M.Sc. Engg. Thesis

LEVERAGING FEATURES FROM EEG AND FREE-HAND SKETCHES FOR EFFECTIVE DIAGNOSIS OF POST TRAUMATIC STRESS DISORDER

by
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Dedicated to my loving parents

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Candidate's Declaration

This is hereby declared that the work titled "LEVERAGING FEATURES FROM EEG AND FREE-HAND SKETCHES FOR EFFECTIVE DIAGNOSIS OF POST TRAUMATIC STRESS DISORDER", is the outcome of research carried out by me under the supervision of Dr. A. B. M. Alim Al Islam, in the Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, Dhaka 1000. It is also declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Abstract

Due to war, violence, and other traumatic events, marginalized communities, e.g., refugees and internally displaced people are more vulnerable to develop Post-traumatic Stress Disorder (PTSD). The diagnosis of PTSD suffers from various human-centered design issues particularly in case of underserved communities. Language and cultural barriers, lack of skilled clinicians, lack of literacy and technological skills, sensitivity around disclosing traumatic experiences, etc., greatly undermine the effectiveness of the existing interview or self-report based diagnostic tools of PTSD. To address these issues, here, we present an automated and quantitative diagnostic model of PTSD based on the features from EEG and free-hand sketches.

In this regard, we performed an in-depth study among four diverse communities, e.g., Rohingya refugees (n = 71), slum-dwellers (n = 35), engineering students (n = 85), and healthy Bangladeshi individuals (n = 45). We used a consumer-grade, low-cost, and portable EEG headset to collect brainwave signals from Rohingya refugees and Bangladeshi citizens during three different activities. Besides, we collected free-hand sketches from the refugees, slum-dwellers, and engineering students. Based on the reported post-traumatic stress symptoms of the refugees, we developed PTSD regulatory network to determine causal associations among PTSD and its different symptoms. This model combines concepts from both reflective and formative models of PTSD. To the best of our knowledge, this is the first of its kind. Besides, we identified several neurobiological abnormalities related to PTSD using the EEG signals collected via our portable EEG headset while talking. Moreover, we used corner and edge detection algorithms to extract three features (number of corners, number of strokes, and average length of strokes) from the images of free-hand sketches. We used these features along with sketch themes, participants' gender and group to train multiple logistic regression models for potentially screening PTSD (accuracy: 82.9-87.9%). We improved the accuracy (99.29%) by integrating EEG data with sketch features in a Random Forest model for the refugee population. Since

both EEG and free-hand sketches help elicit naturalistic expressions through non-verbal communication, our proposed method removes language, cultural, and technological barriers, further enabling it to be easily deployed and adopted among underserved communities.

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Chapter 1

Introduction

With growing cases of forced displacement due to war and violence, addressing the basic needs of the forcibly displaced populations has become crucial for their long-term sustainable well-being. The trauma events during forced displacement affect long-term psychological well-being of the victims [2]. Previous work has revealed that traumatic exposure deteriorates mental health status and reduces social functioning skills [3]. Earlier studies on forcibly displaced populations, e.g., refugees, have showed that cumulative exposure to trauma eventually leads to the development of post-traumatic stress disorder (PTSD) [4, 5, 6, 7] and increases psychiatric morbidity [8, 9]. However, despite various health risks, access to mental health care for the underserved communities suffers from various issues in almost all countries [10, 11].

1.1 Challenges in the Diagnosis of PTSD

Limited resources, inequitable distribution of services, barriers to existing health care system, social stigma, etc., greatly impede mental health care for the forcibly displaced populations [12, 13]. For example, existing interview or self-report based diagnostic tools of PTSD often suffer from under-utilization [14] due to various issues associated with human-human interactions and expectations. Traditional diagnosis of PTSD involves a patient visiting a clinic and being evaluated by a clinical practitioner using a screening tool [15]. Providing such access to screening procedures and specialized treatment in the limited resource settings of underserved communities is difficult and requires significant medical investment. Even establishing such facilities has other challenges, e.g., convincing the victims to seek help, removing barriers associated with language, culture, and literacy, and expecting them to reveal sensitive information to a stranger [13, 14, 16, 17, 18, 19]. Given these challenges, it is essential to look for alternative measures of PTSD that will potentially relieve the underserved communities of the literacy, communication, and technological barriers.

1.2 EEG for Neurobiological Measures of PTSD

Traditionally PTSD is characterized by the presence of several post-traumatic stress symptoms lasting over a month or more. These symptoms might reflect the emergence of an abnormal underlying neurobiological mechanism in response to traumatic stress. Recent findings in neuroscience have demonstrated neurobiological abnormalities among PTSD patients and identified several hallmark neurobiological features of PTSD [20, 21]. In this connection, electroencephalogram or EEG has been used frequently to identify the potential neurobiological markers of PTSD [22, 23, 24].

EEG is a physiological method for measuring the electrical activities of brain. Our motivation behind exploring EEG is that it offers excellent spatio-temporal resolutions for assessing brain activities, which help characterize the abnormalities associated with different post-traumatic stress symptoms. Additionally, being a spontaneous phenomena [25], EEG is less susceptible to conflicts and confusions associated with the responses of the participants while using traditional questionnaire-based diagnostic tools. Moreover, EEG signals are able to identify potential neurobiological markers of PTSD from that of the healthy individuals, even at rest state [26, 27, 28]. Thus, the use of EEG may avoid issues associated with human-human interactions and communications, such as language barrier, lack of literacy to use self-help questionnaires, etc. Therefore, in this work, we investigate the utility of EEG to identify the neurobiological markers of PTSD while doing different activities.

1.3 Sketches for Non-Verbal Measures of PTSD

Apart from EEG, we explore the strength of art, a universal purveyor of expression [29], to look for alternative measures of PTSD. Traditionally, psychiatric community has explored the utility and therapeutic values of creative work, arts, and non-verbal communications among different PTSD diagnosed populations [30, 31, 32, 33, 34, 35, 36]. The non-verbal nature of artwork helps researchers overcome the language and communication barriers while dealing with patients of psychiatric morbidity [37].

Besides, art therapists have observed significantly greater recurring graphic forms (disembodied eyes and wedges) in the sketches prepared by clinically diagnosed PTSD patients, who have been victimized to rape and sexual abuses, compared to the control group [38]. This observation inspires us to examine whether any visual characteristic can be identified from the free-hand sketches of the traumatized individuals using image processing algorithms. Besides, we aim to explore whether such characteristic can be leveraged to assess the potential occurrences of PTSD.

Hence, in this work, we present an initial proof of concept for a novel, low-cost, and creative method to screen the potential cases of PTSD based on free-hand sketches. We show how artwork, particularly free-hand sketches can be integrated with ubiquitous computing applications to improve the screening of PTSD among the undeserved communities in low-income developing countries.

1.4 Our Research Context and Contributions

In this work, we examine the alternative usage of both EEG and free-hand sketches to screen the potential cases of PTSD. We conducted a mixed methods research study among four diverse communities. Our study population includes two underserved groups: Rohingya refugees ($n = 71$) and slum-dwellers ($n = 35$) living in Bangladesh. For comparison, we included healthy Bangladeshi individuals ($n = 45$) and engineering students ($n = 85$) as well. These groups have diverse socioeconomic backgrounds as well as varying levels of exposure to traumatic events.

We teamed with a psychiatrist and an educational psychologist to diagnose PTSD among the participants using a PTSD screening tool adapted from MINI 5.0.0 [39]. Based on the responses of the participants, we determined potential associations among different post-traumatic stress symptoms and PTSD, and developed three models (correlation network, partial correlation network, and regulatory network) to understand the structure of the disorder and its symptoms. To build these models, we combined concepts from both reflective and formative models of PTSD [40, 41]. Our hypothesis in favor of developing these hybrid models is that some symptoms constitute PTSD (formative property) while some are reflective of it (reflective property).

At first, we built a PTSD correlation network (PTSDCN), where the nodes represent PTSD and other post-traumatic stress symptoms. The edges reflect significant correlations among the symptoms and PTSD. However, correlation potentially obscures the directions of functional association. For example, correlation between two entities A and B may arise when A influences B, or B influences A, or a third entity C influences both A and B [42]. Therefore, simple correlation network fails to differentiate between such interactions. However, our motivation behind computing a PTSDCN is to identify clusters or groups, where an entity correlates with all other entities in the same group. We used the notion of maximal clique [43] to derive such groups of correlated symptoms from a PTSDCN (see Preliminaries 3.1). Such groups might be of particular interest in determining potential targets for the treatment of PTSD [44]. It would potentially help us devise different treatment strategies that would target large numbers of post-traumatic stress symptoms simultaneously.

Since PTSDCN does not give us any idea about the type of functional association between the symptoms and the disorder, we also built a partial correlation network of PTSD (PTSDPCN). In a partial correlation network, an edge depicts correlation between two entities where the influences of all other entities have been controlled statistically. Thus, PTSDPCN gets rid of any indirect association that is likely to be induced by a third entity and includes only the ones that arise from the direct interactions between two entities. However, both the PTSDCN and PTSDPCN are undirected graphs. To determine which symptoms actually constitute PTSD and which symptoms are reflective of it, we further built a directed acyclic graph (DAG) for PTSD regulatory network (PTSDRN) using Bayesian network of interactions [45].

Bayesian networks (see Preliminaries 3.2 and 3.3) have been widely used in different fields. It has been used in reflective model analysis of bullying [46] and formative model analysis of PTSD among adults reporting childhood sexual abuse [47]. Bayesian network is a Directed Acyclic Graph (DAG) that tries to capture hierarchical dependencies among a set of variables. The nodes in this DAG represent observable or latent variables and the edges represent the direction of functional associations. The motivation behind developing a directed PTSD regulatory network is that the use of DAGs can provide us insights about admissible causal relationships among PTSD and its various symptoms. Hence, they provide suggestions about potential causal relations [48], such as, which symptoms constitute PTSD and which might be reflective of it. Besides, DAG analysis is capable of determining the series of most likely functional associations among multiple variables. Thus, resulting in a cascade of causal relations. Bayesian inference also controls the indirect influence of other entities, given the entity directly influencing a particular component in the network is known.

To determine which post-traumatic stress symptoms are important in the overall development of PTSD, we calculated two indices of centrality in PTSDPCN and PTSDRN. These measures identify the most important nodes in a graph or network. For our purpose, we calculated two measures of centrality, namely strength [49] and betweenness [50] (see Preliminaries 3.4). Strength quantifies the level of connectivity associated with a particular entity, whereas, betweenness measures the level of control asserted by a particular entity on the interactions among other entities. For all measures of centrality, higher values reflect a node's greater importance to the network. Therefore, identifying such important symptoms would provide us potential targets for the diagnosis and treatment of PTSD [51]. Our analysis revealed sleeping disorder to be the most important post-traumatic stress symptom in the etiology of PTSD. We propose this symptom would be a better target to design interventions for treating PTSD.

Next, to investigate the utility of EEG in diagnosing PTSD, we used a low-cost, consumer-grade, and portable EEG headset among the Rohingya refugees and healthy Bangladeshi individuals. Besides, we collected free-hand sketches from the refugees, slum-dwellers, and engineering students using simple pencil and paper and digitized them using mobile phone camera. We analyzed our collected data using various statistical methods and machine learning algorithms. We identified several neurobiological markers associated with different post-traumatic stress symptoms. For example, we observed significantly lower mid gamma power while talking among the refugees diagnosed with PTSD.

In addition, we trained a Convolutional Neural Network (CNN) using the sketch images to classify the sketches from PTSD and non-PTSD participants. Though the model has 78.3% accuracy, it performs poorly as a classifier (MCC: 0.076). This might be due to small sample size of our training data. Next, we developed multiple logistic regression models with participants' group, gender, qualitative sketch themes, and quantitative sketch features from image processing algorithms. Our developed models were able to screen the potential cases of PTSD with reasonable accuracy (82.9–87.9%, F1-score: 0.807–0.876, MCC: 0.377–0.611, AUC: 0.801–0.939).

To gain a deeper understanding of the drawing task, we studied neurobiological activities while sketching using a low-cost and portable EEG headset. For a subset of our subjects, we collected their EEG data while sketching and trained a Random Forest model using sketch features and EEG data. This greatly improved the accuracy (99.29%, F1-score: 0.993, MCC: 0.985, AUC: 1.0) of screening. Although it is infeasible to record brain signal activities in all circumstances, incorporating them with sketch features can greatly improve the potential assessment of PTSD. Overall, we make the following contributions:

- We provide an initial proof for a novel, low-cost, and creative method that leverages EEG signals and free-hand sketches to screen the potential cases of PTSD within marginalized communities.

- Our proposed low-cost assessment method using pencil, paper, inexpensive mobile phone camera, and portable EEG headsets can be particularly useful in resource-scarce populations.

- Due to the non-verbal nature of sketching and its low overhead, our developed models have the potential to address communication barriers and resource constraints.
- Our method relieves the traumatized individuals of the burden and stigma associated with sharing sensitive, personal traumatic experiences to a stranger and thus, increases individual privacy.
- To the best of our knowledge, our developed hybrid models of PTSD, based on its reflective and formative properties, are the first of its kind.
- Our key findings from the neurobiological abnormalities and underlying structure of PTSD provide potential directions for the diagnosis and treatment of PTSD.
- Finally, due to the automated nature of feature extraction and machine learning models, our proposed method and the metrics are standardized, repeatable, and objective.

Chapter 2

Related Work

We situate our research in a body of related work examining the association among PTSD and its various symptoms. Besides, we focus on the use of ubiquitous systems for screening PTSD and explore the utility of free-hand sketches in studying mental health disorders.

2.1 PTSD as a Causal System

PTSD is a multifaceted psychiatric disorder. Over the years, many models have been proposed to capture the complex and dynamic interactions among PTSD and its symptoms, such as latent variable model (reflective model) [52, 40], network model (formative model) [53, 41], etc.

According to the reflective model, the manifestation of PTSD denotes a latent variable that functions as the common cause for each symptom of PTSD. This implies that PTSD bears the causal relevance for the observed values of each post-traumatic stress symptom [54, 55, 56]. Hence, the symptoms correlate with each other as they share a common determinant. For example, in the traditional latent variable approach, trauma events lead to the development of PTSD. Then the underlying disorder causes the post-traumatic stress symptoms that reflect its presence.

On the contrary, the network or formative model assumes that the symptoms are constitutive of the mental disorder, not reflective of it. According to this view, symptoms correlate not because they share a common dependence on an underlying latent entity, but because they are coupled through direct and homeostatic links [52, 40]. Therefore, in this model, PTSD is not an underlying disease that produces symptoms, rather it is a network of interacting as well as self-reinforcing symptoms [57]. For instance, in formative models of PTSD, some stressors produce certain symptoms that activate other symptoms, possibly in circular and self-reinforcing ways. In this view, post-traumatic stress symptoms are not passive psychometric reflectors of an underlying disorder, rather they are the active constituents of the disorder [58, 59].

However, both of these models (reflective and formative models of PTSD) often miss the complexity, multiplicity, and non-linearity of relationships that lie between the symptoms and the disorder. Since there are so many social, psychological, and neurobiological factors that are important in the etiology of PTSD, it is often difficult to capture all of them into a single model. For instance, with latent variable (reflective) model, it is implausible for a single factor to explain the diversity of all post-traumatic stress symptoms because such a latent construct can not be necessarily isomorphic and generalized across people [60]. Besides, according to this model, all symptoms are caused by a single latent entity. Hence, correlations among the symptoms cannot be direct and are entirely attributable to the underlying disorder. As a result, the symptoms are likely to be locally independent of each other. However, such local independence of the symptoms is implausible in psychopathology [42].

On the other hand, the formative model conceptualizes PTSD as a cluster of directly related symptoms. This model of PTSD is based on a theoretical conjecture resting on the implausibility of local independence among the symptoms. However, in reality, not all symptoms equally contribute to the development of PTSD, which we confirm by our study in this paper. Our investigation reveals that some symptoms may interact with one other and give rise to PTSD, while some symptoms may emerge as a consequence of the disorder. Therefore, a hybrid model comprising aspects from both reflective (latent variable model) and formative (network model) models of PTSD would be inevitable down the road to reveal the interactions among PTSD and its symptoms.

2.2 Ubiquitous Systems for Screening PTSD

Apart from screening PTSD based on user-reported post-traumatic stress symptomatology, many technological interventions have been introduced for this purpose. For instance, Papangelis et al. [61] built an interactive system that can guide a patient through conversation and elicit enough information to fill-up a PTSD checklist. Larsen et al. [62] developed a high-resolution self-tracking application to track precursors of post-traumatic stress symptoms to facilitate collaborative engagement with the therapists.

Moreover, Mallol-Ragolta et al. [63] used machine learning techniques to predict changes in the severity of post-traumatic stress symptoms based on self-reported questionnaires and skin conductance responses. Sheerin et al. [64] used brain wave signals (e.g., EEG) to characterise and discriminate post-traumatic stress symptoms. In addition, Shim et al. [65] deployed machine learning models to classify PTSD patients from healthy controls using neurobiological markers (P300 features) of the disorder.

Advances in EEG technologies have introduced several inexpensive brain computer interfaces (BCIs) making this technology more affordable and accessible than ever before. Its potential for real-time assessment of a person's cognitive state has facilitated various pervasive brain computer interface applications. For instance, consumer-grade EEG devices are being used for real-time pain control [66], tracking mental engagement of people with ADD and ADHD [67], ubiquitous monitoring of blood pressure [68], detecting ischemic stroke [69], and so on. We extend this line of research by introducing a creative method to screen PTSD using low-cost, commercial-grade, and portable EEG headsets during different activities. To the best of our knowledge, this is the first study to leverage portable EEG headsets for screening PTSD out of the laboratory environment, in real world settings of refugees.

2.3 Ubiquity of Free-Hand Sketches

Apart from investigating neurobiological markers to screen for PTSD, we leveraged non-verbal expressions (e.g., free-hand sketching) to identify the presence of underlying disorder. We selected free-hand sketches because they are easy-to-create, lightweight, and provide a unique, complex visual illustration of traumatic experiences and memories [70, 71]. Due to low overhead (requires pencil and paper), this method is suitable for marginalized communities, who may lack literacy and technological skills [72, 73].

Additionally, free-hand drawings have been used for clinical assessments of cognitive dysfunction in amnesia, dementia, and Alzheimer's disease [74, 75]. Standardized clock drawing tests that have been used for diagnosing Alzheimer's disease correlate well with traditional scores of MINI [76, 77]. These tests have greater clinical utility while screening culturally, linguistically, and educationally heterogeneous populations as they require minimal language interpretation and training to administer [78, 79]. However, they require human intervention for evaluating the sketches and are often prone to biases in human interpretation [80, 81].

In this light, Pereira et al. [82] developed an automated machine learning method to recognise patients of Parkinson's disease from the control group based on features from the spirals and meanders drawn by the patients. To the best of our knowledge, no such prior work has investigated the sketches drawn by PTSD patients. Spring [38], however, observed recurring graphic forms in the sketches of sexually abused PTSD patients. Furthermore, Eisenbach et al. [83] qualitatively identified seven symbols (e.g., forest, death, body, etc.,) from the paintings of childhood trauma survivors of loss and sexual abuses.

