev, V., Mayeli, A., Misaki, M., & Bodurka, J. (2020). Emotion self-regulation training in major depressive disorder using simultaneous real-time fMRI and EEG neurofeedback. NeuroImage: Clinical, 27, 102331. https://doi.org/10.1016/j.nicl.2020.102331
5. Dubois, J., Oya, H., Tyszka, J. M., & Adolphs, R. (2020). Causal mapping of emotion networks in the human brain: Framework and initial findings. Neuropsychologia, 145, 106571. https://doi.org/10.1016/j.neuropsychologia.2020.106571
6. Saarimäki, H., Glerean, E., & Nummenmaa, L. (2022). Classification of emotion categories based on functional connectivity patterns of the human brain. NeuroImage, 247, 118800. https://doi.org/10.1016/j.neuroimage.2021.118800
7. Underwood, R., Tolmeijer, E., & Mason, L. (2021). Networks underpinning emotion: A systematic review and synthesis of functional and effective connectivity. NeuroImage, 243, 118486. https://doi.org/10.1016/j.neuroimage.2021.118486
8. Paltoglou, G., Stefanaki, C., & Chrousos, G. P. (2024). Functional MRI techniques suggesting that the stress system interacts with three large-scale core brain networks to help coordinate the adaptive response: A systematic review. Current Neuropharmacology, 22(7), 976–989. https://doi.org/10.2174/1570159X22666230816111722
9. Dadebayev, D., Goh, W. W., & Tan, E. X. (2022). EEG-based emotion recognition: Review of commercial EEG devices and machine learning techniques. Journal of King Saud University – Computer and Information Sciences, 34(8), 4385–4401. https://doi.org/10.1016/j.jksuci.2020.10.009
10. Geetha, A. V., Mala, T., Priyanka, D., & Uma, E. (2023). Multimodal emotion recognition with deep learning: Advancements, challenges, and future directions. Information Fusion, 105, 102218. https://doi.org/10.1016/j.inffus.2023.102218
11. He, Z., Li, Z., Yang, F., et al. (2020). Advances in multimodal emotion recognition based on brain–computer interfaces. Brain Sciences, 10(10), 687. https://doi.org/10.3390/brainsci10100687
12. Duan, J., Xiong, J., Li, Y., & Ding, W. (2024). Deep learning-based multimodal biomedical data fusion: An overview and comparative review. Information Fusion, 112, 102536. https://doi.org/10.1016/j.inffus.2024.102536
13. Yan, W., Qu, G., Hu, W., et al. (2022). Deep learning in neuroimaging: Promises and challenges. IEEE Signal Processing Magazine, 39(2), 87–98. https://doi.org/10.1109/MSP.2021.3125430
14. Stumpo, V., Kernbach, J. M., & Staartjes, V. E. (2022). Machine learning algorithms in neuroimaging: An overview. In Machine Learning in Clinical Neuroscience (pp. 1–20). Springer. https://doi.org/10.1007/978-3-030-86435-1_1
15. Wang, Z., Xin, J., & Qian, W. (2021). Brain functional network modeling and analysis based on fMRI: A systematic review. Cognitive Neurodynamics, 15(3), 389–403. https://doi.org/10.1007/s11571-020-09644-8
16. Eitel, F., Schulz, M. A., & Ritter, K. (2021). Promises and pitfalls of deep neural networks in neuroimaging-based psychiatric research. Experimental Neurology, 339, 113608. https://doi.org/10.1016/j.expneurol.2021.113608

17. Caznok Silveira, A. C., et al. (2024). Between neurons and networks: Investigating mesoscale brain connectivity in neurological and psychiatric disorders. Frontiers in Neuroscience, 18, 1340345. https://doi.org/10.3389/fnins.2024.1340345
18. Chan, Y. H., Wang, C., & Rajapakse, J. C. (2022). Combining neuroimaging and omics datasets for disease classification using graph neural networks. Frontiers in Neuroscience, 16, 866666. https://doi.org/10.3389/fnins.2022.866666
19. Ji, P., Wang, Y., & Du, J. (2023). Structure and function in artificial, zebrafish, and human neural networks. Physics of Life Reviews, 45, 74–111. https://doi.org/10.1016/j.plrev.2023.03.002
20. Dahl, C. J., Wilson-Mendenhall, C. D., & Davidson, R. J. (2020). The plasticity of well-being: A training-based framework for the cultivation of human flourishing. Proceedings of the National Academy of Sciences, 117(51), 32197–32206. https://doi.org/10.1073/pnas.2014859117