Leveraging Free-Hand Sketches for Potential Screening of PTSD

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Post-traumatic stress disorder (PTSD) negatively influences a person's ability to cope and increases psychiatric morbidity. The existing diagnostic tools of PTSD are often difficult to administer within marginalized communities due to language and cultural barriers, lack of skilled clinicians, and stigma around disclosing traumatic experiences. Here, 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 within three different communities in Bangladesh: Rohingya refugees (n = 44), slum-dwellers (n = 35), and engineering students (n = 85). Due to the low-overhead and nonverbal nature of sketching, our proposed method potentially overcomes communication and resource barriers. Using corner and edge detection algorithms, we extracted three features (number of corners, number 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

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model for the refugee population. Our proposed initial assessment method of PTSD based on sketches could potentially be integrated with phones and EEG headsets, making it widely accessible to the underrepresented communities.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: Sketch; PTSD ; EEG; Refugee; Slum-dweller; Home; HCI4D; Ubicomp4D

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1 INTRODUCTION

Post-traumatic stress disorder (PTSD) is a psychiatric disorder that often develops among some people, who have been exposed to trauma and are experiencing psychiatric symptoms related to trauma [62]. Providing access to clinical diagnosis of PTSD with follow-up care is difficult within marginalized communities and requires significant medical investment. Besides, language, cultural, and literacy barriers, stigma associated with seeking help for mental health and revealing sensitive information to a stranger, etc., complicate the scenario [15, 38, 71].

To address this, we utilize art, a universal purveyor of expression [18], to design a creative method for potentially screening the cases of PTSD. Traditionally, the psychiatric community has leveraged the nonverbal nature of artwork to overcome language and communication barriers among different PTSD diagnosed populations, who have impaired ability to articulate their expressions [83, 89].

Moreover, art therapists have observed significantly greater recurring graphic forms (disembodied eyes and wedges) in the sketches of clinically diagnosed PTSD patients, who are victims of rape and sexual abuse, compared to the control group [82]. This observation inspired us to examine whether any visual characteristics can be identified from the free-hand sketches of traumatized individuals using image processing algorithms. In addition, we aim to explore whether such characteristics can be leveraged to potentially screen for PTSD.

Toward this end, we collected free-hand sketches of past/ present and expected future homes from three diverse communities, i.e., Rohingya refugees (n = 44), slum-dwellers (n = 35), and engineering students (n = 85) in Bangladesh. We interviewed the participants using a PTSD screening tool adapted from MINI 5.0.0 [77] and designed for psychiatric emergency settings among the refugees and migrants [33]. We digitized the sketches drawn with simple pencil and paper using a mobile phone camera.

We trained a CNN using the sketch images directly 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). Next, we developed multiple logistic regression models with participants' group, gender, qualitative sketch themes, and 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 free-hand sketches to screen potential cases of PTSD within marginalized communities.
- Our proposed low-cost assessment method using cheap pencil, paper, and mobile phone camera can be particularly useful in resource-scarce populations.

- Due to the nonverbal 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.
- Due to the automated nature of feature extraction and machine learning models, our proposed method avoids biases from human interpretation.
- To facilitate future research, we have released the anonymized free-hand sketches[1] with the consent of the participants. To ensure privacy, we do not share any demographic information of the participants.

2 RELATED WORK

We situate our research in a body of related work examining the use of ubiquitous systems for screening PTSD and exploring the utility of free-hand sketches in studying various mental health disorders.

2.1 Ubiquitous Systems for Screening PTSD

There are many technological interventions for screening PTSD. For instance, Papangelis et al. [64] built an interactive system that can guide a patient through conversation and elicit enough information to fill-up a PTSD checklist. Larsen et al. [41] 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. [47] 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. [78] used brain wave signals (e.g., EEG) to characterise and discriminate post-traumatic stress symptoms. Even Shim et al. [79] deployed machine learning models to classify PTSD patients from healthy controls using neurobiological markers (P300 features) of the disorder. Shahid et al. [76] leveraged portable EEG headsets to identify neurobiological abnormalities of PTSD among the Rohingya refugees while talking. We contribute to this line of research by analyzing the EEG signals of trauma-inflicted Rohingya refugees while sketching.

However, the use of such technological interventions might be limited within marginalized communities, who have little access to both education and technology [15]. Hence, in this work, we propose a creative method for potentially screening PTSD in low-resource communities using cheap pencil, paper, and mobile phone cameras.

2.2 Ubiquity of Free-Hand Sketches and Their Digital Snapshots

We selected free-hand sketches because they are easy-to-create, lightweight, and provide a unique, complex visual illustration of traumatic experiences and memories [45, 48]. Due to low overhead (requires pencil and paper), this method is suitable for marginalized communities, who may lack literacy and technological skills [36, 91].