Similarly, Backos [84] used Kinetic Family Drawing and Draw-A-Person screening tools to identify indicators of PTSD among mothers and children subjected to intimate partner violence. The author reported that the sketches of clinically diagnosed PTSD victims are more estranged and depict more negative interactions with family than that of the control group. O'Flynn [85] found significantly greater number of monstrous grotesque figures and distorted bodies in the human figure drawings of traumatically grieving children.

Hence, we aim to explore whether image processing algorithms, independently from human interaction, are able to identify any visual pattern from the images of free-hand sketches drawn by people with varying experiences of trauma. Additionally, we inspected whether such characteristics can be utilized to screen for the potential cases of PTSD. We used phone camera to digitize the sketches because the falling prices of mobile phones make them suitable to engage marginalized groups [86].

2.4 Ubiquitous Computing for Marginalized Communities

Recently there have been several attempts to democratize the use of pervasive computing applications within underrepresented communities [87]. For example, technological interventions and mobile applications have been used to help refugees resettle, overcome language barriers, and support one another [88, 89]. Digital technology has also been used to improve the healthcare experiences of the marginalized groups. For example, Kreps [90] studied the results of the Digital Divide Pilot Project to test new strategies for disseminating relevant health information to underserved and at-risk audiences. Thinyane et al. [91] used ICT-based solutions to provide e-health services in the rural community of South Africa.

Similarly, Cao et al. [92] used deep learning methods and mobile technologies to improve the diagnosis of tuberculosis among resource-poor and marginalized communities in Peru. Talhouk et al. [93]

studied various factors to design effective digital interventions for improving antenatal health in Syrian refugee camps. In another work, Talhouk et al. [94] explored the implications of community radio shows on the health education of Syrian refugees. Moreover, Ginsberg et al. [95] deployed a randomized, controlled trial to provide smartphone-based mHealth services to rural women in Bangladesh, who reported abnormal clinical breast examinations.

However, despite these efforts, access to technological services is limited within marginalized communities because of financial constraints, poor infrastructure and Internet connectivity, lack of literacy and skilled professionals, and so on [96, 97]. Hence, to reduce the technological burden on the marginalized individuals, we use simple pencil and paper, easily accessible materials that enable the participants to generate ideas freely and naturally [98]. Moreover, Devito et al. [99] pointed out, interdisciplinary collaboration is necessary in order to improve the well-being of marginalized communities. Here, we collaborate with HCI researchers, psychiatrist, psychologist, CS students, and architecture graduate to design a method that eases the burden of verbal communication for traumatized and underrepresented communities.

Chapter 3

Preliminaries

In this chapter, we describe various theoretical and experimental concepts used in our analyses. We first start with the concepts from graph theory used for developing the hybrid models of PTSD (i.e., PTSDCN, PTSDPCN, and PTSDRN).

3.1 Clique

A clique is a subset of nodes in an undirected graph or network such that any two distinct nodes in the clique are adjacent, i.e., there exists an edge that connects them. Therefore, a clique is a complete subgraph of the original graph or network. For example, in the following undirected graph (Figure 3.1), there are two cliques. One clique consists of nodes $\{3, 4, 5\}$ where all of them are connected to each other via edges: (3-4), (3-5), and (4-5). Thus, they make a complete subgraph of three nodes. Another clique consists of nodes $\{1, 2, 3, 4\}$, where any two nodes are connected. This clique is a complete subgraph of four nodes.

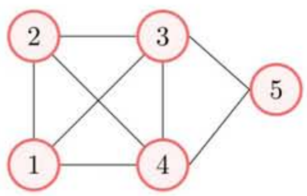


Figure 3.1: An undirected graph

In case of PTSDCN, a clique is a subset of entities where each entity correlates with all other entities in the subset, thus, resulting in a complete subnetwork of association. Such subnetworks will help us identify the group of post-traumatic stress symptoms that affect one another and also influence the manifestation of PTSD. Therefore, these subnetworks might be of particular interest in determining potential psychiatric symptoms, which play crucial role in the developmental hierarchy of PTSD.

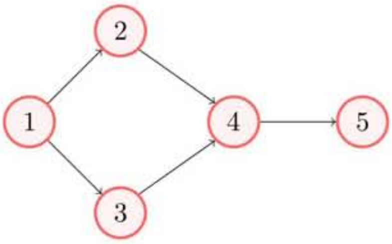
A graph or network may contain multiple cliques. A maximal clique is a clique that cannot be extended by including one more adjacent vertex. For example, in the undirected graph in Figure 3.1, both cliques (i.e., {3, 4, 5} and {1, 2, 3, 4}) are maximal cliques because if we add one more node to the existing set of vertices they will not satisfy the definition of clique. In case of PTSDCN, such maximal cliques might be helpful in representing clusters of symptoms, where the interactions are absolutely self-contained.

On the other hand, the maximum clique of a graph is a clique such that there is no other clique with more nodes. For example, in the undirected graph shown in Figure 3.1, there are two cliques: one comprising 3 nodes {3, 4, 5} and another comprising 4 nodes {1, 2, 3, 4}. The clique with 3 nodes is not a maximum clique because there is another clique consisting of more nodes than it. Therefore, the clique with 4 nodes {1, 2, 3, 4} is the maximum clique of the graph because there is no other clique with more than 4 nodes.

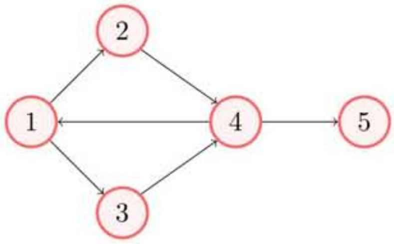
We can see that the clique consisting of nodes {1, 2, 3, 4} is both a maximum clique and maximal clique, whereas, the clique with nodes {3, 4, 5} is only a maximal clique. Therefore, it is worth mentioning that all maximum cliques are maximal cliques because they cannot be extended by adding any more adjacent node. However, the reverse is not true. Such maximum clique in PTSDCN refers to the largest possible group of entities or symptoms, where each entity correlates with all other entities in the same group. Finding the largest possible group of correlated entities would help us figure out how most of these entities are interacting with one another and forming the basis of the disorder.

3.2 Directed Acyclic Graph (DAG)

In graph theory, a directed graph is one where edges have directions. In a directed acyclic graph, there is no cycle, i.e., there is no way to start at any vertex v and follow a sequence of directed edges that eventually loops back again to v. For example, the directed graph in Figure 3.2a is an acyclic graph or DAG because starting from any node in this graph there is no such path that returns to it. But the directed graph in Figure 3.2b is cyclic because if we start from node 1 we can return to it via $1 \rightarrow 2 \rightarrow 4 \rightarrow 1$ or $1 \rightarrow 3 \rightarrow 4 \rightarrow 1$. Or, if we start from node 4, we can return to it via paths $4 \rightarrow 1 \rightarrow 2 \rightarrow 4$ or $4 \rightarrow 1 \rightarrow 3 \rightarrow 4$.



(a) A directed acyclic graph.



(b) A directed cyclic graph.

Figure 3.2: Directed graphs.

As we mentioned earlier, correlation networks are basically undirected graphs. Therefore, they do not suggest the direction of possible causal associations among the entities. On the other hand, DAGs are able to suggest the directions of possible causal associations among different symptoms. Such directed causal associations might help us determine whether a symptom affects another symptom or not. They also suggest which symptoms eventually lead to the development of PTSD as well as which ones are reflective of it. Therefore, building directed networks of PTSD is of particular interest in determining the causal association between PTSD and its various symptoms.

3.3 Bayesian Networks

Many techniques are available to build directed acyclic graphs. One of them is Bayesian inference where Bayes' theorem is used to update the probability of a hypothesis as more information becomes available. We used Bayesian inference to build a Bayesian network for the causal interaction between PTSD and its various symptoms. A Bayesian network is a probabilistic graphical model that represents conditional dependencies among a set of variables via a directed acyclic graph or DAG. For example, in case of PTSD, Bayesian inference may help us evaluate different hypotheses about which symptoms are directly affected by another symptom or how it relates to PTSD. Given enough information about the psychiatric symptoms of PTSD diagnosed population, a Bayesian network can represent probabilistic relationships among the symptoms and the disorder. In Bayesian networks, nodes may represent both observable quantities (various psychiatric symptoms) and latent variables (PTSD) and edges represent conditional dependencies.

For example, in Figure 3.3, we have demonstrated a hypothetical Bayesian network for PTSD

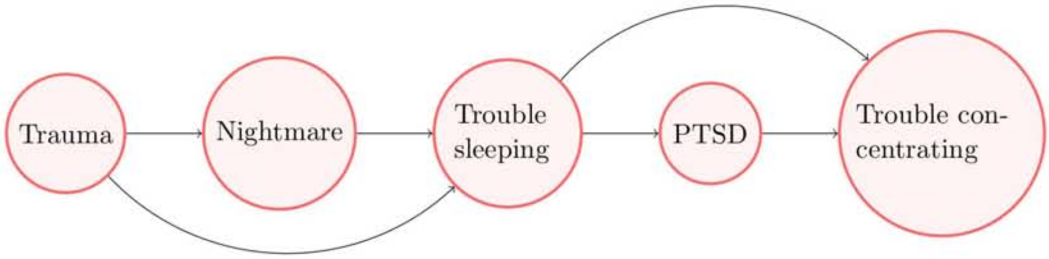


Figure 3.3: A hypothetical Bayesian network for PTSD and its symptoms.

and its symptoms. In this network, the nodes represent PTSD as well as other post-traumatic stress symptoms. The directed edges represent direct associations while a directed pathway from one variable to another implies a causal relationship affected by the intermediate variables on the path. In this hypothetical regulatory network of PTSD, trauma events eventually lead to the development of PTSD via intermediate interference of post-traumatic stress symptoms, such as, nightmares and sleeping disorder.

3.4 Centrality

In a network containing multiple nodes, it is essential to measure the importance/ contribution of each node in the overall functionality of the network. Many measures are available to evaluate the role of a node in a network and centrality is one of them. The centrality of a node measures its contribution to the network. In case of PTSD, centrality finds the most important or influential symptom within the network. In PTSD regulatory networks, the importance of a node (symptom) might refer to its degree of associations with other nodes (symptoms). It may also indicate the degree of influence or control that a particular symptom asserts on the interactions among other symptoms of the network. There are various measures of centrality. For our analysis, we used the following two measures:

- **Strength**: In a network, the nodes that are connected to majority of the nodes are of particular interest. Degree centrality is a measure to quantify the level of connectivity of a particular node. Degree is the number of links incident upon a particular node, i.e., the number of edges connected to it. For example, in Figure 3.4, the degree centrality of node Z is 4 because it has 2 incoming edges and 2 outgoing edges.

  In a weighted network, strength of a particular node is the sum of weights of all the edges incident to it. It reflects the overall strength of association associated with a particular node. For example, in Figure 3.4, the strength of node Z is the sum of weights of all edges incident to it, i.e., $60 + 35 + 78 + 40 = 213$. In case of PTSD regulatory network, strength measures the degree of involvement of a particular symptom in the underlying dynamics of PTSD. We have chosen it over simple degree centrality because to account for the existence of an association is not enough. Since all associations are not of equal strength, we need to consider their respective weights while considering the degree of involvement of a particular symptom. Because, the symptoms that greatly interact with other symptoms might play a crucial role in the underlying dynamics of PTSD.

- **Betweenness centrality**: Betweenness measures the number of times a particular node lies along the shortest path between two other nodes. This measure quantifies how much control an entity exerts over the interactions among other components in the network. For example, in Figure 3.4, node Z lies in the shortest path between node X and node Y. It also lies in the shortest path between nodes E and F. Therefore, node Z has a betweenness score of 2. In case of PTSD, the betweenness centrality of a symptom might be of particular interest to understand how it intermediates the interaction among other symptoms.

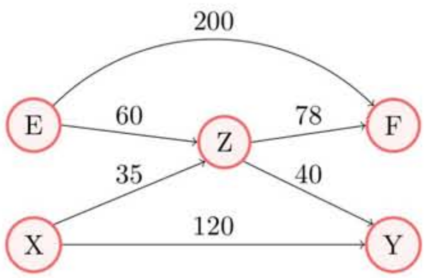


Figure 3.4: A weighted directed graph.

3.5 Statistical Significance Test

We performed different statistical analyses over our collected data. We used *Null Hypothesis* testing for our analyses. Null hypothesis assumes there is no difference between different population parameters. For example, we assumed there is no difference between the neurobiological activities of people screened with PTSD and those who are not or there is no difference among the sketch features of different demographic groups. We used various statistical tests to accept or reject the null hypothesis.

When the data followed normal distribution (based on Shapiro-Wilk normality test [100]), we used parametric tests, such as t-tests and F-tests. Otherwise, we used non-parametric tests that do not assume any underlying distribution of the data. In such cases, we used non-parametric tests, such as Mann-Whitney U test or Wilcoxon signed rank test.

All these tests measure what is the probability that the observed difference between the population parameters is due to random chance. This also gives us the probability of making an error by assuming there is a difference between the population parameters, when in reality there is not any. A statistical significant difference is recorded (i.e., null hypothesis is rejected) when the probability (P value) is less than 0.05. This implies that there is only 5% probability that the observed difference has arisen due to random chance. In other words, we have 5% probability of making an error by rejecting the null hypothesis when in fact it is true. In case the null hypothesis is rejected, we accepted the alternative hypothesis that there exists difference between the population parameters.

Since we performed multiple hypothesis testing for all our analyses and there is 5% probability for each test outcome to be wrong, small probabilities (P value < 0.05) might appear by chance. This could lead us to assume the presence of statistical significance that might not exist. Therefore, we applied Benjamini-Hochberg correction [1] that adjusts P values to help us avoid false positives (i.e., accepting the presence of statistically significant difference when it does not exist).

Chapter 4

Methodology

In this chapter, we present the details of our data collection and analyses. As per our study pipeline, we (1) screened all the participants for potential cases of PTSD, (2) collected free-hand sketches and EEG signals from different groups, and (3) analyzed the data to understand the association among PTSD and its symptoms to develop various machine learning models for screening PTSD (Figure 4.1). One expert psychiatrist and one experienced psychologist helped us interview the participants, score the screening tool of PTSD, conduct drawing tasks as well as interpret the sketches qualitatively. Our study protocol was reviewed and approved by Refugee Relief and Repatriation Commission (RRRC) under Ministry of Disaster Management and Relief, Government of Bangladesh and IRB at the author's institution.

4.1 Participants

We focused on four different groups with seemingly independent socioeconomic and cultural backgrounds to investigate the utility of EEG and free-hand sketches in diagnosing PTSD from a wider and more diverse context. We used *pwr* package[1] from R to estimate the required sample size for our study. There are two possibilities: collected data from the participants may either follow parametric distribution or non-parametric distribution. In case the data followed parametric distribution, we would require 14–28 people per group for intra-group analysis and at least 23 people per group for inter-group analysis. However, if the data followed non-parametric distribution, we would require 15% additional subjects [101], i.e., at least 16–32 people for intra-group analysis and at least 27 people

[1] https://github.com/heliosdrm/pwr

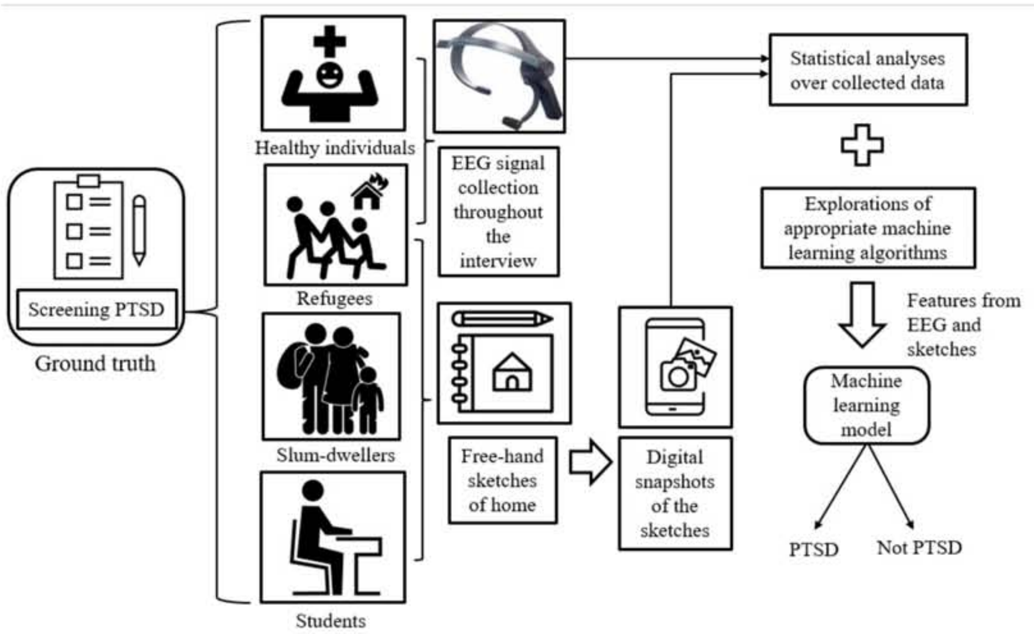


Figure 4.1: Our study pipeline to explore PTSD using EEG and free-hand sketches.

for inter-group analysis. We considered both possibilities and our collected data points exceed the upper limit of these requirements. After collecting data, we used shapiro-wilk normality test to apply parametric or non-parametric tests depending on the type of data.

4.1.1 Healthy Bangladeshi Individuals

In December 2017, two of our interviewers (one male and one female) interviewed and collected data from 45 healthy Bangladeshi citizens (15 female and 30 male) aged between 14–60 years, who volunteered to participate in our study. We conducted the interview sessions in Bengali, which is the mother tongue of both the interviewers and the participants. We used data from this group to examine whether the mental and neurobiological statuses of the Rohingya refugees differ from that of the healthy individuals or not.

4.1.2 Rohingya Refugees

In January 2018, five of our interviewers (two male and three female) collected data from the Rohingya refugees in Kutupalong refugee camp, Cox's Bazar, Bangladesh. It is the world's largest reported refugee camp [102]. With the help of camp officials and *'Majhi'* (Rohingya camp leaders), we recruited

71 refugees (37 female and 34 male) aged between 7–70 years, randomly from the camp area. We interviewed them at the camp registration office instead of their shelters to reduce bias while collecting EEG data.

We conducted all the sessions in Chittagonian dialect (of Bengali language), which is closely related to Rohingya dialect and commonly understood by the refugees [103]. The presence of interviewers and *'Majhi'*, expert in Chittagonian dialect and Rohingya dialect respectively, greatly helped us overcome the language barrier. We collected data from morning to late afternoon so that the refugees could join freely without hampering their day's work. Each participant was offered 100 taka ($1.18) as compensation after the interview. The kids accompanying some of the participants were offered biscuits and bananas. Please note that, during recruitment we did not mention monetary incentive to reduce undue influence in participation.

4.1.3 Slum-Dwellers

Next, in September 2019, four of our interviewers (two male and two female) collected data from the slum-dwellers in Korail Slum (known as *Korail Bosti*), Dhaka, Bangladesh. This is the largest slum in the capital city Dhaka [104]. At first, we tried to recruit participants from the local tea stalls, a common place for hang-out in the slum. However, people there denied to talk to us without the approval of their local leaders assuming we were inspecting illegal housing in the slum.