Additionally, free-hand drawings have been used for the clinical assessment of cognitive dysfunction in amnesia, dementia, and Alzheimer's disease [10, 32]. Standardized clock drawing tests that have been used for diagnosing Alzheimer's disease correlate well with traditional scores of MINI [80, 84]. These tests have greater clinical utility while screening culturally, linguistically, and educationally heterogeneous populations as they require minimal language interpretation and training to administer [9, 49]. However, they require human intervention for evaluating the sketches and are often prone to biases in human interpretation [37, 73].

In this light, Pereira et al. [66] 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 [82], however, observed recurring graphic forms in the sketches of sexually abused PTSD patients.

[1] https://github.com/farhana-shahid/PTSD-Free-Hand-Sketches

Furthermore, Eisenbach et al. [20] qualitatively identified seven symbols (e.g., forest, death, body, etc.,) from the paintings of childhood trauma survivors of loss and sexual abuses.

Similarly, Backos used Kinetic Family Drawing and the Draw-A-Person screening tools to identify indicators of PTSD among mothers and children subjected to intimate partner violence [6]. The author reported that the sketches of clinically diagnosed PTSD victims are more estranged and depict negative interaction with family than that of the control group. O'Flynn found significantly more monstrous grotesque figures and distorted bodies in the human figure drawings of traumatically grieving children [63].

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 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 [42].

2.3 Ubiquitous Computing for Marginalized Communities

Recently there have been several attempts to democratize the use of pervasive computing applications within underrepresented communities [90]. For example, technological interventions and mobile applications have been used to help refugees resettle, overcome language barriers, and support one another [1, 16]. Digital technology has also been used to improve the healthcare experiences of the marginalized groups. For example, Kreps [40] 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. [88] used ICT-based solutions to provide e-health services in the rural community of South Africa.

Similarly, Cao et al. [11] used deep learning methods and mobile technologies to improve the diagnosis of tuberculosis among resource-poor and marginalized communities in Peru. Talhouk et al. [86] studied various factors to design effective digital interventions for improving antenatal health in Syrian refugee camps. In another work, Talhouk et al. [85] explored the implications of community radio shows on the health education of Syrian refugees. Moreover, Ginsberg et al. [28] 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 [14, 21]. 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 [2]. Moreover, as Devito et al. [17] point 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.

3 METHODOLOGY

As per our study pipeline, we (1) collected free-hand sketches from three different groups, (2) screened them for potential cases of PTSD, (3) collected EEG data from the refugees, and (4) analyzed the data to develop various machine learning models for screening PTSD (Figure 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 the Refugee Relief and Repatriation Commission (RRRC) under the Ministry of Disaster Management and Relief, the government of Bangladesh and IRB at the authors' institution.

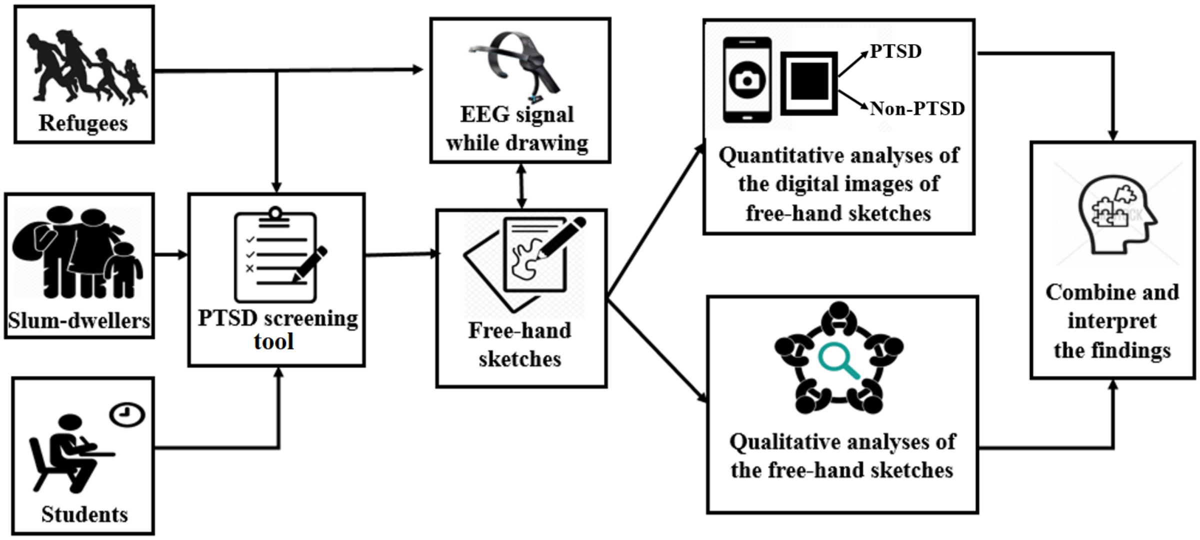


Fig. 1. Our study pipeline to explore free-hand sketches with pervasive computing systems in the context of PTSD.