When we approached the local political leaders, they readily helped and took us to different households. After receiving assurance from them, the slum-dwellers felt free to talk to us. With their help, we were able to interview and collect data from 35 slum-dwellers (32 female and 3 male) aged between 10–65 years. We conducted our sessions in Bengali, which is the mother tongue of both the researchers and the slum-dwellers. Our sessions continued from morning to early afternoon when the male members of most of the households were outside at work. As a result, most (n = 32, 91%) of our participant slum-dwellers are females.

4.1.4 Engineering Students

Lastly, in September 2019, we collected data from the Engineering students of a university in Dhaka, Bangladesh. With the help of some university students and teachers, we recruited 85 students (35 female and 50 male) aged between 18–22 years, who volunteered to participate in our study. With the help from university faculty members, four of our interviewers (two male and two female) interviewed and collected data from the students in separate classrooms. We conducted our sessions in Bengali (mother tongue of both the researchers and the students) within regular class hours (from 8am–5pm) of the university.

4.1.5 Consent

We briefed the participants about our study and took informed consent from them prior to data collection. We took verbal consent from the illiterate participants (43 refugees and 22 slum-dwellers). In case of minors (9 refugees and 8 slum-dwellers), we took informed consent from their parents.

4.2 Tools for Data Collection

Our data collection encompasses multiple phases comprising screening of PTSD, collection of EEG data, and free-hand sketches. In the following, we describe the details of our study procedure.

4.2.1 PTSD Screening Tool

To identify the potential cases of PTSD, we used a screening tool adapted from the PTSD module of MINI 5.0.0 [39]. This tool has been designed specifically for psychiatric emergency settings among the refugees and migrants [105]. Because it is difficult for the psychiatric patients in underserved communities to receive any follow-up diagnosis after initial consultation [106]. In contrast, the tool we used is simple and takes feasible time to administer. Moreover, its items could be communicated easily to the low-literate and linguistically different participants in our study. It asks the following questions to identify probable cases of PTSD:

1. During this event, have you experienced severe physical injury or harm regarding your physical identity, or experienced any loss of your family member or significant other or relative?
2. Do you often think about this event in a distressing way, do you dream about it, or do you frequently have the impression of re-experiencing it?
3. Since the occurrence of this event, have you tended to avoid everything that could remind you of the event?
4. Do you have trouble recalling exactly what had happened?
5. Since this event, have you experienced any of the following changes:

(a) having trouble in falling asleep or waking up often?

(b) feeling irritable or having outbursts of anger?

(c) having trouble in concentrating on regular activities?

(d) feeling nervous or constantly on guard?

(e) feeling easily startled?

Questions 1–3 are the screening questions and questions 4–5 are the diagnostic questions. All the questions are coded with simple 'yes'/ 'no' response. The diagnostic questions are asked, only if all the screening questions are answered positively. A potential case of PTSD is recorded if the question 4 or at least two out of five items in question 5 are answered positively along with positive responses to all the questions 1–3.

We conducted semi-structured, one-to-one interviews with the Rohingya refugees (in Chittagonian dialect) and slum-dwellers (in Bengali) using our screening tool due to low literacy rates among these groups. For the engineering students and healthy Bangladeshi individuals, we used self-report form of the Bengali translated questionnaire. The translation process was carried through the following steps.

- We conducted several focus group discussions to achieve conceptual equivalence, i.e., we tried to clarify each item in the PTSD screening tool to accommodate the values, beliefs, and characteristics of the Bangladeshi population and the variations in the presentation and meaning of PTSD in Bangladesh [107].
- Next, two university faculty members and one graduate engineering student, who are native Bengali speakers and have good background in English translation, performed forward translation of the questionnaire.
- We made minor revisions to the original translation based on the reviews from two other university faculty members, who are also native Bengali speakers and experienced in research studies conducted in English.
- The original PTSD screening tool and the translated version, together with corresponding explanations and rationale behind the translations, were examined by an expert, multi-disciplinary committee formed by the authors and the translators. They cross-checked the translation from the perspectives of both mental health and language compatibility. The committee approved

the contextual and conceptual equivalence between the original English and Bengali translated version of the questionnaire at the best possible level.

Our interviewers focused on building rapport with the participants to elicit spontaneous responses through naturalistic conversation. Besides, we were cautious so that the participants could not overburden themselves with the reflections of traumatic events and could maintain their composure.

4.2.2 EEG Headset

To collect EEG data from the Rohingya refugees and healthy Bangladeshi individuals, we used a low-cost, consumer-grade, and portable EEG headset called NeuroSky MindWave mobile headset [108]. The headset has one main electrode that is placed at FP1 site and a reference electrode that is attached to the ear following the International 10–20 system of placing EEG electrodes [109]. It produces EEG power values for eight commonly recognized brain-waves, i.e., delta, theta, low alpha, high alpha, low beta, high beta, low gamma, and mid gamma. Besides, the headset characterizes different mental states, such as attention and relaxation on a relative scale of 1–100 (lower to higher).

For our study, we recorded background EEG signals during different activities. For the Bangladeshi citizens, we collected EEG data while they were (i) talking (casual conversation) ($n = 26$), (ii) at rest ($n = 9$), and (iii) at calm sitting positions ($n = 30$). For the Rohingya refugees, we collected EEG data while they were (i) talking (casual conversation) ($n = 51$), (ii) recalling and sharing trauma events ($n = 54$), and (iii) sketching ($n = 45$). Some participants took part in all the activities while some participated in one or two.

When we requested our participants to wear this non-invasive headset, most of them readily agreed. However, a few refugees expressed concern that the interviewers might know their thoughts by using the headset. Therefore, our interviewers put on the headset themselves. This along with the participation of the fellow refugees assured them that the device was not probing in any way. In fact, none reported any discomfort while wearing the device.

4.2.3 Free-Hand Sketching

As our subject of drawing, we selected **'Home'** for its universal appeal irrespective of the diverse backgrounds of our participants. Home is one of the basic human needs comprising physiological, safety, and security needs in Maslow's hierarchy [110]. Prior studies describe home as a place of permanence and continuity [111], comfort, and center of activities [112]. It strengthens and secures relationships [113] and offers reflection on personal ideas and values [114].

For example, earlier studies situate home at the root of refugee identity [115], belongingness [116], pride [117], their desire for safety [118], and sustaining continuity [119]. Analysis of the sketches of *"home and war"* from Iraqi refugee children confirms that their understanding of war and trauma precedes that of peace [120].

For the slum-dwellers, home is associated with their livelihood [121], safety [122], and is a pre-condition of their ability to benefit from developmental practices [123]. Besides, home environment greatly influences the academic performance of the students [124, 125]. Moreover, Gomes et al. [126] showed that the international students adopt social networks for virtually maintaining their home-based networks to create a *"home away from home"*.

Now, during our study, we requested the participants to draw both of their past (refugees) or present (slum-dwellers and engineering students) homes and expected future homes (all). To ensure uniformity across the groups, each participant was given at most 10 minutes to complete their sketches. We chose simple pencil and paper as drawing tools considering their familiarity, ease of use, and affordability among the participants.

We spent substantial time to make the participants feel comfortable through interactive discussions and invited them to sketch only when they felt prepared. Our experiences confirm that the participants did not find the subject unfamiliar and did not exhibit any sign of feeling uncomfortable. One refugee mentioned that the drawing session helped him refresh his memories of home. Another reported that she was excited and happy to sketch for the first time in life. However, a few refugees and slum-dwellers shied away mentioning their illiteracy. We assured them that the sketches will not be used to assess their drawing skills or literacy levels. This along with the participation of others motivated them.

4.3 Data Preprocessing and Analysis

After de-identifying the collected data properly, we analyzed them using various quantitative and qualitative methods. With the help from psychiatrist and psychologist, we analyzed the interviews, discussions, recordings, and responses of the participants to the PTSD screening tool and identified potential cases of PTSD.

4.3.1 EEG Signals

We transferred the EEG signals from the headset to our laptops using Bluetooth connection. Due to some technical difficulties during data collection, EEG data from 8 Rohingya refugees were corrupted. To identify the potential neurobiological markers of PTSD, we compared EEG signals from the Rohingya refugees and healthy Bangladeshi individuals while they were engaged in casual conversation (talking). However, the length of the collected EEG signals varied among different individuals. Therefore, we considered EEG power values of 40 seconds duration by truncating the signals at both ends.

On the contrary, to explore brain signal activities while sketching we analyzed EEG data from the refugees. To ensure uniformity we truncated the available signals at both ends and considered the middle 60 seconds. To understand the neurobiological characteristics of the refugees while sketching, we selected two different time frames. These are the first and the last 20 seconds of the truncated EEG signal that potentially correspond to the brain activities while sketching their past and expected future homes respectively. The reported EEG values have no units and are only meaningful when compared to each other and to themselves. Therefore, we calculated relative power by taking the absolute power in each frequency band as a percentage of total absolute power over all the bands [127].

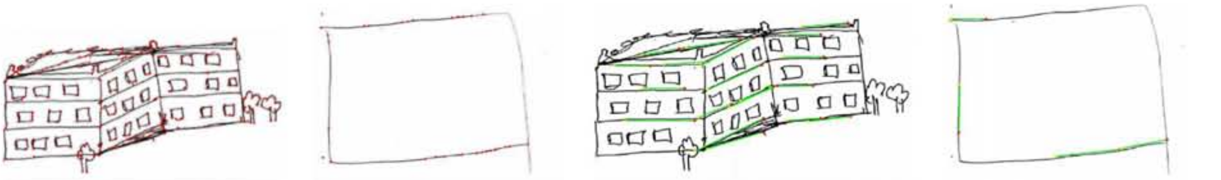
4.3.2 Free-Hand Sketches

We performed different analyses on the free-hand sketches drawn by our participants.

Qualitative Analysis

We formed a multidisciplinary body comprising the interviewers, a psychologist, two CS graduates, and an architecture graduate to interpret the sketches qualitatively using the critical visual methodology framework proposed by Rose [128]. It was used previously to understand the experiences of chronic pain from the drawings of chronic pain patients [129]. Rose suggests that the meanings of a visual image are formed at three different sites: how an image is made, what it looks like, and how it is seen.

We particularly focused on the compositional interpretation of sketch form and content to reduce biases in human interpretation of what the artists might have implied through their sketches [80, 81].



(a) 332 corners in a sketch (b) 29 corners in a sketch (c) 19 strokes, avg length 57 (d) 4 strokes, avg length 56

Figure 4.2: Different features identified from the digital images of two sample free-hand sketches drawn by our participants.

We used written annotations or descriptions, occasionally provided by the participants, to inform our interpretation. We posed a series of questions about sketch content, organization, and expression to guide our analysis. We assigned preliminary codes to the sketches to describe their contents and later grouped them into various common themes via thorough discussions and review process at multiple iterations.

Quantitative Analysis

We converted the free-hand sketches into digital images using a mobile phone (Xiaomi Redmi Note 5A) camera. We used *detectHarrisFeatures* and *houghlines* methods from MATLAB [130] to extract three features (Figure 4.2) from the images that correspond to various details present in the sketches [131, 132] and also correlate well with the semantics of the object being sketched [132]. These are:

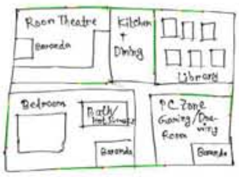
1. Number of corners
2. Number of strokes/ line segments of length greater than or equal to a minimum value
3. The average length of all such identifiable strokes/ line segments (in pixels)

To detect corners, we used MATLAB implementation of corner and edge detection method *detectHarrisFeatures* [133]. Besides, we utilized Hough transformation method *houghlines* [134] from MATLAB to extract the line segments/ strokes. The outcome of *houghlines* method relies on the input image and four different parameters:

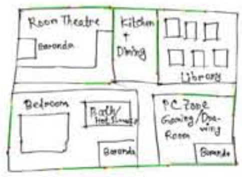
1. *numpeaks*: maximum number of peaks to be identified.
2. *threshold*: minimum threshold to be considered as a peak.
3. *FillGap*: threshold to merge two line segments if their distance is less than this value.

4. *MinLength*: minimum allowable segment length.

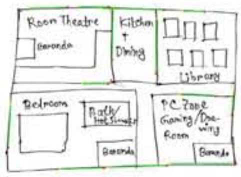
The *houghlines* method is based on Hough transformation technique proposed by Duda and Peter [135]. At first, the method creates a Hough transform matrix of the input image and then identifies peaks from it. The value of *numpeaks* controls the number of peaks that needs to be identified from the image. After tuning this parameter across a wide range of values (keeping other parameters unchanged) for all the sketches, we found that the number of possible line segments becomes saturated after crossing a certain threshold of *numpeaks* (Figure 4.3). For example, from Figures 4.3e and 4.3f, we can see that the number of line segments or strokes in all the sketches saturate at the higher values of *numpeaks*, which is evident from the identical box plots at higher values. Therefore, for our analysis, we initialized *numpeaks* at a value $(1,000)$ greater than the saturation point.



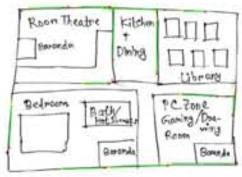
(a) 11 strokes, avg length 73, *numpeaks* 10



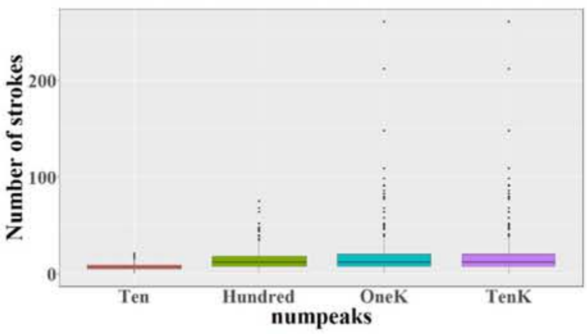
(b) 13 strokes, avg length 78, *numpeaks* 100



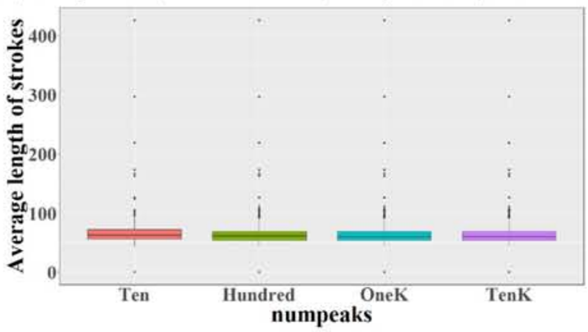
(c) 13 strokes, avg length 78, *numpeaks* 1,000



(d) 13 strokes, avg length 78, *numpeaks* 10,000



(e) Number of strokes for different values of *numpeaks*

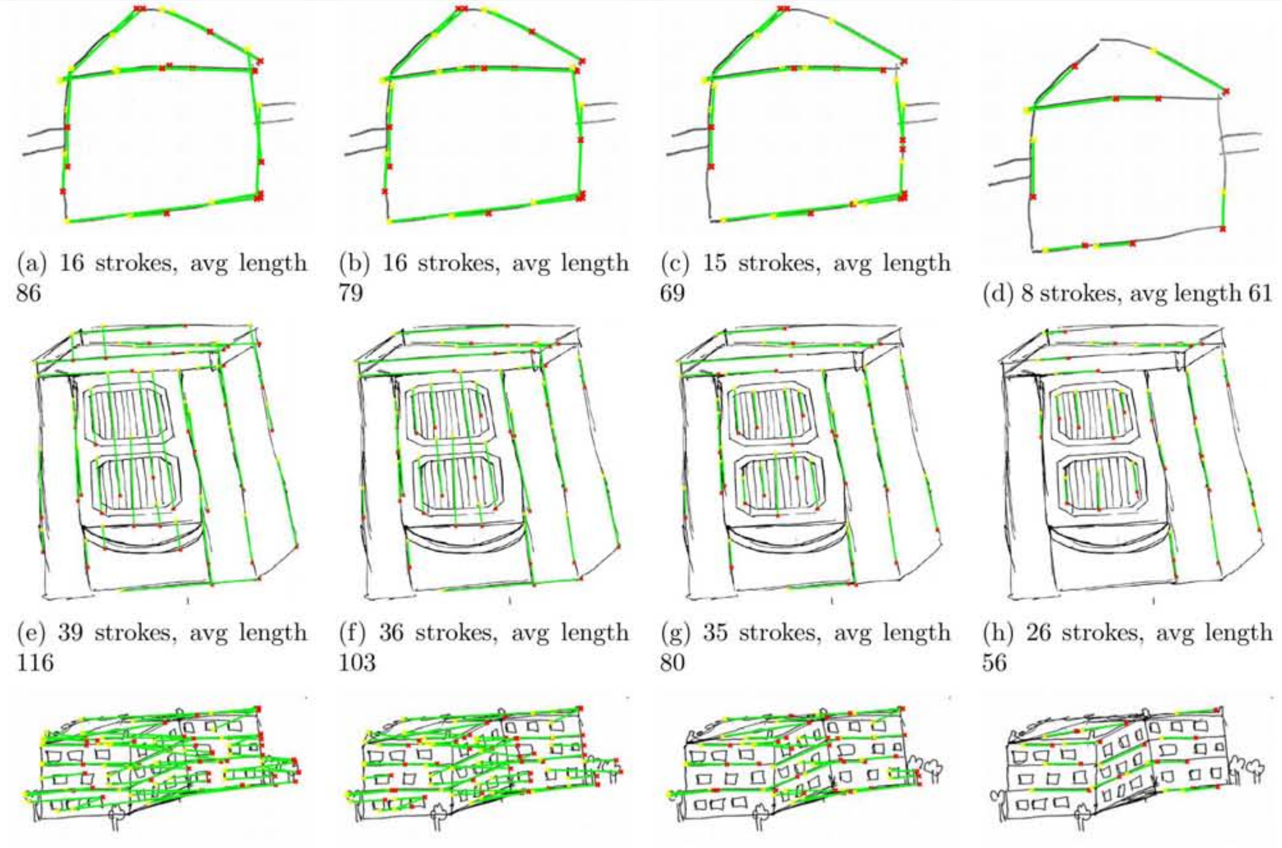


(f) Average length of strokes for different values of *numpeaks*

Figure 4.3: Figures a–d show a sample sketch for which the number of identifiable line segments/ strokes becomes saturated after crossing a certain threshold of *numpeaks*. Figures e and f show the number of strokes and average length of strokes respectively in all the sketches across different values of *numpeaks* (keeping other parameters unchanged).

Next, for *threshold* we used the default value, 50% as it has been used previously to identify strokes of varying orientations [136]. The *FillGap* parameter of *houghlines* refers to the minimum distance between two line segments associated with the same Hough transform bin. If the distance between two line segments is less than the value of *FillGap*, then *houghlines* merges them. Now, due to the nature of free-hand drawing, the sketches usually contain multiple piece-wise segments. However, the segments that belong to the same line are likely to have smaller distance between them than the ones that belong to different lines. Since the default value (20) of *FillGap* is large enough, *houghlines* tends to merge the segments that belong to different lines.