3.1 Participants in Our Study

We used the *pwr* package[2] from R to estimate the required sample size assuming normal distribution of the data. We found that to determine any significant (significance level, $\alpha = 0.05$, power = 80%) difference (large effect size, $d = 0.8$) or correlation (large effect size, $r = 0.5$) for intra-group analysis, we would need at least 14–28 people per group. However, for inter-group analysis, we would need data from at least 23 people per group. For non-parametric distribution, we would require 15% additional subjects [44], i.e., at least 16–32 people for intra-group analysis and at least 39 people for inter-group analysis. Our collected data points exceed these minimum requirements.

3.1.1 Refugees. In January 2018, five of our authors (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 [69]. With the help of camp officials and *'Majhi'* (Rohingya camp leaders), we recruited 44 voluntary refugees (24 female and 20 male), aged between 7–70 years randomly from the camp. 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, which is closely related to Rohingya dialect and commonly understood by the refugees [24]. The presence of a female interviewer in our team and *'Majhi'*, who are 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.

3.1.2 Slum-Dwellers. Next, in September 2019, four of our authors (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 [61]. At first, we tried to recruit participants from the local tea stalls, a common place for

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

hanging out in the slum. However, people there, assuming we were inspecting illegal housing in the slum, denied to speak to us without the approval of their local leaders.

When we approached the local political leaders, they readily helped and took us to different households. After receiving assurance from them, the slum-dwellers agreed 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 participating slum-dwellers are females.

3.1.3 Engineering Students. Lastly, in September 2019, we collected data from the students of an engineering 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 authors (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 the regular class hours (from 8am–5pm) of the university.

3.2 Tools for Data Collection

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 (25 refugees and 22 slum-dwellers). In case of minors (5 refugees and 8 slum-dwellers), we took informed consent from their parents.

3.2.1 Screening PTSD. To identify the potential cases of PTSD, we used a screening tool adapted from the PTSD module of MINI 5.0.0 [77] and designed specifically for psychiatric emergency settings among the refugees and migrants [33]. It is difficult for psychiatric patients in marginalized settings to receive any follow-up diagnosis after initial consultation [23]. In contrast, the tool we used is simple and takes a feasible amount of time to administer. Moreover, its items could be communicated easily to the low-literate and linguistically different participants in our study. Please see Supplementary Section 1 for more details.

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, we used a self-report form of the Bengali translated questionnaire. Please see Supplementary Section 1.2 for more details on translation. Our interviewers focused on building rapport with the participants to elicit spontaneous responses through naturalistic conversation. We were also careful to not overburden the participants with reflections of traumatic events so that they could maintain their composure.

3.2.2 Free-Hand Sketching. As our subject for the 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 [50]. Prior studies describe home as a place of permanence and continuity [68], comfort, and the center of activities [26]. It strengthens and secures relationships [31] and offers reflection on personal ideas and values [81].

For example, earlier studies situate home at the root of refugee identity [25], belongingness [74], pride [56], their desire for safety [51], and sustaining continuity [4]. Analysis of the sketches of *home and war* from Iraqi refugee children confirms that their understanding of war and trauma precedes that of peace [34]. However, in another study it was observed that Rohingya refugees were significantly more attentive and relaxed while sketching their homes than during casual conversations [76].

For the slum-dwellers, home is associated with their livelihood [3], safety [39], and is a precondition of their ability to benefit from developmental practices [27]. Home environment also greatly influences the academic performance of the students [12, 19]. Moreover, Gomes et al. [29] showed that 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 for the participants.

We spent substantial time making sure the participants felt comfortable through interactive discussions and invited them to sketch only when they felt prepared. To our experience, there were no signs that participants found the subject unfamiliar or felt 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.

3.2.3 EEG Headset. We used a low-cost, consumer-grade, and portable EEG headset called NeuroSky MindWave mobile headset [59] among the Rohingya refugees to study their brain signal activities while sketching. Previous studies show that the reported cases of PTSD are higher among Rohingya refugees (36–69%) [70, 76] compared to the other groups in our study (3.2–54.6% PTSD among the slum-dwellers [55, 57] and no study yet among the Bangladeshi students). Traditionally brain computer interfaces have been used within different refugee settings for diagnosing PTSD [5, 7, 76]. Thus, the context of refugees provides us a better opportunity to study the neurobiological abnormalities associated with PTSD while sketching. Moreover, we could not collect EEG data from the slum-dwellers due to the intervention of local political leaders.

Our EEG headset 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. The headset characterizes different mental states, such as attention and relaxation on a relative scale of 1–100 (lower to higher).

When we requested the refugees to wear this non-invasive headset while sketching, 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 fellow refugees assured them that the device was not probing in any way. None reported any discomfort while wearing the device. Moreover, we observed that as the refugees got involved in sketching, they hardly noticed the headset.

3.3 Data Preprocessing and Analysis

After de-identifying the collected data properly, we analyzed them using various quantitative and qualitative methods. With the help from a 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.