FillGap=20	*FillGap*=15	*FillGap*=10	*FillGap*=5



(a) 16 strokes, avg length 86 (b) 16 strokes, avg length 79 (c) 15 strokes, avg length 69 (d) 8 strokes, avg length 61

(e) 39 strokes, avg length 116 (f) 36 strokes, avg length 103 (g) 35 strokes, avg length 80 (h) 26 strokes, avg length 56

(i) 48 strokes, avg length 103 (j) 48 strokes, avg length 78 (k) 33 strokes, avg length 67 (l) 14 strokes, avg length 55

Figure 4.4: Line segments/ strokes identified by *houghlines* for different values of *FillGap* (keeping other parameters unchanged).

For example, in case of sketches with simple and fewer details (Figure 4.4 a–d), the default value of *FillGap* works as well as any smaller value of it. However, for the sketches with lots of sparse details (Figure 4.4 e–h), higher values of *FillGap* tend to merge the segments that belong to different lines (Figure 4.4 e–f). This phenomena, i.e., the incorrect merging of strokes across different lines reduces with the lower values of *FillGap* (Figure 4.4 g–h). Even for the sketches with lots of dense details, the proportion of incorrectly merged strokes or line segments across different lines is higher (Figure 4.4 i–k) at large values of *FillGap* compared to that of the sketches with sparse details. Again, lowering the value of *FillGap* reduces this incorrect merging of strokes (Figure 4.4 l). Therefore, based on our empirical observations, we initialized *FillGap* with a lower value (5) that has been used previously to properly identify the line segments that belong to the same object [136].

For *MinLength*, we used its default value, 40. Since this value is large enough, the number of identifiable strokes using this value is reflective of the degree to which people can keep their hand steady while sketching quick, firm, and longer strokes [137, 138]. Because, traditionally, smooth and longer strokes have been associated with the confidence of the artist [139]. Finally, we used *norm* [140] from MATLAB to calculate the average length of the strokes identified using the *houghlines* method.

4.3.3 Analyses over the Collected Data

We performed different statistical analyses on our collected data to find how traumatic experiences, neurobiological measures, and sketch features either vary or coordinate across different groups. We used parametric tests for data that follow normal distribution and performed non-parametric tests otherwise. To control false discovery rate for multiple hypothesis testing, we applied Benjamini-Hochberg error correction [1] on all the results.

We used *qgraph* package [141] from R to build the networks of PTSD. We used Pearson's correlation coefficient to determine the associations among different entities in the PTSDCN. In PTSDCN, the edges reflect statistically significant correlations ($r \geq 0.25$, $P < 0.05$) between two entities, whereas, in PTSDPCN, the edges reflect statistically significant partial correlations. We used *bnlearn* package from R [142] to develop PTSDRN based on post-traumatic stress symptomatology of the Rohingya refugees. To build PTSDRN, we used greedy hill-climbing search along with Bayesian Dirichlet sparse score. Because, this score is less sensitive to the values of model hyper-parameter and appears to provide better accuracy in case of structure learning [143].

To identify maximal clique in PTSDCN and PTSDPCN, we used two implementations of Bron-Kerbosch's maximal clique finding algorithm [144, 145]. To calculate the importance of each symptom in PTSDPCN and PTSDRN, we used *centrality* method available in *qgraph*. For all the models we built for our analysis, we used the following abbreviations to designate various symptoms of PTSD:

Moreover, we developed a Convolutional Neural Network (CNN) using *Keras* [146] from Python to see if the implicit features from the sketches could point to the occurrences of PTSD. To find the

Table 4.2: Abbreviated terms for different post-traumatic stress symptoms.

Abbreviation	Symptom	Abbreviation	Symptom
Dst	Feeling distressed	Ngh	Nightmare
Avd	Avoiding trauma-related stimuli including trauma-related thoughts or feelings and reminders	Rcl	Inability to recall key features of trauma
Slp	Difficulty in sleeping	Irr	Irritability or outbursts of anger
Cnc	Difficulty in concentrating	Nrv	Feeling nervous or being on guard

optimal model, we used grid search from *scikit-learn* [147] to tune various model hyper-parameters, e.g., number of epochs, size of dense layer, optimizer function, and dropout rate. Next, we developed linear regression models to screen the potential cases of PTSD using sketch features and other demographic characteristics. We chose a simple linear regression model with five fold cross validation due to the small size of our dataset. Finally, we combined sketch features and EEG data while sketching to identify the potential cases of PTSD. Through extensive experimentation in *Weka* [148], we found that Random Forest model with five fold cross validation works best in screening the potential cases of PTSD based on EEG and sketch features.

Chapter 5

Findings

Table 5.1 lists the demographic information of all the participants. Majority of the refugees ($n = 63, 88.7\%$) in our sample migrated to Bangladesh a few months before our study following the deadly crackdown by Myanmar's army on the Rohingya Muslims [149]. Some refugees ($n = 8, 11.3\%$) migrated long ago due to 1991–92's violence by the Burmese armed forces [150]. Among the Rohingya refugees, 28 (39.4%) refugees have received some form of formal education (primary: 15, secondary: 12, higher secondary: 1). In the refugee camp, some of them ($n = 16, 22.5\%$) are working as day laborers, tailors, farmers, house maids, small retailers, and camp volunteers.

Table 5.1: Summary of the demographic information of different groups of participants.

Demographic information	Rohingya refugees ($n = 71$)	Slum-dwellers ($n = 35$)	Engineering students ($n = 85$)	Bangladeshi individuals ($n = 45$)
Female	37 (52%)	32 (91.4%)	35 (41.2%)	15 (33.3%)
Male	34 (48%)	3 (8.6%)	50 (58.8%)	30 (66.7%)
Mean age	30.15 years (SD = 13.37 years)	28.09 years (SD = 12.4 years)	19.08 years (SD = 1.2 years)	25.77 years (SD = 10.76 years)
Mean migration period	to Bangladesh 2.14 years (SD = 5.75 years)	to Dhaka 8.18 years (SD = 7.34 years)	NA	NA
Illiterate	43 (60.6%)	22 (62.8%)	0 (0%)	0 (0%)
Employed	16 (22.5%)	12 (34.3%)	0 (0%)	36 (80%)

Majority of the slum-dwellers ($n = 30, 85.7\%$) migrated to the capital city Dhaka in quest of a steady income. Illiteracy rate is high within this group. Majority of the participant female slum-dwellers are homemakers. Besides, many work as house maids, raw material sellers, tailors, security guards, rickshaw pullers, garment workers, etc. On the other hand, all the engineering students in our sample are only involved in study. Among the healthy Bangladeshi individuals, many (80%) have full-time jobs and are working as teachers, IT professionals, government service holders, doctors, etc.

5.1 Traumatic Events, Distress, and PTSD

During our interviews, many participants shared their personal experiences of sorrows, sufferings, losses, abuses, and violence. Table 5.2 lists various traumatic events and causes of distress as reported by the participants. The Rohingyas reported a wide range of traumatic events as they experienced collective violence, killings, tortures, and abuses. A 30-year-old female refugee reported,

> "*I lost my family. They killed my husband, three children, and brother. I cannot sleep due to nightmares.*"

Besides, most of the slum-dwellers and their family members suffered terribly due to various diseases, poverty, and poor access to resources. There were many cases of miscarriage and loss of young children among the female slum-dwellers. On the contrary, the narratives of griefs and sorrows of the engineering students appeared to be more personal rather than communal. Some students expressed concern about their continued academic failures, loss of parents or close family members, financial problems, and relationship turmoil. The healthy Bangladeshi individuals reported no cases of traumatic events or personal distress.

Table 5.2: Reported cases of traumatic events and distress among different groups.

Rohingya refugees		Slum-dwellers	
Beating	5		
Physical injury	30	Death of spouse	7
Physical injury of family member/ friend	3	Death of family members	6
Murder of spouse	12	Death of children/ miscarriage	13
Murder of child	10	Financial distress	9
Murder of family member/ friend	48		
Forced to risk the life of family member/ friend	1	**Engineering students**	
Combat situation	2		
Imprisonment	1	Death of family members	4
Abduction	2	Abusive relationship	2
Destruction of personal property	4	Academic failure	2
Rape	2	Financial distress	1

Next, we analyzed the responses of the participants to the PTSD screening tool to measure the prevalence of PTSD (Table 5.3). As the healthy Bangladeshi individuals did not report any traumatic events, none of them passed the PTSD screening test. We found significant differences between the cases of PTSD among the Rohingya refugees and slum-dwellers ($\chi^2(1) = 23.14, P = 1.51 \times 10^{-6}$), refugees and engineering students ($\chi^2(1) = 85.14, P < 2.2 \times 10^{-16}$) as well. In our sample, the prevalence of PTSD is higher among the Rohingya refugees than that of the other groups. Even we observed significant effect of gender ($\chi^2(1) = 5.27, P = 0.021$) on the prevalence of PTSD among the Rohingya refugees. However, there was no such effect of gender on the cases of PTSD in other groups. Overall, PTSD was significantly more prevalent ($\chi^2(1) = 6.92, P = 0.025$) among the females than the males.

Table 5.3: Prevalence of PTSD among different groups of participants in our study.

Group	Male (% of male)	Female (% of female)	Total (% of all participants)
Rohingya refugees	21 (61.8%)	28 (75.77%)	49 (69.0%)
Slum-dwellers	1 (33.3%)	11 (34.4%)	12 (34.3%)
Engineering students	1 (2%)	3 (8.6%)	4 (4.7%)

5.2 PTSD Correlation Network (PTSDCN)

To understand the dynamics among PTSD and its symptoms, we built a PTSD correlation network (PTSDCN) (Figure 5.1). For this, we used the post-traumatic stress symptomatology experienced by the Rohingya refugees as they have the highest prevalence of PTSD among all the groups. The undirected edges in PTSDCN represent Benjamini-Hochberg corrected significant correlations among PTSD and its various symptoms. For example, the width and shade of the edges represent the strength of correlation between two entities. The stronger the correlation, the wider and darker the edge.

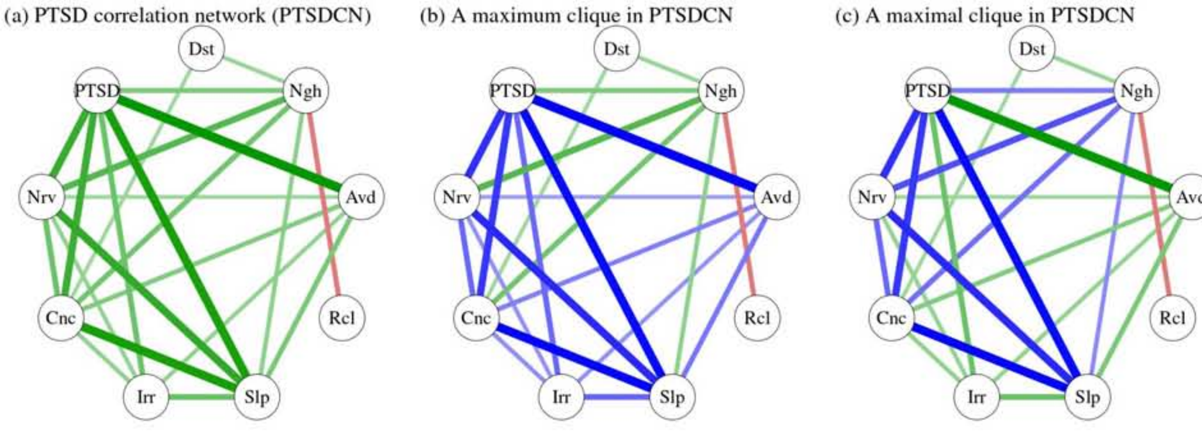


Figure 5.1: PTSD correlation network (PTSDCN) based on Benjamini-Hochberg corrected statistically significant correlations (r $\geq$ 0.25, P $<$ 0.05) among different post-traumatic stress symptoms and PTSD. Blue subgraphs in Figure b and c represent the maximal cliques. The maximal clique in Figure b is also a maximum clique.

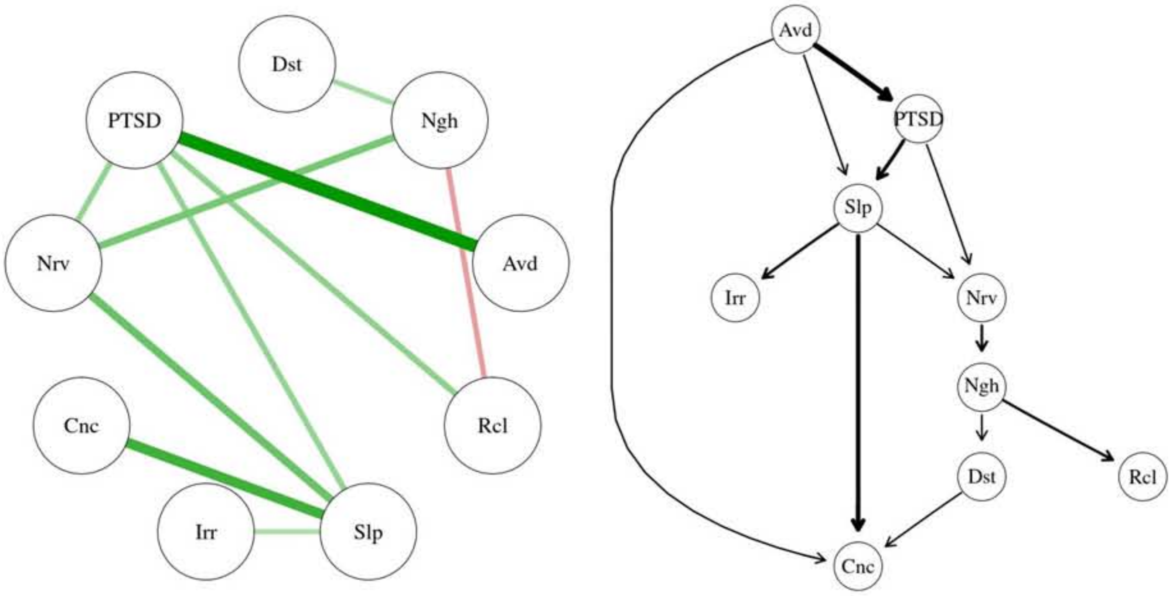
As evident from PTSDCN (Figure 5.1a), strong positive correlations (green edges) exist between PTSD and other psychiatric symptoms except for feeling distressed and inability to recall trauma events. The strongest correlation ($r = 0.74$) appears between PTSD and avoidance of trauma related stimuli. The only negative correlation (red edge, $r = -0.38$) appears between nightmare and trouble in recalling trauma events. The correlations among sleeping disorder, irritability or outbursts of anger, difficulty in concentrating, and feeling of nervousness conform to the clinical observations as embodied in the DSM-5 clusters of trauma-related arousal and reactivity [151].

We found two maximal cliques of large cardinality in our developed PTSDCN that include PTSD along with its various symptoms (blue subgraphs in Figure 5.1b and c). One of them consists of six entities: five symptoms along with PTSD (Figure 5.1b). These symptoms are: avoidance, difficulty in sleeping, irritability, difficulty in concentrating, and feeling of nervousness. This maximal clique is also a maximum clique. It captures the largest possible group of interactions among PTSD and its various symptoms. According to DSM-5 criteria of PTSD [151], this maximum clique successfully groups the symptoms associated with trauma-related arousal and reactivity. Besides, this group contains some of the strongly correlated entities within the network, such as correlation between PTSD and other post-traumatic stress symptoms, e.g., avoidance of trauma-related stimuli ($r = 0.74$), sleeping disorder ($r = 0.68$), difficulty in concentrating ($r = 0.57$), and so on.

The second maximal clique contains four post-traumatic stress symptoms (i.e., nightmare, difficulty in sleeping, difficulty in concentrating, feeling nervous) and PTSD (Figure 5.1c). This maximal clique also captures some of the strongly correlated entities within the network, such as correlation between PTSD and other psychiatric symptoms, e.g., sleeping disorder ($r = 0.68$), feeling nervous ($r = 0.59$), difficulty in concentrating ($r = 0.57$), etc.

5.3 PTSD Partial Correlation Network (PTSDPCN)

Next, we developed a PTSD partial correlation network (PTSDPCN) to figure out the direct interactions among PTSD and its different symptoms. The PTSDPCN derived from the post-traumatic stress symptoms of the Rohingya refugees appears in Figure 5.2a. The edges in this network represent Benjamini-Hochberg corrected statistically significant partial correlations ($r \geq 0.25$, $P < 0.05$) among different entities. The stronger the partial correlations, the wider and darker the edges. We can see PTSDPCN (Figure 5.2a) is less dense, i.e., contains fewer edges than PTSDCN (Figure 5.1). This is because, the edges in PTSDPCN reflect only direct associations, whereas, the edges in PTSDCN may reflect both direct and indirect associations.



(a) PTSD partial correlation network

(b) PTSD regulatory network

Figure 5.2: PTSD partial correlation network (PTSDPCN) and PTSD regulatory network (PTSDRN) based on post-traumatic stress symptoms of the Rohingya refugees.

Significant positive correlations (green edge) appear between PTSD and avoidance (r = 0.74), sleeping disorder (r = 0.31), difficulty in recalling trauma events (r = 0.33), and feeling of nervousness (r = 0.31). If we compare this network with PTSDCN, we can see that the correlations that appear between PTSD and irritation or PTSD and nightmares are likely to be indirect associations because there is no direct edge between them in PTSDPCN. Sleeping disorder might have worked as an intermediary between PTSD and irritability, because in PTSDPCN, difficulty in sleeping is directly correlated with both PTSD and irritability or outbursts of anger (Figure 5.2a).

Both trouble in recalling trauma events and feeling of nervousness might have influenced the indirect association between PTSD and nightmares as observed in PTSDCN. Both of them are directly associated with PTSD and nightmares as evident from their correlations in PTSDPCN. This also applies to the interactions among other symptoms. For example, in PTSDCN, sleeping disorder is significantly correlated with nightmares (Figure 5.1). However, there is no direct association between them as suggested by PTSDPCN. This indirect association might have arisen from their direct interactions with feeling of nervousness (Figure 5.2a).

To measure the importance of symptoms in PTSDPCN, we used two centrality measurements: strength (Figure 5.3a) and betweenness (Figure 5.3b). Sleeping disorder, feeling of nervousness, nightmare, and avoidance emerged as highly central symptoms. The importance of these symptoms is evident from PTSDPCN, where strong partial correlations appear between these symptoms and PTSD. Among all the symptoms, sleeping disorder has the highest strength and betweenness scores. It is the only post-traumatic stress symptom that directly interacts with majority of the symptoms (high strength score). For example, it is strongly correlated with PTSD, nervousness, concentration problem, and irritability (Figure 5.2a). Besides, it is likely to mediate the interactions among other symptoms and PTSD (high betweenness score). For example, it intermediates the indirect associations among PTSD and irritability or outbursts of anger, difficulty in concentrating, etc.

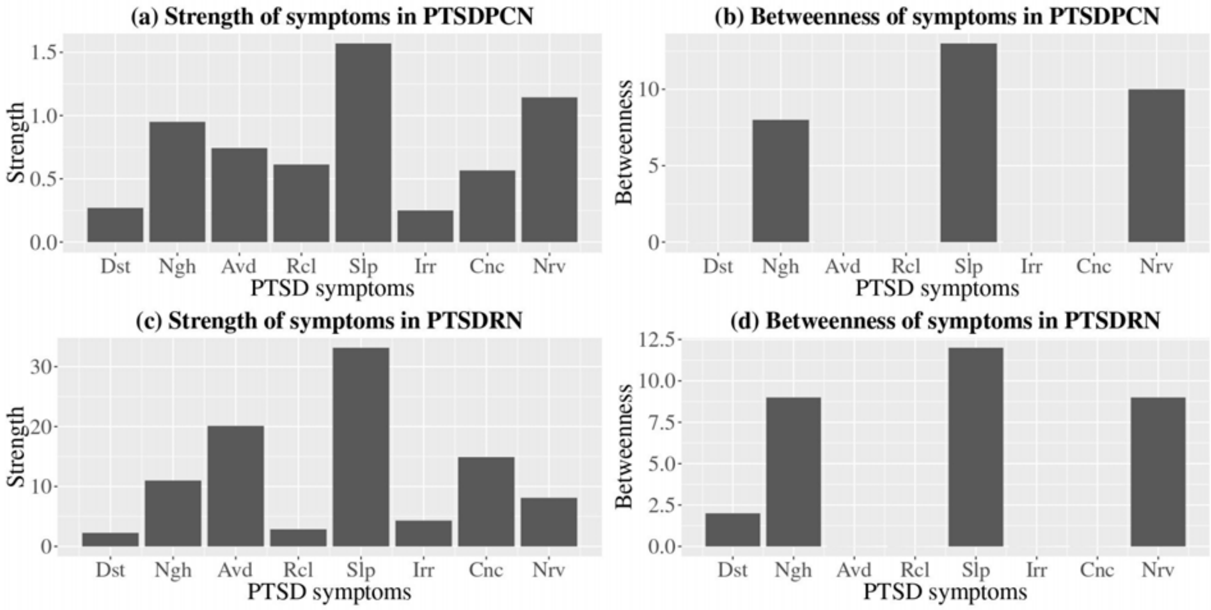


Figure 5.3: Measure of centrality (strength and betweenness) for different post-traumatic stress symptoms in PTSDPCN and PTSDRN.

On the other hand, irritability has the lowest positive strength score. In PTSDPCN, it shares the weakest interaction ($r = 0.25$) with sleeping disorder. Feeling of distress, avoidance, irritability, and difficulty in concentrating have zero betweenness score (Figure 5.3b) because they correlate with only one entity (Figure 5.2a) and therefore, could not mediate the interactions among other entities. In addition, there is a maximum clique in PTSDPCN including PTSD and two highly central symptoms:

sleeping disorder and nervousness. These two symptoms have the highest strength and betweenness scores in PTSDPCN (Figure 5.3a and b).

5.4 PTSD Regulatory Network (PTSDRN)

Figure 5.2b shows the PTSD regulatory network (PTSDRN) built from Bayesian inference of the post-traumatic stress symptoms of the Rohingya refugees. This model reveals a complex structure of relationships among PTSD and its various symptoms. This enables us to infer the directions of several associations more securely. The thickness of the edges signifies the level of confidence that the prediction (and potentially causation) flows in the direction as depicted in the network. Several significant features are evident from this regulatory network.

First, avoidance of trauma related stimuli is the only significant constituent of PTSD, whereas, sleeping disorder and feeling of nervousness reflect the presence of the underlying disorder. Avoidance of trauma related stimuli also functions as a constituent of sleeping disorder. The network directly predicts that difficulty in concentrating is likely to be caused by interactions among sleeping disorder, feeling of distress, and tendency to avoid trauma related arousal. It also predicts that difficulty in sleeping directly affects the mood of the refugees and gives rise to irritability and nervousness. Besides, feeling of nervousness leads to nightmares and consequently, the nightmares affect the victim's ability to recall traumatic memories and make them feel more distressed.

When we measured the centrality or importance of each symptom in this network, we found sleeping disorder to be the strongest interacting symptom within the network (Figure 5.2c and d). This symptom is not only reflective of PTSD but also affects other post-traumatic stress symptoms, such as difficulty in concentrating, feeling of nervousness, and irritability or outbursts of anger. Among other symptoms that are central to the hierarchy of PTSDRN are nightmare, tendency to avoid trauma related stimuli, difficulty in concentrating, feeling of nervousness, etc. Among these symptoms, tendency to avoid trauma-related stimuli is constituent of PTSD while sleeping disorder and nervousness are reflective of it. Besides, nightmare is influenced by feeling of nervousness and difficulty in concentrating is affected by two other central symptoms: sleeping disorder and avoidance. Therefore, we can see that influential symptoms in PTSDRN also interact mutually.

PTSDRN differs from both PTSDCN and PTSDPCN in a number of ways. As per PTSDRN, PTSD is directly associated with three post-traumatic stress symptoms: avoidance, sleeping disorder, and feeling of nervousness (Figure 5.2b). PTSDPCN suggests that difficulty in recalling trauma events is also directly associated with PTSD along with these three symptoms. However, PTSDRN suggests no such interaction between PTSD and difficulty in recalling trauma events. This is because, the Bayesian network connects two entities as cause-effect pairs based on conditional dependency between them, instead of simple correlations.

Moreover, the strength scores of the symptoms in PTSDRN (Figure 5.2c) vary from that of the symptoms in PTSDPCN (Figure 5.2a). This is because, in PTSDPCN edge weights are partial correlations (values between 0 to 1). Therefore, the strength score of each symptom is comparatively small. On the other hand, in PTSDRN, edge weight is a measure of confidence for each edge, calculated using Bayesian Dirichlet sparse score [152]. The weight of each edge in this model is the difference between the scores of the networks including the edge and without this edge. Since these two models adopt different measures to calculate edge weights, the strength scores of the symptoms differ accordingly.

5.5 Relative EEG Power while Talking

Next, to examine neurobiological abnormalities associated with PTSD, we compared relative EEG power values while talking both from the refugees and healthy Bangladeshi individuals (Table 5.4). Here, F-test reveals whether temporal values of background EEG activities show similar variance or not and t-test measures if EEG activities are similar or different across different groups.

Table 5.4: Benjamini-Hochberg corrected F-test and t-test results on the relative EEG power values at $\mathrm{P} < 0.05(*), \mathrm{P} < 0.01(**), \text{and } \mathrm{P} < 0.001(***)$.

Category	Low alpha	High alpha	Low beta	High beta	Low gamma	Mid gamam	Delta	Theta
PTSD	F(1602)=1.28*** t(2365)=4.16***	F(1602)=1.16 t(2289)=1.03	F(1602)=1.32*** t(2386)=-3.03**	F(1602)=1.19 t(2314)=6.68***	F(1602)=0.86 t(2057)=-4.13***	F(1602)=4.55*** t(2441)=15.78***	F(1602)=1.13 t(2273)=-9.66***	F(1602)=1.06 t(2219)=1.86
Dst	F(1079)=1.22*** t(2110)=3.68***	F(1079)=1.46*** t(2035)=0.98	F(1079)=1.23*** t(2166)=-3.75***	F(1079)=1.15 t(2215)=3.84***	F(1079)=0.54*** t(2617)=-7.55***	F(1079)=2.28*** t(1726)=13.56***	F(1079)=1.06 t(2278)=-8.3***	F(1079)=1.1 t(2253)=0.4
Avd	F(1363)=1.09 t(2620)=2.35*	F(1363)=1.20 t(2622)=-0.91	F(1363)=1.05 t(2614)=-4.22***	F(1363)=1.09 t(2619)=2.83**	F(1363)=0.46*** t(2195)=-8.18***	F(1363)=2.49*** t(2329)=10.52***	F(1363)=1.07 t(2617)=-5.02***	F(1363)=1.1 t(2620)=0.13
Slp	F(1628)=1.27*** t(2294)=3.54***	F(1628)=1.17 t(2227)=1.27	F(1628)=1.36*** t(2348)=-2.99**	F(1628)=1.15 t(2213)=5.5***	F(1628)=0.74*** t(1866)=-5.04***	F(1628)=4.88*** t(2451)=18.42***	F(1628)=1.11 t(2187)=-10.05***	F(1628)=1.1 t(2179)=1.26
Cnc	F(1748)=1.23 t(1923)=1.94	F(1748)=1.01 t(1757)=-0.04	F(1748)=1.25*** t(1937)=-2.44*	F(1748)=1.04 t(1782)=1.71	F(1748)=0.71*** t(1514)=-4.54***	F(1748)=3.34*** t(2603)=12.75***	F(1748)=1.09 t(1816)=-5.25***	F(1748)=1.05 t(1789)=-0.91
Ngh	F(1649)=1.18 t(2180)=2.33*	F(1649)=1.44*** t(2336)=3.36***	F(1649)=1.50*** t(2368)=-0.81	F(1649)=1.21 t(2202)=5***	F(1649)=1.18 t(2179)=-1.92	F(1649)=3.67*** t(2588)=16.25***	F(1649)=1.16 t(2165)=-9.41***	F(1649)=1.07 t(2100)=0.16
Rcl	F(2424)=0.89 t(229)=-1.04	F(2424)=2.41*** t(285)=4.22***	F(2424)=1.95*** t(267)=1.98	F(2424)=3.15*** t(314)=5.91***	F(2424)=4.36*** t(363)=3.61***	F(2424)=0.90 t(229)=0.82	F(2424)=1.18 t(239)=-3.26	F(2424)=1.39 t(247)=2.92**
Irr	F(1831)=1.08 t(1562)=0.58	F(1831)=1.02 t(1519)=-0.12	F(1831)=1.04 t(1530)=-3.43***	F(1831)=0.99 t(1499)=1.89	F(1831)=0.61*** t(1225)=-5.63***	F(1831)=4.27 t(2593)=16.62***	F(1831)=1.04 t(1532)=-5.95***	F(1831)=0.97 t(1483)=-0.81
Nrv	F(1438)=1.23*** t(2602)=4.22***	F(1438)=1.42*** t(2622)=2.97**	F(1438)=1.36*** t(2618)=-2.75**	F(1438)=1.29*** t(2611)=8***	F(1438)=0.75*** t(2361)=-5.5***	F(1438)=5.02*** t(2070)=20.33***	F(1438)=1.14 t(2580)=-13.42***	F(1438)=1.13 t(2576)=2.82**

Here, asterisks represent statistically significant test results. Cases reporting lower P values point to greater significance. The key findings from our analyses are as follows.

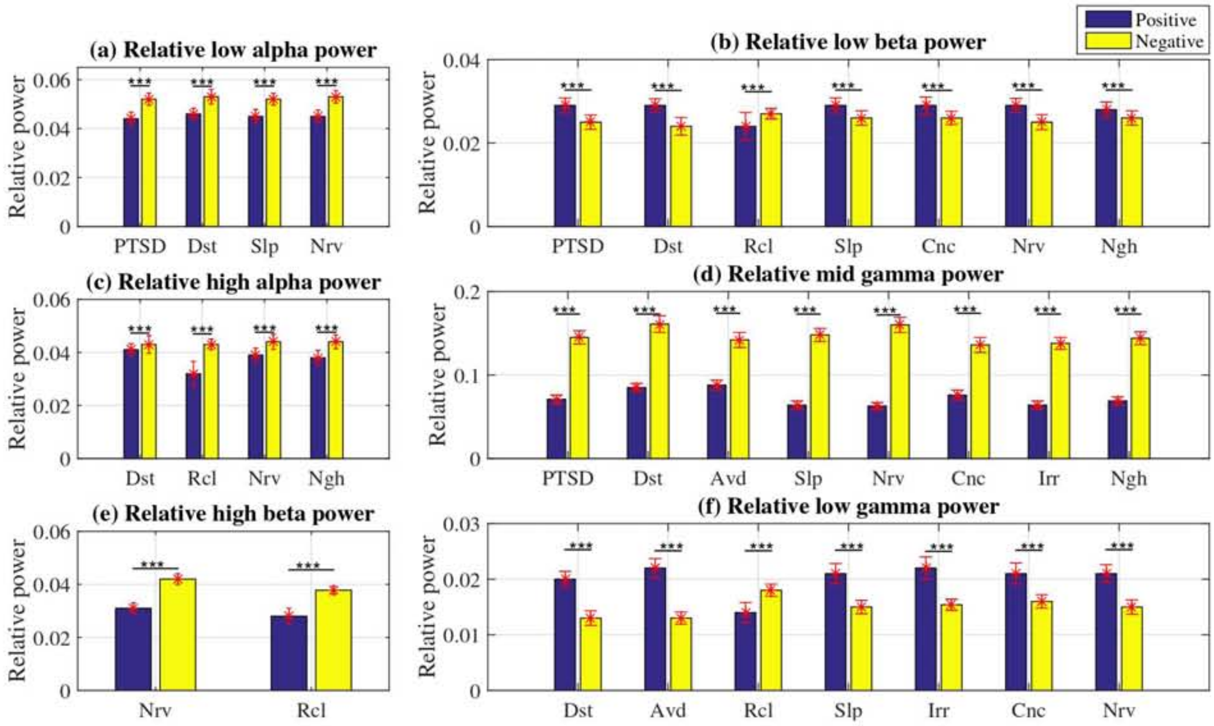


Figure 5.4: Comparison of relative EEG power values between (1) PTSD and non-PTSD cases, and (2) the participants with or without different post-traumatic stress symptoms. Here, asterisks represent Benjamini-Hochberg corrected statistically significant results at P < 0.001 (***).

- We observed significant variance in low alpha, low beta, and mid gamma waves of the PTSD and non-PTSD groups while talking (Table 5.4, Figure 5.4a, b, d).
- Participants diagnosed with potential cases of PTSD or afflicted with one of the symptoms in the maximum clique of PTSDCN (i.e., avoidance, sleeping disorder, irritability, difficulty in concentrating, or nervousness) (Figure 5.1b) exhibited significant variance and lower relative power in mid gamma frequency bands while talking (Figure 5.4d and Table 5.4).
- Besides, participants screened with PTSD or having one of the symptoms in the maximal clique of PTSDCN (i.e., nightmare, sleeping disturbance, difficulty in concentrating, or feeling of nervousness) (Figure 5.1c) showed significant variances in both low beta (Figure 5.4b) and mid gamma frequency bands (Figure 5.4d) while talking. They also showed significantly greater relative power in low beta band but smaller relative power in mid gamma frequency band (Figure 5.4b, d and Table 5.4).

- Moreover, we observed significant variances in the relative low alpha, low beta, low gamma, and mid gamma powers among people suffering from sleeping disorder compared to those who did not report this symptom (Figure 5.4a, b, d, f).

- Participants who tended to avoid trauma-related stimuli exhibited significant variance in their relative low gamma and mid gamma band activities compared to those not facing this post-traumatic stress symptom (Figure 5.4d, f and Table 5.4).

- We observed significantly greater variances in the alpha, beta, and gamma frequency bands among people who reported about feeling nervous than those without such case (Figure 5.4 and Table 5.4).

- Apart from these, we observed significant variances in the low beta, high alpha, and mid gamma bands among refugees who reported about having nightmares compared to those not suffering from nightmares (Figure 5.4b, c, d and Table 5.4).

- Moreover, refugees who suffered from difficulties in concentrating showed significant variance in the relative powers of low beta, low gamma, and mid gamma bands (Table 5.4). They exhibited significantly lower mean relative power in mid gamma frequency band than those without such problem (Figure 5.4b, d, f).

- We did not observe any significant variance in the relative powers of delta and theta frequency bands among different groups of participants while talking. However, refugees suffering from PTSD and various post-traumatic stress symptoms showed significantly increased delta activity than those without such issues (Table 5.4).

Table 5.5 provides a brief summary of our analysis. It is evident that relative powers in delta and theta frequency bands do not account for any neurobiological abnormalities associated with PTSD and its symptoms. Relative power in mid gamma frequency band shows significant variances among people suffering from PTSD and other post-traumatic stress symptoms except for difficulty in recalling trauma events. Besides, people feeling nervous or constantly on guard showed significant variances across a wide range of background EEG activities, from low alpha to mid gamma.

Table 5.5: An overview of relative EEG power analysis. Checkmark indicates statistically significant variance exists between the relative EEG power values of the participants reporting different post-traumatic stress symptoms and those who did not.

Effects	Relative EEG power							
	Low alpha	High alpha	Low beta	High beta	Low gamma	Mid gamma	Delta	Theta
PTSD	✓		✓			✓		
Dst	✓	✓	✓		✓	✓		
Ngh		✓	✓			✓		
Avd					✓	✓		
Rcl		✓	✓	✓	✓			
Slp	✓		✓		✓	✓		
Irr					✓	✓		
Cnc			✓		✓	✓		
Nrv	✓	✓	✓	✓	✓	✓		

5.6 Attention and Relaxation Levels

Apart from background EEG activities, we investigated attention and relaxation levels during three different activities (talking, recalling trauma events, and sketching) for the refugees who reported difficulty in concentrating and feeling nervous. We found that the refugees who faced difficulty in concentrating showed significantly lower mean attention values (Figure 5.5a and Table 5.6) while talking than those without this symptom. However, we found no significant difference between these two groups while they were discussing trauma events (Figure 5.5b) and sketching (Figure 5.5c).

Table 5.6: Benjamini-Hochberg corrected statistically significant differences in the attention and relaxation levels of the refugees who faced different psychiatric symptoms vs those who did not at $P < 0.001$ (***).

Category	Talking	Recalling trauma events	Drawing
Faced difficulty in concentrating vs did not	t(1430)=-3.46***	t(1659)=0.8	t(1533)=-1.23
Felt nervous vs did not	t(960)=-0.52	t(911)=-3.95***	t(1133)=-6.03***

Table 5.7: Benjamini-Hochberg corrected statistically significant differences in the attention and relaxation levels of different refugees while doing different activities at $P < 0.001$ (***).

Category	Talking vs Recalling trauma events	Recalling trauma events vs Drawing	Drawing vs Talking
People who reported attention deficiency	$t(1901) = -2.04$	$t(1618) = 7.43^{***}$	$t(1563) = 9.06^{***}$
People who did not report attention deficiency	$t(1447) = 0.53$	$t(1425) = 5.36^{***}$	$t(1352) = 4.76^{***}$
People who reported feeling nervous	$t(2399) = 0.89$	$t(2188) = 0.27$	$t(2172) = 1.07$
People who did not report feeling nervous	$t(917) = 4.58^{***}$	$t(1021) = -3.58$	$t(916) = 7.02^{***}$

We also found that the refugees who reported difficulty in concentrating showed significantly greater mean attention values while sketching than talking and recalling trauma events (Figure 5.5d and Table 5.7). Similarly, the refugees without any attention deficit exhibited significantly greater mean attention values while sketching than that of while talking and recalling trauma events (Figure 5.5e and Table 5.7).