3.3.1 Free-Hand Sketches. We performed different analyses on the free-hand sketches drawn by the 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 [72]. It was used previously to understand the experiences of chronic pain from the drawings of chronic pain patients [67]. 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 bias in human interpretation of what the artists might have implied through their sketches [37, 73]. 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

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

Fig. 2. Different features identified from the digital images of two sample free-hand sketches drawn by our participants.

preliminary codes to the sketches to describe their contents and later grouped them into various common themes via thorough discussions and review processes 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 [87] to extract three features from the images that correspond to various details (Figure 2) present in the sketches [46, 58] and also correlate well with the semantics of the object being sketched [46]. These are:

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

Please see Supplementary Section 2 for more details on the calculation of these features.

3.3.2 EEG Signals. We transferred all the EEG signals from the headset to our laptops using Bluetooth connection. The EEG recordings of the participants were of varying duration ranging from 65–110 seconds. To ensure uniformity, we truncated the signals at both ends and considered the middle 60 seconds. To understand the neurobiological characteristics of the refugees while sketching their past and expected future homes, 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 future homes respectively.

3.3.3 Analyses. We performed different statistical analyses on our collected data to find how the 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 [52] on all the results.

Next, we developed a convolutional neural network using *Keras* [13] from Python to see if the implicit features from the sketches could point to the occurrences of PTSD. To find the optimal model, we used grid search from *scikit-learn* [65] 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 due to 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 [30], we found that Random Forest works best in screening the potential cases of PTSD based on EEG and sketch features.

4 FINDINGS

Table 1 lists the demographic information of all the participants. Majority of the refugees ($n = 38, 86.4\%$) in our sample migrated to Bangladesh a few months before our study following the deadly crackdown by Myanmar's army on the Rohingya Muslims [8]. Some refugees ($n = 6, 13.6\%$) migrated long ago due to 1991–92's violence by Burmese armed forces [60]. Among the refugees, 19 (43.2%) have received some form of formal education

Table 1. Summary of the demographic information of different groups of participants.

Demographic information	Rohingya refugees (n = 44)	Slum-dwellers (n = 35)	Engineering students (n = 85)
Female	24 (54.5%)	32 (91.4%)	35 (41.2%)
Male	20 (45.5%)	3 (8.6%)	50 (58.8%)
Mean age	29.11 years (SD = 13.52 years)	28.09 years (SD = 12.4 years)	19.08 years (SD = 1.2 years)
Mean migration period	to Bangladesh 2.68 years (SD = 6.18 years)	to Dhaka 8.18 years (SD = 7.34 years)	NA
Illiterate	25 (56.8%)	22 (62.8%)	0 (0%)
Employed	10 (22.7%)	12 (34.3%)	NA

Table 2. Reported cases of traumatic events and distress among different groups of participants.

Rohingya refugees (n)				Slum-dwellers (n)		Engineering students (n)	
Beating	2	Murder of spouse	7	Death of spouse	7	Academic failure	2
Physical injury	16	Murder of children	2	Death of family members	6	Death of family members	4
Injury of family members and friends	2	Murder of family members and relatives	42	Death of children or miscarriage	13	Abusive relationship	2
Imprisonment	1	Rape	1	No access to treatment for financial distress	9	Financial distress	1

(primary: 10, secondary: 8, higher secondary: 1). In the refugee camp, some of them ($n = 10, 22.7\%$) are working either as boatmen, day laborers, tailors, farmers, house maids, small retailers, or camp volunteers.

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 among this population. A majority of the participating female slum-dwellers are homemakers. Others work as house maids, raw material sellers, tailors, security guards, rickshaw pullers, garments workers, etc. On the other hand, all the engineering students in our sample are only involved in study.

4.1 Traumatic Experiences, Personal Distress, and PTSD

During our interviews, many participants shared their personal experiences of sorrow, suffering, loss, abuse, and violence. Table 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, killing, torture, and abuse. 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.*"

Most of the slum-dwellers and their family members suffered terribly from various diseases due to poverty and poor access to resources. There were many cases of miscarriage and loss of young children among the female slum-dwellers. On the other hand, the narratives of grief and sorrow 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.

Next, we analyzed the responses of the participants to the PTSD screening tool to measure the prevalence of PTSD (Table 3). We found a significant difference between the cases of PTSD among the Rohingya refugees and slum-dwellers ($\chi^2(1) = 11.58, P = 0.0007$), and refugees and engineering students ($\chi^2(1) = 64.55, P = 9.44 \times 10^{-16}$) as well. The prevalence of PTSD among the Rohingya refugees in our sample is higher than the other groups. We even observed significant effect of gender ($\chi^2(1) = 5.27, P = 0.021$) on the prevalence of PTSD among the

Table 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	10 (50%)	16 (66.67%)	26 (59.1%)
Slum-dwellers	1 (33.3%)	11 (34.4%)	12 (34.3%)
Engineering students	1 (2%)	3 (8.6%)	4 (4.7%)

Table 4. 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

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.

4.2 Visual Analysis of the Free-Hand Sketches of Home

Four main themes emerged from the visual analysis of the free-hand sketches of homes (Table 4). The themes embody a sense of safety, security, personal ideas, and values centering on homes.

□ *Home as a Shelter*: Around 90% sketches represent home as a shelter. Among them, some participants sketched the front elevation of homes (Figure 3a), i.e., a straight-on view of the home when looked from the front [35]. Others sketched the perspective view (Figure 3b) that projects a three-dimensional view of the home in two dimensions [35]. Another group sketched the floor plan (Figure 3c), i.e., top view of home [35]. Only the students annotated their floor plans with writing and used various door symbols, e.g., door swing (Figure 3c).

□ *Home as a Place for Activities*: In these sketches, the engineering students focused on the amenities of urban life (Figure 3c), e.g., bedroom, kitchen and dining room, living room/ drawing room, swimming pool, gaming room/ computer zone, library/ bookshelf (Figure 3d), room theatre/ television, etc. Some students even tied their ambitions of higher studies and research work, dream jobs, and living abroad to their depiction of home.

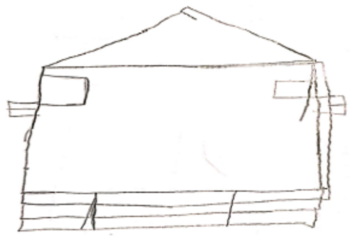
□ *Home as a Place for Strengthening Relationships*: In the three sketches under this category, the students expressed their desire to be with their near and dear ones. For example, one of the students focused on his future family while drawing his expected future home (Figure 3e).

□ *Home and Nature*: In this theme, the participants integrated various natural components (Figure 3f) in their sketches of homes, e.g., trees, flower, hills, river, forest, sea, etc. These sketches evoke a sense of love for Nature, and exploration.

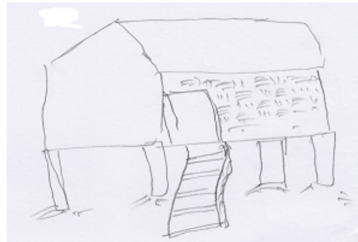
The distribution of themes across the groups suggest that the sketches drawn by the students are more varied.

4.3 How Do Computing Methods Interpret Free-Hand Sketching?

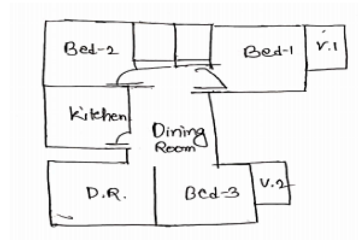
Next, we performed different quantitative analysis on the free-hand sketches and EEG data while sketching.



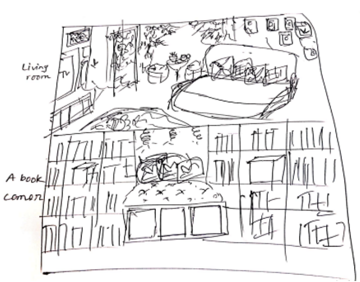
(a) Present home of slum-dweller S23



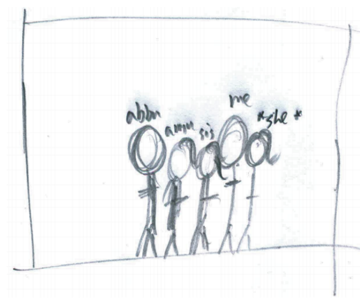
(b) Past home of refugee R1



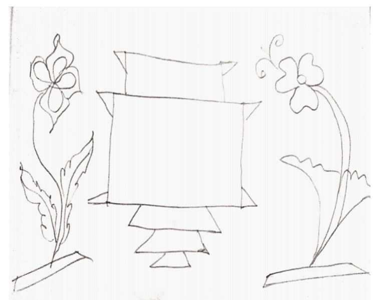
(c) Present home of student E48



(d) Future home of student E62



(e) Future home of student E26



(f) Future home of slum-dweller S19

Fig. 3. Different themes present in the free-hand sketches of the participants.

Table 5. 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

4.3.1 Inter-Group Analysis. Table 5 shows different features present in the free-hand sketches of the participants. Tables 5 and 6 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, 6). 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.

Next, we analyzed the features of free-hand sketches from PTSD and non-PTSD cases across all groups (Figure 4). 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

Table 6. Differences in the features of free-hand sketches among different groups. Only the statistically significant results are shown after Benjamini-Hochberg error correction [52] on Mann-Whitney 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	

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

4.3.2 Intra-Group Analysis. We compared the features of sketches between the male and female participants within the same group (Figure 5). 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 are significantly greater ($W = 162, P = 0.01$) compared to the corresponding sketches made by 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 of corners in the past and future homes of the refugees correlate significantly ($r_\tau = 0.42, P = 0.0016$) as well.

4.3.3 Brain Activities while Sketching. When we analyzed the EEG signals from the refugees while sketching, we found that they were significantly more attentive ($W = 311771.5, P = 0.0036$) (Figure 6a) but less relaxed ($W = 267895, P = 0.0073$) (Figure 6b) 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 6c). However, the refugees without PTSD showed significantly greater relaxation levels ($W = 66020.5, P = 0.02$) while sketching their expected future homes (Figure 6d). 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 6e).