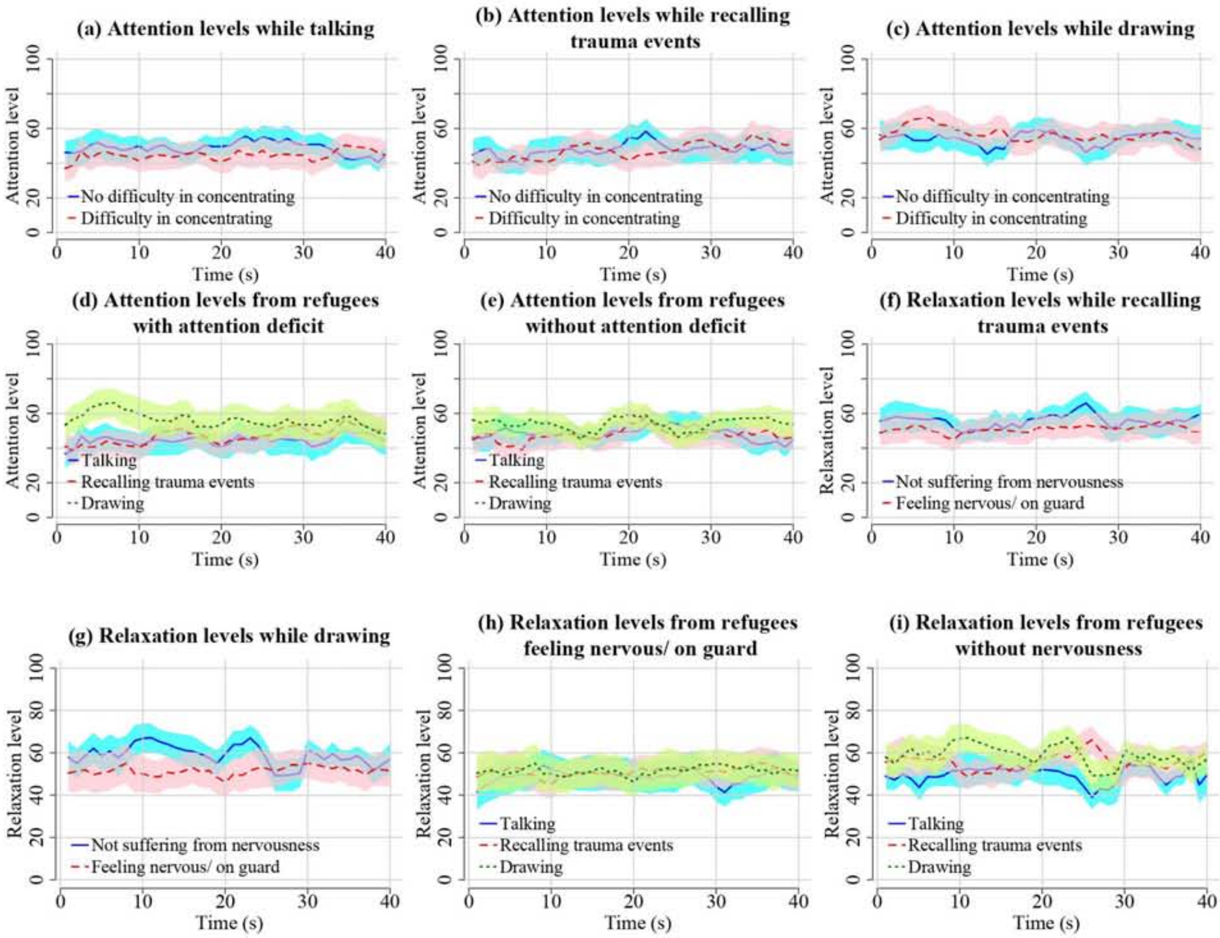


Figure 5.5: Attention and relaxation levels of the Rohingya refugees with difficulty in concentrating and feeling of nervousness.

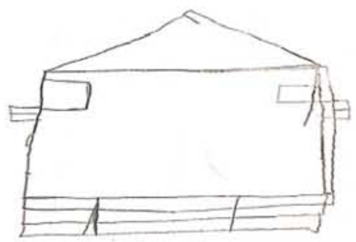
Next, we compared the relaxation levels of the refugees who reported feeling nervous with those who did not. We observed that the refugees feeling constantly nervous were significantly less relaxed while discussing their traumatic experiences and sketching than those without such problems (Figure 5.5f, g and Table 5.6). The relaxation levels of the refugees who reported being nervous did not show any significant difference across three different activities (Figure 5.5h and Table 5.7). However, the refugees without any case of nervousness showed significantly greater mean relaxation values while sketching and talking than that of while recalling traumatic events (Figure 5.5i and Table 5.7).

5.7 Visual Analysis of the Free-Hand Sketches of Home

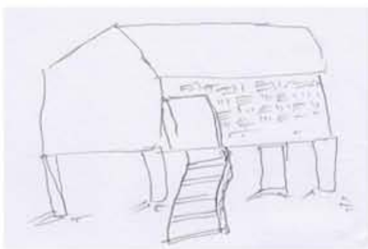
We analyzed all the sketches to explore any non-verbal sign of PTSD. Four main themes emerged from the visual analysis of the free-hand sketches of homes (Table 5.8). The themes embody a sense of safety, security, personal ideas, and values centering homes.

Table 5.8: Distribution of the sketches across different themes.

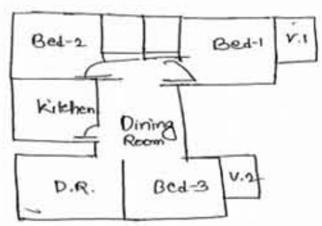
Theme	Count (%)	Subtheme	n	Sketches from three groups (%)		
				Refugees	Slum-dwellers	Students
Shelter	90	Front elevation	120	50	57	25
		Perspective view	23	1.1	1.4	13
		Floor plan	63	23	4	25
Activities	13.4	-	40	-	-	23
Relationship	1.01	-	3	-	-	1.86
Nature	7.4	-	22	1.15	4.22	10



(a) Present home of slum-dweller S23

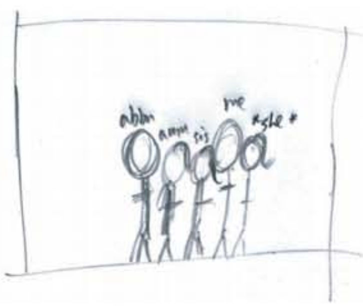


(b) Past home of refugee R1

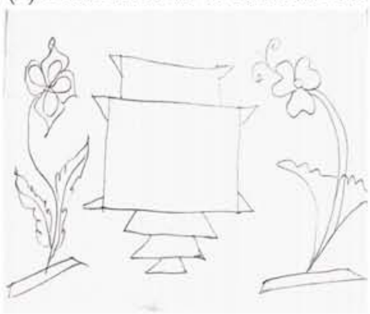


(c) Present home of student E48

(d) Future home of student E62



(e) Future home of student E26



(f) Future home of slum-dweller S19

Figure 5.6: Different themes present in the free-hand sketches of the participants.

■ *Home as a Shelter*: Around 90% sketches represent home as a shelter. Among them, some participants sketched the front elevation of homes (Figure 5.6a), i.e., a straight-on view of home when looked from the front [153]. Others sketched the perspective view (Figure 5.6b) that projects a three-dimensional view of the home in two dimensions [153]. Another group sketched the floor plan (Figure 5.6c), i.e., top view of home [153]. Only the students annotated their floor plans with writing and used various door symbols, e.g., door swing (Figure 5.6c).

■ *Home as a Place for Activities*: In these sketches, the engineering students focused on the amenities of urban life (Figure 5.6c), e.g., bedroom, kitchen and dining room, living room/ drawing room, swimming pool, gaming room/ computer zone, library/ bookshelf (Figure 5.6d), room theatre/ television, etc. Some students even tied their ambitions of higher studies, research work, dream jobs, and living abroad to their depictions of home.

■ *Home as a Place for Strengthening Relationships*: In the three sketches under this category, the students expressed their desire to be with their near and dear ones. For example, one of the students focused on his future family while drawing his expected future home (Figure 5.6e).

■ *Home and Nature*: In this theme, the participants integrated various natural components (Figure 5.6f) in their sketches of homes, e.g., trees, flowers, hills, rivers, forests, seas, etc. These sketches evoke a sense of love for Nature and exploration.

The distribution of themes across the groups suggest that the sketches drawn by the students are more diverse.

5.8 Computing Methods to Interpret Free-Hand Sketching

Next, we performed different quantitative analysis on the free-hand sketches and EEG data while sketching.

5.8.1 Inter-Group Analysis

Table 5.9 shows different features present in the free-hand sketches of the participants. Tables 5.9 and 5.10 show that the number of corners in the sketches of future homes follows this order from the highest to lowest: students > slum-dwellers > refugees. The sketches of present homes of the students also contain significantly more corners than that of the refugees. This may imply that the sketches drawn by the students contain more details.

The sketches of the slum-dwellers contain significantly less number of strokes compared to the other groups (Table 5.9, 5.10). Similarly, the average length of strokes is significantly smaller in the sketches of the refugees. These might be due to the presence of fewer details in the sketches of slum-dwellers and refugees.

Table 5.9: Average values of different features present in the free-hand sketches of home.

Features	Home type	Engineering students	Rohingya refugees	Slum-dwellers
Number of corners	Future	258.18	104.66	138.6
	Past/ Present	203.73	124.20	111.31
Number of strokes	Future	18.39	38.41	11.2
	Past/ Present	18.43	23.62	10.14
Average length of strokes	Future	66.08	56.81	66.67
	Past/ Present	72.10	60.64	66.41

Table 5.10: Differences in the features of free-hand sketches among different groups. Only the statistically significant results are shown after Benjamini-Hochberg error correction [1] on Wilcoxon signed rank test results.

Feature	Sketch type	Observed difference	P value	Comment
Number of corners	All	Student > Refugee	1.13×10^{-8}	
	Future	Student > Refugee	8.47×10^{-6}	Student > Slum-dweller > Refugee
		Student > Slum-dweller	0.002	
		Slum-dweller > Refugee	0.005	
	Past/ Present	Student > Refugee	0.0002	
Number of strokes	All	Refugee > Slum-dweller	0.0009	The sketches from slum-dwellers have significantly less number of strokes than that of the other groups.
		Student > Slum-dweller	0.0009	
	Future	Refugee > Slum-dweller	0.002	
		Student > Slum-dweller	0.003	
Average length of strokes	All	Student > Refugee	2.27×10^{-6}	The average length of strokes in the sketches of the refugees is significantly smaller than that of the strokes in other groups.
		Slum-dweller > Refugee	3.18×10^{-5}	
	Future	Student > Refugee	7.49×10^{-5}	
		Slum-dweller > Refugee	0.001	
	Past	Student > Refugee	0.0038	
		Slum-dweller > Refugee	0.0039	

Next, we analyzed the features of free-hand sketches from PTSD and non-PTSD cases across all groups (Figure 5.7). We observed that the sketches of the participants with potential cases of PTSD contain significantly less corners both in their past/ present ($W = 1004, P = 0.0002$) and expected future homes ($W = 1074, P = 0.0009$) compared to non-PTSD cases. Likewise, the average length of strokes is significantly smaller both in the sketches of past/ present ($W = 1307, P = 0.03$) and future homes ($W = 1112, P = 0.002$) of the participants with potential cases of PTSD. This may imply that

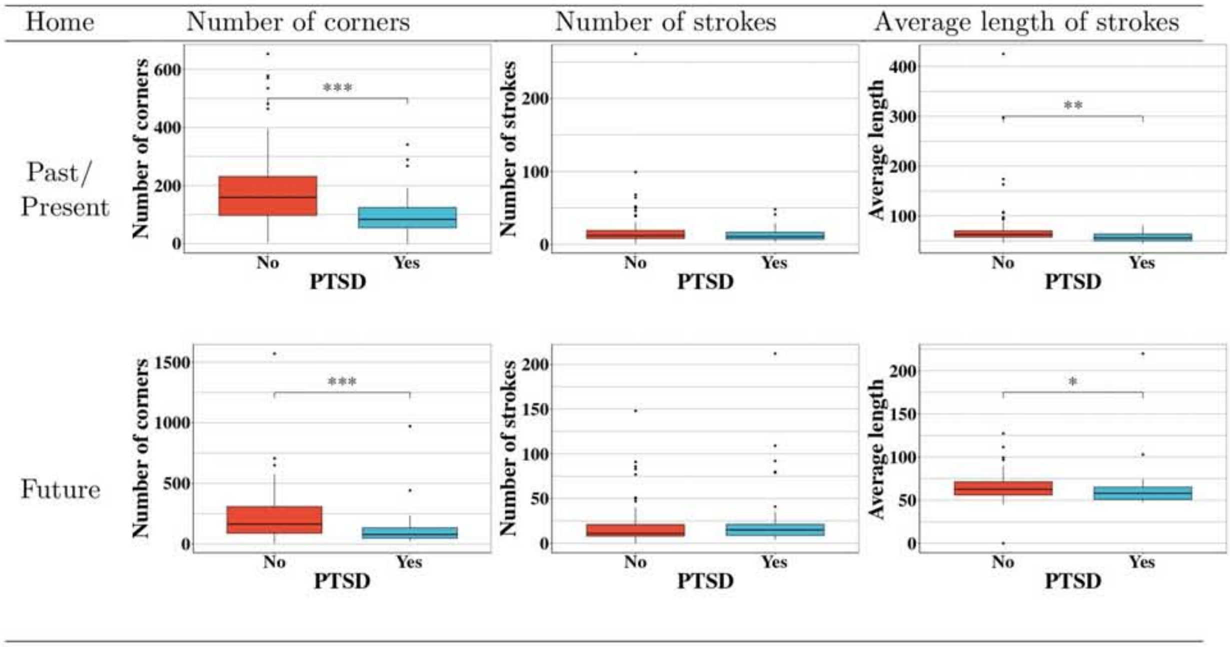


Figure 5.7: Different features of free-hand sketches from PTSD and non-PTSD participants. * denotes Benjamini-Hochberg corrected statistically significant results from Mann-Whitney test at $P < 0.05$ (*), $P < 0.01$ (**), and $P < 0.001$ (***).

the sketches of individuals with potential cases of PTSD contain fewer details.

5.8.2 Intra-Group Analysis

We compared the features of sketches from male and female participants within the same group (Figure 5.8). From our analyses, we observed statistically significant differences only in the sketches of male and female Rohingya refugees. We found that the sketches of past homes by male refugees contain significantly greater number of corners ($W = 168.5, P = 0.005$) and the average length of strokes in their future homes is significantly greater ($W = 162, P = 0.01$) compared to the corresponding sketches made by the female refugees. On the contrary, the sketches of future homes created by female refugees contain significantly greater ($W = 184.5, P = 0.0004$) number of strokes than that of the male refugees.

Moreover, we analyzed the features from the past/ present and expected future homes of the participants. We found that the number of corners in the present and future homes of the students correlate significantly ($r_\tau = 0.403, P = 2.3 \times 10^{-7}$). Additionally, the number of strokes in both of the sketches of the students correlate significantly ($r_\tau = 0.28, P = 0.0004$). On the other hand, the number

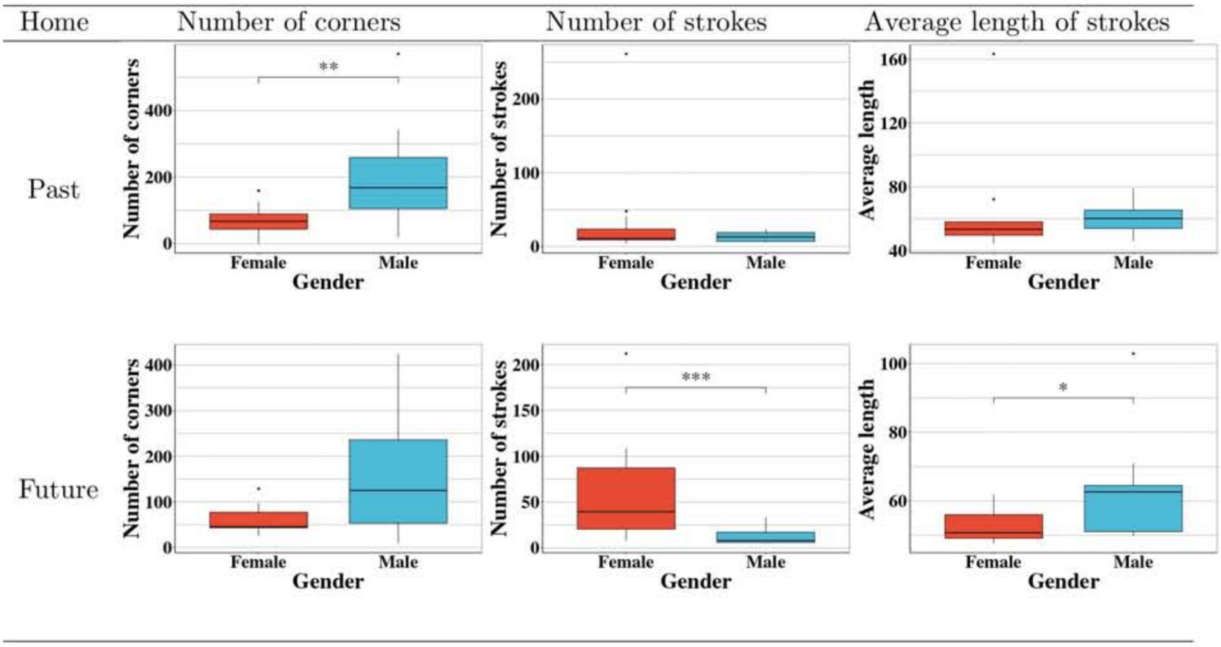


Figure 5.8: Different features of free-hand sketches from the male and female Rohingya refugees. * denotes Benjamini-Hochberg corrected statistically significant results from Mann-Whitney test at $P < 0.05$ (*), $P < 0.01$ (**), and $P < 0.001$ (***).

of corners in the past and future homes of the refugees correlate significantly ($r_\tau = 0.42, P = 0.0016$) as well.

5.8.3 Brain Activities while Sketching

To get a deeper understanding of the drawing task from neurobiological point of view, we also analyzed the EEG signals from the Rohingua refugees while they were sketching. We found that the refugees were significantly more attentive ($W = 311771.5, P = 0.0036$) (Figure 5.9a) but less relaxed ($W = 267895, P = 0.0073$) (Figure 5.9b) while sketching their past homes than the future homes.

Moreover, the refugees with potential cases of PTSD were significantly more attentive ($W = 83807, P = 6.22 \times 10^{-5}$) while sketching their past homes (Figure 5.9c). However, the refugees without PTSD showed significantly greater relaxation levels ($W = 66020.5, P = 0.02$) while sketching their expected future homes (Figure 5.9d). Overall, the non-PTSD refugees were significantly more relaxed ($W = 268302.5, P = 0.008$) than the refugees with potential cases of PTSD while preparing the sketches (Figure 5.9e).