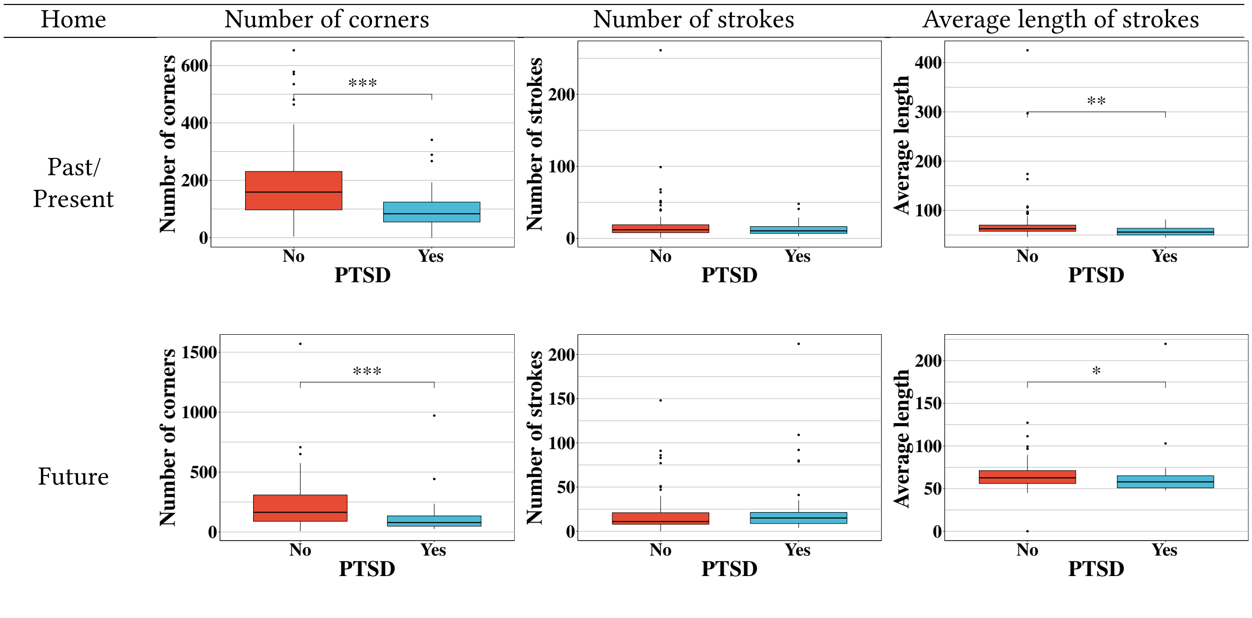


Fig. 4. Different features of free-hand sketches from PTSD and non-PTSD participants. * denotes Benjamini-Hochberg corrected statistically significant results from Mann-Whitney test at $P < 0.05$ (*), $P < 0.01$ (**), and $P < 0.001$ (***).

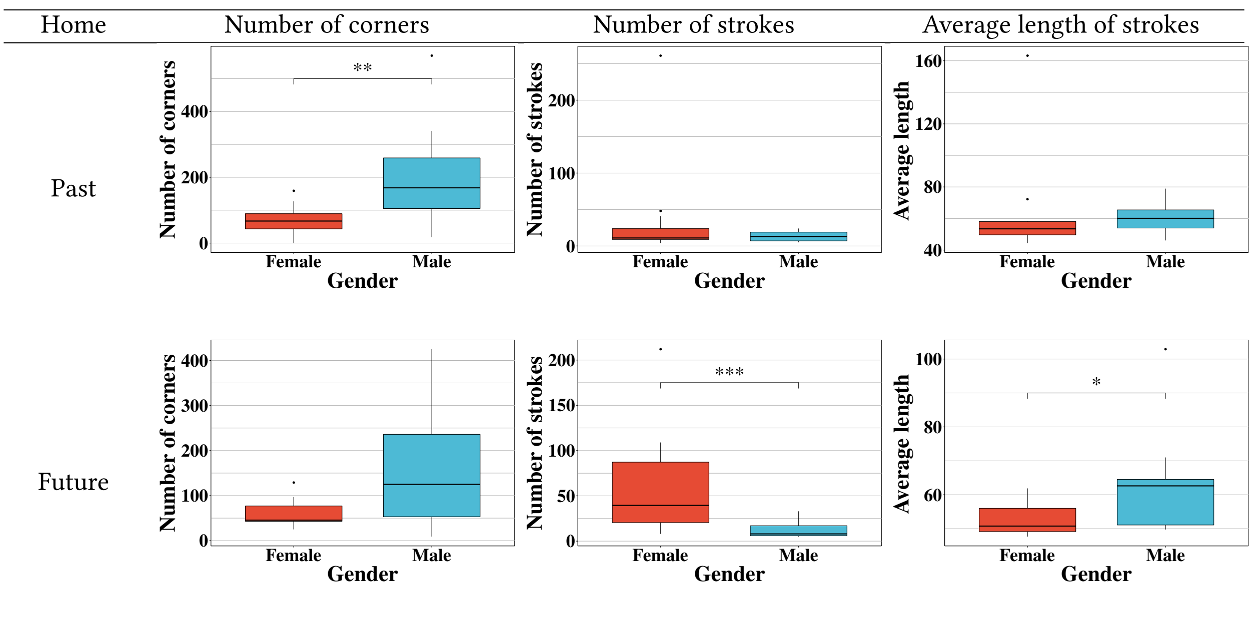


Fig. 5. Different features of free-hand sketches from the male and female Rohingya refugees. * denotes Benjamini-Hochberg corrected statistically significant results from Mann-Whitney test at $P < 0.05$ (*), $P < 0.01$ (**), and $P < 0.001$ (***).

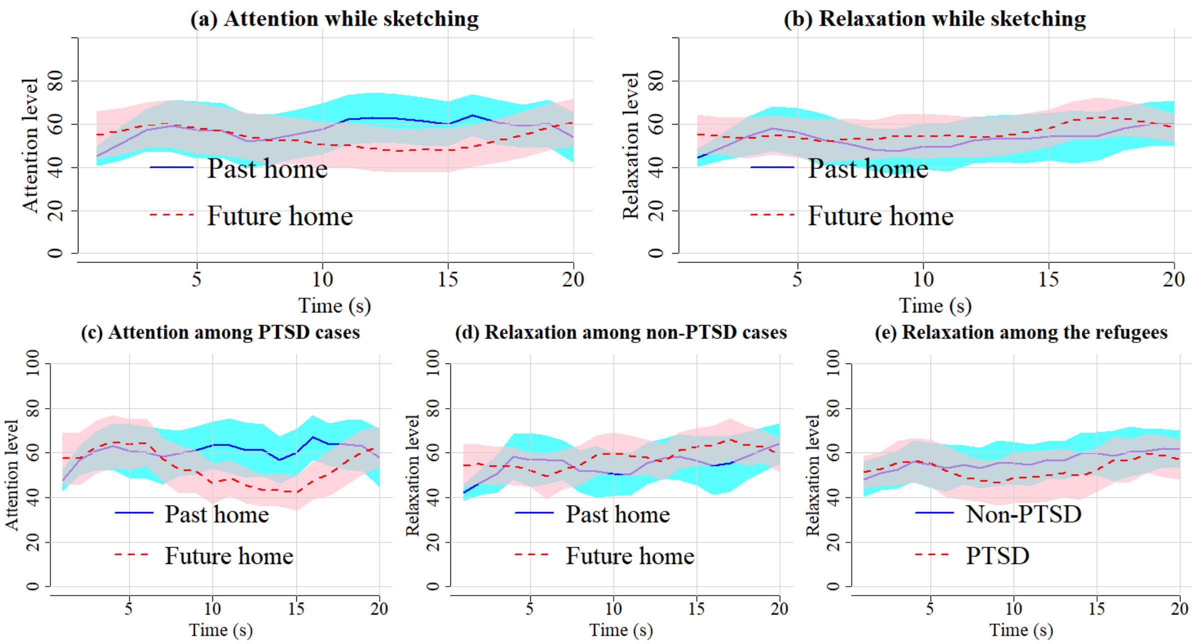


Fig. 6. Neurobiological activities among Rohingya refugees while sketching their past and expected future homes.

4.4 Screening the Potential Cases of PTSD

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

4.4.1 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 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.

4.4.2 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 9). Among all the features, 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 9). 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 10). This might be due to the lower prevalence of PTSD within these groups (Table 2).

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 9). We used the following interactions to develop our model:

$$PTSD = B_0 + B_1 \times Gender \times Corner_F + B_2 \times Gender \times Stroke_P + B_3 \times Group \times Corner_F + B_4 \times$$

Table 9. 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

Table 10. 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

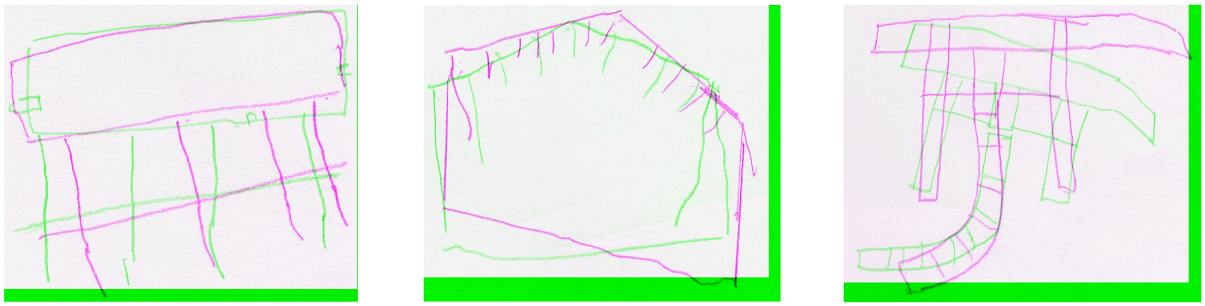
$$Group \times Stroke_F + B_5 \times Group \times Length_P + B_6 \times Group \times Length_F$$

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 9). Though it has greater weighted MCC and AUC values, its specificity (TNR) is low across the groups (Table 10). Here, the number of strokes in the sketches of future home significantly affects ($\chi^2(1) = 5.3, P = 0.02$) the model outcome.