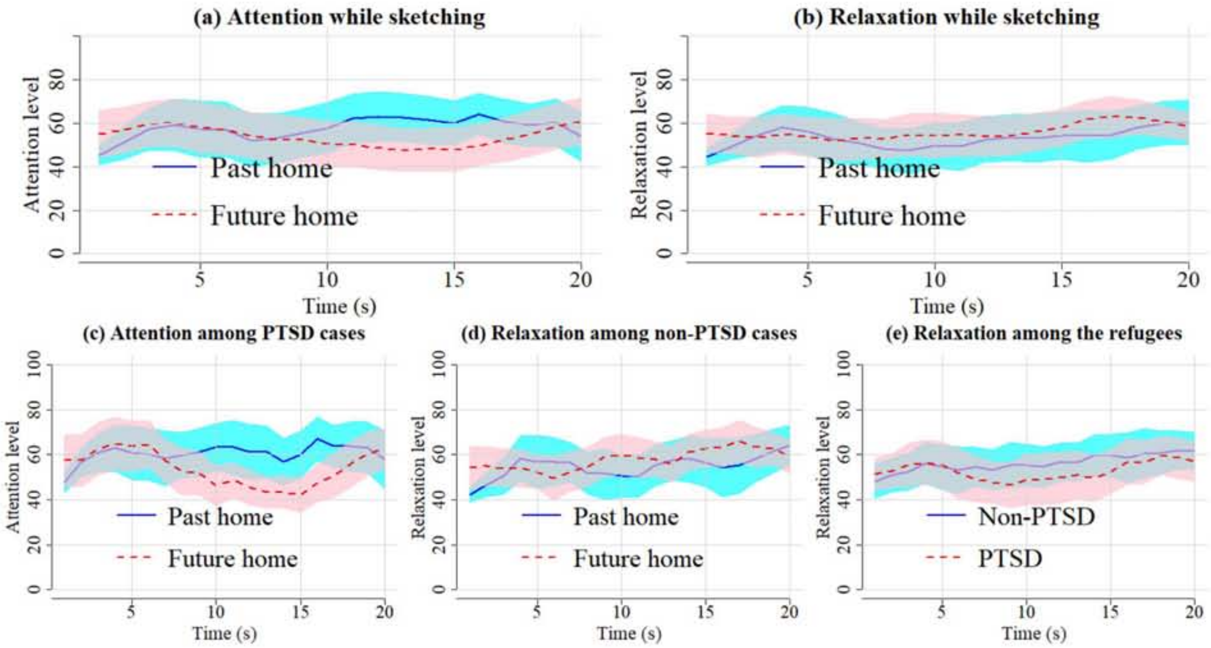


Figure 5.9: Neurobiological activities among Rohingya refugees while sketching their past and expected future homes.

5.9 Screening the Potential Cases of PTSD

We trained multiple machine learning models to screen the potential cases of PTSD.

5.9.1 CNN

Due to small number of sketches ($n = 297$) in our sample, we used image augmentation while training our CNN with 80% sketches to avoid over-fitting. After tuning some of the model hyper-parameters (epochs: 10, optimizer: 'adam', dropout_rate: 0.5, dense_layer_sizes: [64, 64]), the optimal model resulted in 78.3% accuracy when tested with the remaining 20% sketches. However, this model has low Matthews Correlation Coefficient (MCC=0.076) that points to its ineffectiveness in screening PTSD. This might be due to small sample size of our training data.

5.9.2 Logistic Regression

Next, we developed several logistic regression models and tested them using five-fold cross validation. Our first model is based on sketch features, gender, and participants' group that has 87.2% accuracy, and high weighted precision, recall, F1-score, MCC, and AUC (Table 5.13). Among all the features,

Table 5.13: Different weighted performance measures of the models developed for screening potential cases of PTSD.

Model	Accuracy	Precision	Recall	Specificity	F1-score	MCC	AUC
CNN	0.783	0.699	0.759	0.282	0.707	0.076	0.777
Logistic Regression with group (gender + group + sketch features)	0.872	0.867	0.872	0.676	0.865	0.611	0.878
Logistic Regression without group (gender + sketch features)	0.829	0.820	0.830	0.509	0.807	0.377	0.801
Logistic Regression with interaction effects	0.879	0.875	0.880	0.722	0.876	0.597	0.939
Logistic Regression with themes (sketch features + sketch themes)	0.828	0.822	0.828	0.681	0.822	0.545	0.865
Random Forest (sketch features + EEG)	0.993	0.993	0.993	0.988	0.993	0.985	1.0

participants' group ($\chi^2(2) = 14.5, P = 0.00072$) and average length of strokes in past/ present home ($\chi^2(1) = 4.2, P = 0.04$) have significant effects on the model outcome. Next, we built *'without group'* model leaving out the participants' group. This model has an accuracy of 82.9% and high weighted precision, recall, F1-score, and AUC (Table 5.13). In this model, average length of strokes in past/ present home ($\chi^2(1) = 6.3, P = 0.012$) significantly affects the model outcome. Both of these models have a high PTSD miss rate/ FNR for the slum-dwellers (0.583) and engineering students (1.0) (Table 5.14). This might be due to the lower prevalence of PTSD within these groups (Table 5.2).

Table 5.14: Group-wise performance of the logistic regression models.

Logistic Regression models	Rohingya refugees				Slum-dwellers				Students			
	TPR	TNR	FPR	FNR	TPR	TNR	FPR	FNR	TPR	TNR	FPR	FNR
With group	0.88	0.69	0.31	0.13	0.42	0.96	0.04	0.58	0	1	0	1
Without group	0.44	0.85	0.15	0.56	0.42	0.96	0.04	0.58	0	0.99	0.01	1
Interaction effect	1	0.77	0.23	0	0.33	0.87	0.13	0.67	0.25	1	0	0.75
Sketch themes	0.73	0.78	0.22	0.27	0.44	0.92	0.08	0.56	0.33	0.94	0.06	0.67

TPR=true positive rate, TNR=true negative rate, FPR=false positive rate, FNR=false negative rate

Since we observed statistically significant inter-group and intra-group differences within the sketch features, we identified interaction effects among the variables using *interaction.plot* in R. We found that a logistic regression model based on these interactions improved the accuracy (87.9%), weighted precision, recall, specificity, F1-measure, and AUC (Table 5.13). We used the following interactions to develop our model:

$$PTSD = B_0 + B_1 \times Gender \times Corner_F + B_2 \times Gender \times Stroke_P + B_3 \times Group \times Corner_F + B_4 \times Group \times Stroke_F + B_5 \times Group \times Length_P + B_6 \times Group \times Length_F$$

Here, *Corner*, *Stroke*, and *Length* are the number of corners, strokes, and average length of strokes respectively. The subscripts P and F represent the sketches of past/ present and future homes respectively. Next, we developed another model with quantitative sketch features and qualitative visual themes. Its accuracy, weighted precision, and recall are on a par with the *'without group'* logistic regression model (Table 5.13). Though this model with sketch features and sketch themes has greater weighted MCC and AUC values than the *'without group'* model, its specificity (TNR) is lower across the groups (Table 5.14). Here, the number of strokes in the sketches of future home significantly affects ($\chi^2(1) = 5.3, P = 0.02$) the model outcome.

5.9.3 Random Forest

Finally, we combined quantitative sketch features and temporal EEG data (eight brain-waves, attention, and relaxation levels) from the Rohingya refugees to screen for the potential instances of PTSD among them. This model with five-fold cross validation has 99.3% accuracy, greater weighted precision, recall, specificity, F1-score, MCC, and AUC values (Table 5.13). Out of 840 temporal instances of PTSD, it misclassified only six instances.

Chapter 6

Discussion

Among all the groups in our study, the Rohingyas have the highest prevalence (69%) of PTSD. This is greater than the previously reported moderate diagnostic rate of PTSD (36%) among this population [154]. Earlier study [155] identified several factors associated with the higher prevalence of PTSD, such as reported torture, cumulative exposure to trauma, shorter time since traumatic experiences, etc.

During the interviews, the Rohingyas reported the highest ($n = 120$) number of traumatic events and causes of distress (Table 5.2). Around 56% refugees in our sample reported experiencing more than one traumatic events. On the other hand, the slum-dwellers and the engineering students reported 35 (second highest) and 9 (the lowest) cases of trauma and distress respectively (Table 5.3). These observations are consistent with the finding from previous research studies that multiple exposures to trauma are associated with a higher prevalence of PTSD [8, 9]. Besides, most of the refugees in our sample (88.7%) have a mean migration period of about 4 months, and therefore, they are the latest survivors and witnesses of violence, ethnic cleansing, and criminal abuses that took place in Myanmar in late 2017.

On the contrary, the cases of PTSD among the female slum-dwellers (34.4%) in our sample is lower than the previously reported cases of PTSD (54.6%) among them [156]. This might be because, many of them reported suffering from financial distress and no access to healthcare, which might not be true traumatic events according to DSM-5 criteria. In addition, to the best of our knowledge, this is the first study exploring the cases of PTSD among Bangladeshi students.

6.1 The Underlying Structure of PTSD

To understand the dynamic interactions among PTSD and its symptoms, we developed several hybrid models that are the first to take into account the properties of both reflective and formative models of PTSD. Collectively, our models provide cues to the symptoms that are constitutive of PTSD and also to the ones that are reflective of it, at least in the context of trauma-inflicted Rohingya refugees. In the following we elaborate our findings on the interactions among PTSD and its symptoms.

■ **Sleeping Disorder**. This is the most highly central symptom in both PTSDPCN and PTSDRN (Figure 5.3). This symptom is also part of the maximum and maximal cliques derived from PTSDCN (Figure 5.1) and PTSDPCN (Figure 5.2). According to PTSDPCN, sleeping disorder is significantly correlated with PTSD, nervousness, difficulty in concentration, and irritability or outbursts of anger. These correlations are consistent with findings from previous research studies done by McNally and Bryant et al., [53, 47, 41]. Besides, according to PTSDRN, sleeping disorder reflects PTSD and leads to nervousness, difficulty in concentration, and irritability or anger. This supports earlier evidence that when people are sleep deprived, they feel more irritable and angry [157]. In addition, their reasoning and ability to concentrate are affected negatively due to mood changes [158, 159]. This illustrates how our hybrid models are close to earlier findings regarding trauma-related arousal and reactivity.

■ **Nervousness and Nightmare**. Both of them emerged as symptoms of high importance in the networks we built. Both PTSDPCN and PTSDRN revealed strong interaction between these two symptoms (Figure 5.2). Positive association between them emerged earlier in the network analysis of acute and chronic post-traumatic stress symptoms of PTSD [41]. However, not all network models of PTSD have been able to identify this association [53, 47]. Earlier study among PTSD diagnosed rape victims and veterans revealed positive association between nightmare and exaggerated startle response [160, 161]. It shows that our developed PTSDRN is robust enough not to miss this crucial association.

Besides, both in PTSDCN and PTSDPCN, nervousness is significantly correlated with PTSD (Figure 5.1 and 5.2). In PTSDRN (Figure 5.2), nervousness is reflective of PTSD. The association between PTSD and nervousness is also observed in the previously developed acute stress symptoms network of PTSD [51].

Moreover, both PTSDCN and PTSDPCN showed negative correlation between nightmare and difficulty in recalling trauma events (Figure 5.1 and 5.2). This can be explained from the fact that PTSD patients very often re-experience nightmares [162] and have a feeling as if the trauma events were recurring. This might lead to negative correlation with difficulty in recalling trauma events. Besides, our PTSDRN suggests that nightmare is responsible for the feeling of distress among the Rohingya refugees. This is consistent with earlier studies that reported frequent nightmares are associated with psychological distress [163, 164].

■ **Avoidance**. This is another highly central symptom in our developed hybrid models of PTSD (Figure 5.3). We observed the strongest positive correlation between avoidance and PTSD both in PTSDCN and PTSDPCN (Figure 5.1 and 5.2). In PTSDRN, this is the only symptom that constitutes PTSD. Earlier study also reported avoidance as a distinct cluster of post-traumatic stress symptoms [165]. Besides, our study suggests that avoidance leads to sleeping disorder and concentration problem. These associations were amiss in the previously developed network models of PTSD. However, research study on patients suffering from major psychiatric depression revealed that intrusive thoughts and avoidance cause sleep disturbances [166]. This illustrates how Bayesian inference might be useful in disclosing association among various post-traumatic stress symptoms that are not immediately obvious.

■ **Attention Deficit**. It is another highly central symptom in PTSDRN (Figure 5.3). According to PTSDRN, difficulty in concentrating is influenced by avoidance, sleeping disorder, and distress. Though we did not find any direct evidence of how avoidance might influence attention deficit, earlier study suggested that tendency to avoid unbearable feelings or trauma related memories may indirectly impair attention [167]. Besides, it has been observed that children with attention deficit have heightened risk of suffering from psychological distress than others [168]. As in our PTSDRN, the direction of association between attention deficit and psychological distress is reversed, further analysis might be required to validate this association.

Nonetheless, we can see that our hybrid regulatory model of PTSD is able to correctly hypothesise the interactions between different post-traumatic stress symptoms and PTSD as identified in previous research studies [53, 51, 41]. Moreover, when we compared our hybrid regulatory model of PTSD among the Rohingya refugees with the post-traumatic stress symptoms network of the U.S. military veterans [169], we found that findings from both models are well-consistent. For instance, both models successfully encoded the interactions between nightmares and feeling of distress, sleeping disorder and irritability, sleeping disorder and feeling of nervousness, and so on. Therefore, we may conclude that our hybrid regulatory model of PTSD can be extended and well-adapted to the diverse settings of post-traumatic stress disorder among different populations.

6.2 Neurobiological Signatures of PTSD

Apart from understanding the dynamics of PTSD, we explored alternative measures to screen for PTSD to address the issues that arise while using traditional questionnaire based diagnostic tools of PTSD. When we compared EEG signals of the refugees who faced different post-traumatic stress symptoms with that of the individuals with no psychiatric complications, we found substantial differences in the relative power of different brainwaves while talking (Figure 5.4). An overall summary of our findings is given below.

■ **Alpha Activity**. From Table 5.5, it is evident that the participants who suffered from sleeping disorder, felt nervousness and distress, and were diagnosed with PTSD showed significant variance in their relative low alpha power. When we compared EEG signals of the PTSD diagnosed refugees with that of the ones who screened negative, we found PTSD is associated with significant decrease in relative low alpha power (Figure 5.4a). Earlier study on PTSD patients identified abnormal pattern of electroencephalogrpahic alpha asymmetry, i.e., decrease in alpha power at FP1 site during eye-opening state [170]. Besides, low level of alpha power is associated with anxiety, high stress, and insomnia [171]. Accordingly, participants in our study who reported sleeping disorder, feeling distressed as well as nervous, exhibited a decrease in their relative low alpha power compared to those who experienced none of these symptoms (Figure 5.4a).

Besides, the participants who reported feeling nervous and distressed, suffered from nightmares, and faced difficulties in recalling trauma events showed significant variance in their high alpha power (Table 5.5). Primarily, the participants who reported feeling nervous or on guard exhibited significantly lower relative power in their high alpha band (Figure 5.4c). This is corroborated by finding from earlier study that indicates increase in alpha power is associated with lower levels of anxiety and increased levels of calmness [172]. This suggests that abnormality in relative high alpha power corresponds to underlying anxiety and qualms.

Moreover, people who reported having nightmares showed significantly decreased relative power in high alpha band at FP1 site than those without such problem (Figure 5.4c). This is consistent with finding from earlier study where lower relative power in high alpha band was observed at O1 site among people having nightmares [173]. In addition, earlier study associated increase in upper alpha band with good cognitive and memory performance [174]. Hence, a decrease in relative power of high alpha band suggests poor memory performance. This is evident from significantly lower mean relative power of high alpha band among the refugees who reported difficulties in recalling trauma events (Figure 5.4c).

■ **Beta Activity**. The maximal clique in PTSDCN (Figure 5.1c) includes PTSD, sleeping disturbance, nightmare, nervousness, and difficulty in concentrating. Refugees who either screened positive for PTSD or reported at least one of these symptoms exhibited significant variances in their relative low beta power (Table 5.5). Moreover, refugees who felt distressed and faced difficulty in recalling trauma events showed neurobiological abnormalities in their low beta band.

Low beta power at FP1 site among the PTSD diagnosed Rohingya refugees is significantly higher than that of those without PTSD (Figure 5.4b). This is consistent with the findings from previous research studies, where increase in beta power at FP1 site was observed among PTSD patients during rest [175] and card-sorting test [176]. Even increased beta power was observed among combat veterans suffering from PTSD [177, 178].

Refugees with sleeping disorder and nightmares also showed significant increase in their low beta activity (Figure 5.4b). Earlier study associated increased beta activity with insomnia [179]. Moreover, higher beta power was observed in waking state at C3, C4, F3, F4, and O1 regions of scalp among PTSD patients and nightmare recallers [173]. Though the nightmare recallers in our sample did not show any significant change in their low beta activity at FP1 site, relative power in their high beta band was significantly less than that of the people who did not suffer from trauma related nightmares (Figure 5.4e).

Besides, high level of beta power has been associated with anxiety, stress, and hyper arousal [171]. Accordingly, the Rohingya refugees in our sample, who reported feeling distressed, nervous, or constantly on guard showed significant increase in their relative low beta power (Figure 5.4b). Moreover, the refugees who reported difficulty in concentrating showed significant increase in their relative low beta power (Figure 5.4b). This coincides with earlier finding, where significantly increased low beta power was observed among the victims of childhood traumatic experiences, who suffered from attention deficit [180]. In addition, the refugees who reported difficulty in recalling trauma events exhibited significantly lower relative power in low beta bands (Figure 5.4b). Even earlier study showed that increased low beta activity reflects memory promoting state [181]. This implies decreased power in low beta band might be associated with PTSD related memory impairment.

In our study, high beta frequency band accounted for the neurobiological abnormalities associated with nervousness and difficulty in recalling trauma events (Table 5.5). The refugees who reported being nervous or on guard showed significantly less relative power in their high beta frequency band (Figure 5.4e). This contradicts the findings from earlier studies, where increased levels of high beta activity were observed during anxiety or periods of emotional intensity [182, 183]. Therefore, neurobiological abnormality connecting high beta activity with nervousness and hyper arousal requires further attention.

Refugees who faced difficulty in recalling trauma events also showed significantly decreased relative high beta power (Figure 5.4e). This is consistent with the findings from a previous study where increase in high beta activity was found to be associated with better memory outcome [184]. This suggests that decrease in relative high beta power might be associated with memory impairment of the Rohingya refugees.

■ **Gamma Activity**. In our study, relative power from low gamma and mid gamma frequency bands exhibited significant variances across a wide range of post-traumatic stress symptoms (Table 5.5). First of all, the refugees who were screened with a potential case of PTSD, showed significantly decreased relative mid gamma power at FP1 region while talking (Figure 5.4d). This is contrary to findings from previous research studies, where increased gamma band activity was observed at the frontal regions of PTSD diagnosed women [176] and PTSD patients during rest [185].

Besides, recent findings have associated decrease in low gamma band activity at antero-frontal region and decrease in mid gamma band activity at centro-parietal region with attention deficiency [186]. Similarly, participants in our study, who reported difficulty in concentrating exhibited decreased relative power in mid gamma band at FP1 region while talking (Figure 5.4d). However, they exhibited increased low gamma power at FP1 region (Figure 5.4f).

Increase in gamma brainwave has been associated with anxiety, stress, and hyper arousal [187, 188]. Analogously, we found that refugees, who reported about feeling distressed or nervous showed significant increase in their relative low gamma power (Figure 5.4f). However, they showed significant decrease in their relative mid gamma power (Figure 5.4d).

In addition, the refugees who tried to avoid trauma related stimuli showed significant increase in relative low gamma power (Figure 5.4f) but significant decrease in relative mid gamma power (Figure 5.4d) at FP1 site while talking. It has been observed earlier that increase in gamma power is associated with fear-motivated avoidance of memory related to PTSD [189]. Also, it has been identified that increase in frontal gamma power is associated with recalling memory [190]. Therefore, decrease in this frequency band might be associated with poor ability to recall events. This is evident from the neurobiological characteristics of our participants, who reported facing difficulty in recalling trauma events and exhibited significantly decreased relative power in low gamma band (Figure 5.4f).

Besides, a recently developed rodent model has observed sustained increase in low gamma power and decrease in high gamma power in case of PTSD-related sleeping disturbances [191]. In our study, we observed an increase in relative low gamma power (Figure 5.4f) and decrease in relative mid gamma power (Figure 5.4d) among the refugees with sleeping disorder. Moreover, the refugees having nightmares exhibited reduced relative power in mid gamma band at FP1 region (Figure 5.4d). Though elevated gamma band activity has been observed among the nightmare recallers in a prior study [173], decreased gamma band activity among the Rohingya refugees in our sample might be associated with their difficulties in recalling trauma events. This is because, gamma activity is reported to be associated with the ability to recall dreams [192].

The refugees in our sample, who felt irritation or outbursts of anger showed significant decrease in relative mid gamma power (Figure 5.4d) and increase in relative low gamma power (Figure 5.4f). However, to the best of our knowledge, no prior work reported any association between relative gamma power and irritability or outbursts of anger.

■ **Delta Activity**. Though none of the refugees suffering from PTSD and other psychiatric symptoms showed significant variance in their delta activity, they exhibited significantly greater relative power in this frequency band (Table 5.4). Even earlier study identified increased delta power as potential neuro-physiological correlate to differentiate PTSD from other psychiatric disorders [193].

■ **Attention and Relaxation Levels**. In our study, participants who reported difficulty in concentrating showed significantly lower mean attention values while talking than those without such problems (Figure 5.5a). However, both of these groups exhibited similar levels of attention while recalling trauma events (Figure 5.5b) and sketching (Figure 5.5c). The reason behind this could be that the evocation of traumatic experiences was so strong for both groups that they exhibited similar levels of attention. Besides, activities such as, sketching require some level of concerted attention and we observed that the participants, who reported attention deficit were equally able to engage themselves in sketching as well as those without such problems.

Moreover, all the refugees, with or without attention deficit, showed significantly greater levels of attention while sketching than during conversation (Figure 5.5d, e). Higher level of attention while sketching asserts the usefulness of impromptu sketching activity in facilitating self-expression and creating awareness of self and others. In many studies, art therapy is found to be highly effective in reinforcing positive behavior among the people with attention deficit [194, 195].

The refugees who constantly felt nervous or on guard exhibited significantly lower levels of relaxation while recalling traumatic experiences and sketching than those who did not report feeling nervous (Figure 5.5f, g). Even the refugees, who did not report any case of nervousness showed significantly greater mean relaxation values while sketching than talking or recalling trauma events (Figure 5.5i).

Previously, many studies suggested that art therapy is particularly suitable to treat trauma effects [196, 197] by utilizing different sensory triggers as part of therapeutic techniques. It helps to modify emotional and physiological responses, which assist in desensitizing physiological reactions. Higher relaxation level of the refugees while sketching indicates that this activity helped them divert their mind off the stress and direct their flow of meditation in something creative. Therefore, our findings suggest that incorporating creative activities in various treatment program of PTSD patients is likely to improve their cognitive performance.

However, the refugees who reported feeling nervous or on guard did not show any improved relaxation state while sketching (Figure 5.5h). This might be because their psychiatric morbidity was too severe to benefit from a single session of sketching. Though in our work we tried to explore the usefulness of art therapy in small scale, a larger setting within the context of refugees might reveal important findings in this regard.

6.3 Implications of Free-Hand Sketches

Another part of our study focuses on eliciting non-verbal cues from free-hand sketches to identify traces of psychiatric morbidity related to PTSD. In the following we elaborate our findings based on the free-hand sketches drawn by our participants.

6.3.1 Collective Observations and Communal Needs

Most of the refugees and slum-dwellers either sketched simple front elevation or floor plans of homes. On the contrary, the engineering students sketched the exterior and interior of homes with various details, furnishings, and natural components that are missing in the sketches of other groups. This might be due to the differences in their educational and socioeconomic backgrounds, observation skills, and prior experiences of sketching.

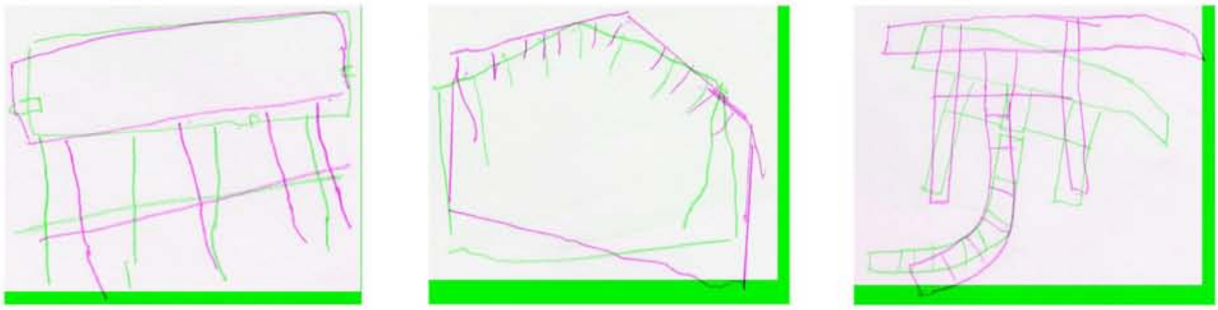
We can also explain this through Maslow's hierarchy of needs [110]. Since refugees and slum-dwellers are living in temporary shelters, both groups might feel the need for a safe and permanent home. This might be the reason of their focus on the structure rather than the interior of homes. In this regard, one of the slum-dwellers expressed her interest to live in the secured environment of a building rather than in the slum.

According to Maslow's hierarchy, people can focus on their needs of love and belonging, esteem, and self-actualization only when their basic physiological needs are fulfilled. The engineering students in our study have secured and permanent arrangements for shelter. We assume this helped them focus on other aspects of life. This is in line with a previous finding from Farokhi et al. [198]. They observed that the children in lower grades mainly sketch the basic structures of their homes, whereas, the sketches of older children incorporate lots of natural components as their range of interests grow with time and their needs extend beyond the scope of home.

6.3.2 Group-wise Variation in Free-Hand Sketches

Since the free-hand sketches of the students depict home from varying perspectives, the complexity of their sketches might have given rise to a significantly greater number of corners (Table 5.10). On the other hand, significantly less number of strokes in the sketches of slum-dwellers might be the result of fewer details in their sketches (Table 5.10). Though a majority of the sketches from the refugees contain less details than that of the slum-dwellers, significantly greater number of strokes in their (refugee) sketches (Table 5.10) might have resulted from the fidgeting of hands due to prior inexperience of sketching. Besides, the presence of strokes with significantly smaller length (Table 5.10) implies that the refugees tend to sketch with multiple short strokes.

Correspondingly, though the average number of strokes in the sketches of engineering students is less than that of the refugees (Table 5.9), the average length of these strokes is significantly greater than that of the refugees (Table 5.10). This might be because, the students have prior experience with both free-hand sketching and engineering drawing, which enabled them to draw with few steady and longer strokes rather than multiple short strokes. Although the sketches of their present and future homes usually vary widely, number of corners and strokes in both sketches correlate significantly, which may be a testament to their consistent and rehearsed drawing style.



(a) Sketches of refugee R4 (b) Sketches of refugee R10 (c) Sketches of refugee R24

Figure 6.1: Similarity in the sketches of past (red) and expected future (green) homes of the Rohingya refugees.

On the contrary, significant correlation between the number of corners in the sketches of past and future homes of the refugees and the similarity in both of their sketches observed via manual inspection (Figure 6.1) might imply their desire to get back their past home in the future. In this regard, one of the refugees commented that he wanted to get back his house in Myanmar instead of finding a new home in Bangladesh.

6.3.3 Sketch Features and Brain Signal Activities while Sketching

The number of corners and average length of strokes dropped significantly in the free-hand sketches of the Rohingya refugees (Table 5.10) and among the participants with potential cases of PTSD (Figure 5.7). As we observed a significant effect of group on the prevalence of PTSD (Table 5.3), prior inexperience of sketching and lack of education among the PTSD-dominant refugees might have contributed to fewer details in their sketches.

The presence of significantly greater number of corners and significantly fewer strokes of greater length in the sketches of male Rohingya refugees (Figure 5.8) might imply that the male refugees prepared their sketches more confidently than the female refugees. This is because, smooth and longer strokes traditionally represent the confidence of the artist [139]. These differences can also be attributed to the educational experiences of Rohingya men (59% men are literate compared to 23% of women) and significantly greater prevalence of PTSD among the Rohingya women (Table 5.3).

Moreover, the Rohingya refugees were significantly more attentive but less relaxed while sketching their past homes than the future homes (Figure 5.9). Such reverse association between attention and relaxation levels has been observed among archers with mid level shooting performance [199]. Following the explanation from Lee et al. [199], we assume that the lack of experience of sketching made the refugees more attentive and less relaxed. Alternatively, it might be due to memories associated with their past homes. However, as time progressed, the refugees adapted well and became more relaxed at the end of the drawing session while sketching their expected future homes. Since most of the refugees sketched both of their past and future homes similarly (Figure 6.1), then maybe the thought of a new home or getting back their past homes gave them comfort and made them feel more relaxed.

6.3.4 Screening PTSD based on Free-Hand Sketches of Home

As we observed significant differences in the sketch features among different groups of participants, we tried to utilize these differences in screening PTSD. We observed significant group-effect in our *'with group'* logistic regression model for screening PTSD. This model has greater TPR for the refugees and greater TNR for the other groups (Table 5.14). This might be due to high prevalence of PTSD among the refugees and non-PTSD cases among the other groups. Now, removing group from our *'without group'* logistic regression model results in greater TNR but reduces TPR for the refugees. However, the removal of group doesn't affect model performance in case of slum-dwellers and students (Table 5.14).

When we considered interaction effect, there was no PTSD miss rate (FNR=0) for the refugees. The model was also able to identify one PTSD case among the students. However, this model performed worse in case of slum-dwellers than the *'with/ without group'* logistic regression models (Table 5.14). Integrating sketch themes into our logistic regression model improved TPR for the slum-dwellers and engineering students. However, integrating qualitative themes from the sketches as model features will limit process automation and introduce biases from human interpretation [80, 81] without participants' feedback. This is because, some sketches from low-literate participants were ambiguous and difficult to interpret.

On the other hand, improved performance of our Random Forest model based on sketch features and EEG data from the refugees might be because it is a single population model. In contrast, our CNN and logistic regression models combine data from three diverse communities. Group-wise differences in the sketches might have influenced the learning of those algorithms while screening PTSD.

The Random Forest model based on sketch features and EEG data of the refugees is more robust than the Random Forest models based on sketch features (accuracy: 0.724, AUC: 0.72, F1-score: 0.725) or EEG data (accuracy: 0.720, AUC: 0.798, F1-score: 0.2) of the refugees only. The Random Forest model combining sketch features and EEG outperforms a previously developed diagnostic model of PTSD [65] based on only brain signal activities (accuracy: 80%, recall: 0.71). This indicates that sketch features might improve model performance when combined with EEG data. However, one thing worth mentioning here is that Shim et al. [65] used P300 features of EEG data from parietal lobe for their analyses, whereas, we used relative EEG power values from pre-frontal region.

Moreover, there are significant effects of average length of strokes in past/ present home and number of strokes in future home on the outcomes of our *'with/ without group'* and *'interaction effect'* logistic regression models respectively. This also indicates that there are significant effects of these features in screening PTSD.

6.4 Potential Interventions for Diagnosis and Treatment of PTSD

Apart from potential diagnostic implications of EEG signals and PTSD regulatory networks, they can provide us useful directions for the treatment of PTSD. Targeting the highly central symptoms within PTSDPCN and PTSDRN may help us in this regard. For example, according to our models, targeting the most central symptom, i.e., sleeping disorder may help alleviate problems. This is because, sleeping disturbance is closely associated with many other chronic post-traumatic stress symptoms and PTSD. Previous cohort studies on treating PTSD patients through targeting trauma-specific sleep disturbance provide support in favor of our argument [200, 201, 202]. These studies found that such target-specific interventions produce large short-term effects, including substantial reductions in PTSD symptoms, and thereby improve functional outcomes [200, 201, 202].

Besides, it has been observed that many individuals with post-traumatic stress symptoms, prefer to address their sleeping disturbances (insomnia and nightmares) first, and then PTSD, as applicable [203]. Hence, targeting this particular neurobiological mechanism might be helpful in addressing the etiology of the disease. In this regard, we may address the neurobiological abnormalities associated with sleeping disorder through EEG biofeedback [204]. EEG biofeedback or neurofeedback is a specific protocol to improve brainwave activity and is particularly useful for treating various neurological conditions. It has been used as an adjunct therapy for specialized chronic refugee trauma experiences to make their treatment more effective [205, 206]. Recent findings have showed that EEG biofeedback is particularly capable of being used in reducing post-traumatic stress symptoms [207, 208].

For example, decrease in mid gamma band activity associated with attention deficit among the Rohingya refugees might be addressed by using neurofeedback designed to increase local gamma band activity. Earlier study showed that enhancing gamma band activity via neurofeedback led to greater flexibility in episodic bindings and improved recollection of memory [209]. Moreover, as lower relative power in high alpha frequency band is associated with poor memory performance among the Rohingya refugees, cognitive performance might be improved by enhancing this frequency band as a neurofeedback parameter [210].

Therefore, we can say that targeting particular chronic symptoms within PTSD regulatory network might not only reduce the intrusion of that symptom but is also capable to affect other symptoms that are related to it via direct or indirect causal association. This would result in cumulative remission of post-traumatic stress symptoms and the disorder.

Chapter 7

Avenues for Future Work

Now, considering the promising outcomes of our study, we further report some scopes of future work. Even though PTSD regulatory network (DAG model) is very informative to understand the underlying hierarchy of PTSD, caution is still required because DAG depends a lot on the quality of data. Besides, another feature of DAG is that it does not allow cycle. As a result, it cannot encode feedback loop among the symptoms. For example, a symptom might affect another symptom which, in turn would affect others. Thus, the feedback might often loop back to the first symptom. However, such cycles cannot be encoded into DAG though they play an important role in the self-reinforcing nature of PTSD networks [53]. Therefore, in future, it will be valuable to explore techniques for developing directed cyclic graph of PTSD that is capable of encoding feedback loops among the symptoms.

Besides, in our study, we used a consumer-grade, single-electrode, and portable EEG headset. Though such devices are more affordable and easier to use, the quality of the produced data is not as good as that of the devices with large numbers of electrodes or sensors. In addition, one of the biggest challenges in using BCI devices (e.g., EEG devices) is to understand and resolve the issue of "BCI illiteracy" [211]. This concept is used for explaining difficulties that users generally face while operating BCI systems. There exists a methodologically weak concept that BCI users possess physiological or functional traits that prevent their efficient performance while using BCI devices [212]. In existing studies involving BCI systems, it has been observed that BCI control does not work for a significant portion ($20-30\%$) of users [213]. However, this concept still remains under rigorous research and a clear understanding of the BCI illiteracy or a solution to this problem is yet to be reported. Moreover, there are many biological and technical artifacts that influence the quality of the recorded EEG signals [214]. Therefore, before adopting BCI devices to the mass screening of PTSD, we need to properly take these factors into consideration.

Moreover, further research is required to measure the ease of use and acceptability of EEG devices among the users. This is of particular interest as we observed that participants reacted differently to the use of EEG headsets. Hence, before integrating EEG devices into main-stream diagnosis of PTSD, we need to think of ways to familiarize this technology to enable users to overcome the initial stigma associated with its use.

Besides, due to significantly greater prevalence of PTSD among the Rohingyas, our developed models have high PTSD miss rates (FNR) among the slum-dwellers and engineering students. To address this, we tried to balance our dataset by oversampling, undersampling, and both while training our models. However, balancing the classes worsened the model performance. Therefore, we plan to collect more data with post-traumatic stress symptoms from the other groups. On the other hand, the PTSD screening tool we used was designed specifically for refugees and migrants [105]. A broader study involving large diverse populations would require diagnostic tools with good psychometric properties.

Although our model based on EEG and sketch features from the refugees work well to classify PTSD, integrating data from other groups may influence the model outcome differently. We plan to investigate this in future. Besides, integrating temporal EEG signals with the number of corners, number of strokes, and average length of strokes from a finished sketch might not be appropriate. One way to handle this is to use interactive devices for sketching to get temporal sketch features. However, the marginalized individuals might feel uncomfortable sketching with such interactive tools. The reverse, using mean EEG values with sketch features instead of temporal EEG data, would miss the nuances of temporal brain activity while sketching.

On the other hand, the sketch features of home might point to socioeconomic and cultural differences among the participants. The ability to draw details could be related to memory, attentional control, and other cognitive abilities. Alternatively, negative beliefs about the world and one's future may impact the motivation to draw details. Thus, sketch features would correlate with many variables that also correlate with PTSD but are distinct from it.

However, despite all these, findings from our study can be well adapted to pervasive mental health care and diagnostic systems. EEG headsets and free-hand sketching can be tailored to measure neurobiological abnormalities and non-verbal cues respectively, associated with PTSD even outside refugee settings, particularly in case of war veterans, victims of physical or sexual assault, abuse, accident, or other disasters. This is because, recently potential of EEG signals in differentiating PTSD from other trauma related brain injuries and providing better diagnostic techniques have been of particular interest in veteran affairs [215, 175].

Chapter 8

Conclusion

PTSD is a multifaceted psychiatric disorder, where various social, psychological, and neurobiological factors play important role in the etiology of the disorder. Here, we present initial proofs for low-cost, nonverbal assessment methods to potentially screen PTSD within marginalized communities. We used portable EEG headset and image processing algorithms to discover neurobiological abnormalities of PTSD and nonverbal cues of the disorder in free-hand sketches respectively. Our analyses reveal significant associations among PTSD and its different symptoms along with their underlying structure, neurobiological abnormalities related to PTSD, and effects of group, gender, and PTSD on the features of free-hand sketches from the participants. Our developed logistic regression and Random Forest models are able to identify potential cases of PTSD with reasonable accuracy. In future, this work could greatly inform HCI and UbiComp communities to explore alternative, low-cost, and off-the-shelf tools (e.g., brainwave signals and sketching) to assess PTSD among resource-scarce populations. We anticipate the proposed solutions in this paper paving the way for affordable and accessible clinical assessment of PTSD within low-resource communities. In a time of COVID-19 pandemic when lots of people do not have the means to receive in-person clinical diagnosis, our proposed tool could help many with an initial screen of PTSD.

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