4.4.3 Random Forest. Finally, we combined quantitative sketch features and temporal EEG data (eight brainwaves, attention, and relaxation) from the Rohingya refugees to screen for 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 9). Out of 840 temporal instances of PTSD, it misclassified only six instances.

5 DISCUSSION

Among the three groups, the Rohingyas reported the highest ($n = 73$) number of traumatic events and causes of distress (Table 2). They also have the highest prevalence (59.1%) of PTSD, which is comparable to the previously reported cases of PTSD (69%) among them [76]. The slum-dwellers and the engineering students reported 35 and 9 cases of trauma and distress respectively. They have the second highest and lowest prevalence of PTSD



(a) Sketches of refugee R4

(b) Sketches of refugee R10

(c) Sketches of refugee R24

Fig. 7. Similarity in the sketches of past (red) and expected future (green) homes of the Rohingya refugees.

respectively (Table 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 [53, 54].

Now, 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 [57]. This might be because many of them reported suffering from financial distress and no access to treatment for illnesses, which might not be true traumatic events according to DSM-5 criteria. To our knowledge, this is the first study exploring the cases of PTSD among Bangladeshi students.

5.1 Collective Observations and Needs through the Free-Hand Sketches of Home

Most of the refugees and slum-dwellers either sketched the simple front elevation or floor plan of homes. On the contrary, the engineering students sketched the exterior and interior of homes with various details, furnishings, and natural components, which 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 [50]. 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 for 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.

Now, 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. [22]. 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.

5.2 Group-Wise Variation in the Features of Free-Hand Sketches of Home

Since the free-hand sketches from the students depict home from varying perspectives, the complexity of their sketches might have given rise to a significantly greater number of corners (Table 6). 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 6). 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 6) might have resulted from the fidgeting of hands due to prior inexperience of sketching. Besides, the presence of strokes with significantly smaller length (Table 6) 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), the average length of these strokes is significantly greater than that of the refugees (Table 6). 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.

On the contrary, the 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 7) 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.

5.3 PTSD, 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 Rohingya refugees (Table 6) and among the participants with potential cases of PTSD (Figure 4). As we observed a significant effect of group on the prevalence of PTSD (Table 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 a significantly greater number of corners and significantly fewer strokes of greater length in the sketches of male Rohingya refugees (Figure 5) 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 [75]. These differences can also be attributed to the educational experiences of Rohingya men (65% men are literate compared to 25% women) and significantly greater prevalence of PTSD among the Rohingya women (Table 3).

Moreover, the Rohingya refugees were significantly more attentive but less relaxed while sketching their past homes than the future homes (Figure 6). Such reverse association between attention and relaxation levels has been observed among archers with mid level shooting performance [43]. Following the explanation from Lee et al. [43], 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 7), then maybe the thought of a new home or getting back their past home gave them comfort and made them feel more relaxed.

5.4 Screening PTSD based on Free-Hand Sketches of Home

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 10). This might be due to high prevalence of PTSD among the refugees and non-PTSD among the other groups. Now, removing the 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 the model performance in the case of slum-dwellers and students (Table 10).

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 the case of slum-dwellers than the *'with/ without group'* logistic regression models (Table 10). Integrating the sketch themes into our logistic regression model improves 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 [37, 73] without participants' feedback. This is because, some sketches from low-literate participants are ambiguous and difficult to interpret.

On the other hand, the 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 with both sketch features and EEG outperforms a previously developed diagnostic model of PTSD [79] based on only brain signal activities (accuracy: 80%, recall: 0.71). This indicates that sketch features improve model performance when combined with EEG data.

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 LIMITATIONS AND FUTURE WORK

Despite the promising outcome, we acknowledge some limitations in our work. Firstly, 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 [33]. A broader study involving large diverse populations would require diagnostic tools with good psychometric properties.

Secondly, 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 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.

Finally, the features of a sketch depicting home might point to socioeconomic, 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.

7 CONCLUSION

We present the initial proof for a low-cost, nonverbal assessment method to potentially screen PTSD within marginalized communities. We used image processing algorithms to discover features from the free-hand sketches of home. Our analysis reveals significant 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. However, this is only an initial step. We believe this work will greatly inform HCI and UbiComp communities to explore alternative, low-cost, and off-the-shelf tools (e.g., sketching) to assess PTSD among resource-scarce populations. Particularly, in a time of COVID-19 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. We envision this work would pave the way for affordable and accessible clinical assessment of PTSD within low-resource communities.

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