social sciences

MDPI

*Article*

# Enhancing Mental Health Predictions: A Gradient Boosted Model for Sri Lankan Camp Refugees

**Indranil Sahoo [1,*], Elizabeth Amona [1], Miriam Kuttikat [2] and David Chan [3]**

[1] Department of Statistical Sciences and Operations Research, Virginia Commonwealth University, Richmond, VA 23284, USA; amonaeb@vcu.edu
[2] School of Social Work, Virginia Commonwealth University, Richmond, VA 23284, USA; kuttikatm@vcu.edu
[3] Department of Applied Mathematics, Virginia Commonwealth University, Richmond, VA 23284, USA; dmchan@vcu.edu
* Correspondence: sahooi@vcu.edu

**Abstract:** This study explores the mental health challenges encountered by Sri Lankan camp refugees, a population often marginalized in mental health research, and analyzes a range of factors including socio-demographic characteristics, living conditions in camps, and psychological variables. In quantitative mental health research, linear regression serves as a conventional approach for assessing the influence of diverse factors on mental health outcomes. However, this method fails to accommodate non-linear relationships between mental health variables and predictors and relies on stringent model assumptions that often do not align with real-world conditions. This study introduces a model-agnostic, advanced machine learning/artificial intelligence (ML/AI) technique, `glmboost`, as a viable alternative to linear regression. The `glmboost` algorithm is capable of fitting non-linear prediction models while also conducting variable selection. Moreover, the coefficients obtained from the `glmboost` model retain the same interpretability as those derived from linear regression. While the `glmboost` model identifies several key factors including post-migration living difficulties, post-traumatic stress disorder, difficulty in sleeping, poor family functioning, and lower informal support from families as markers of declining mental well-being among the Sri Lankan refugees, the linear regression overlooks vital predictors such as family functioning and family support, highlighting the importance of utilizing advanced ML/AI techniques like `glmboost` to comprehensively capture complex relationships between predictor variables and mental health outcomes among refugee populations. Thus, by introducing a novel, data-driven approach to mental health risk assessment, this study paves the way for more precise and efficient analyses and interventions in refugee settings, with the potential for improved resource allocation and personalized support, thus revolutionizing mental health service delivery in challenging environments. Additionally, it contributes to the academic discussion on refugee mental health while emphasizing the pivotal role of advanced data analytics in addressing complex health issues within humanitarian contexts.

**Keywords:** refugee mental health; gradient boosted model; Sri Lankan camps; predictive analytics; risk assessment; humanitarian data science

check for updates

**Citation:** Sahoo, Indranil, Elizabeth Amona, Miriam Kuttikat, and David Chan. 2024. Enhancing Mental Health Predictions: A Gradient Boosted Model for Sri Lankan Camp Refugees. *Social Sciences* 13: 255. https://doi.org/10.3390/socsci13050255

Academic Editors: Barbara Fawcett and Nigel Parton

Received: 16 March 2024
Revised: 5 May 2024
Accepted: 7 May 2024
Published: 9 May 2024



## 1. Introduction

In an era marked by increased globalization, conflict and climate change, migration and refugee crises have dramatically increased and have emerged as pressing issues in the modern world. By the end of 2022, the global landscape, as reported by the United Nations High Commissioner for Refugees (UNHCR), comprises a staggering 108.4 million individuals grappling with forced displacement, with 35.3 million classified as externally-displaced refugees. These figures consist of hundreds of thousands of Sri Lankan Tamil refugees, compelled to seek asylum after being displaced from their homeland due to a three-decade-long civil war. Among these numbers also stand millions of people fleeing from Venezuela, the Syrian Arab Republic, Afghanistan and Ukraine during the period spanning 2014 to 2022, predominantly due to warfare. The migration trajectory of forcibly displaced persons is often fraught with physical and psychological traumas, which can have profound implications on their long-term health, particularly in the volatile ecological, political and social contexts prevalent among displaced communities (Bhui et al. 2003; Chattoraj 2022; Kulandai 2021; Silove et al. 1997).

The global phenomenon of forced displacement has propelled millions of individuals to seek refuge in foreign lands, often enduring perilous journeys and unwelcoming receptions. The causes of migration range from armed conflicts and political persecution to environmental disasters and economic hardships. As a result, the impact of forced displacement on the mental health of refugees is profound and far-reaching (George 2012; Kuttikat et al. 2022; Pandalangat et al. 2013; Porter and Haslam 2001). Refugees suffer from violent and perilous journeys, and once in host countries, they face numerous adversities, including adapting to a new culture, language and social environment while supporting their families at the same time. They are also confronted with an array of challenges stemming from prolonged displacement, legal ambiguity, documentation deficiencies, coercive encampment policies, systemic discrimination, economic deprivation, and legal disenfranchisement within inhospitable socio-legal frameworks (Amrutkar 2012; De Vries 2001; Rogers and Sweeney 1998; Weaver 2016). Notably, a substantial portion of camp residents, as highlighted by the UNHCR, comprises children, either accompanying their migrating parents or born into displacement (Lustig et al. 2004), which adds to their ongoing psychological stress. These cumulative stressors can lead to a range of mental health issues, including post-traumatic stress disorder (PTSD), depression and anxiety disorders (George and Jettner 2015). Previous research indicates an association among forced displacement, familial challenges, and parental capacities (Al-Simadi and Atoum 2000; Herath et al. 2012; Morantz et al. 2012; Somasundaram 2010; Steel et al. 2006). Furthermore, research underscores the potential of resource allocation in alleviating the adverse mental health outcomes associated with compromised family dynamics (Fadhlia 2023; George and Jettner 2016; Siriwardhana and Wickramage 2014).

However, despite these insights, a noticeable gap persists in comprehending the role of resource accessibility and family functioning in mitigating the detrimental impacts of transmigration stress experienced by camp refugees, thereby impeding the development and implementation of effective mental health interventions within camp settings. As such, identifying the underlying factors associated with the mental health issues of refugees is crucial to facilitating their integration into the host society. This research sheds light on the complex relationship between mental health and migration stressors by employing a data-driven, model-agnostic predictive framework for mental health scores using an innovative gradient-boosted statistical model.

Quantitative research in social work often employs linear regression as a fundamental statistical tool to explore the relationships between variables. Linear regression is valued for its ease of implementation and interpretation, making it accessible to researchers and practitioners alike. As a result, linear regression is very popular in migration research and has been widely used to model the mental health of migrants (Alemi et al. 2015; Costa et al. 2020; Nesterko et al. 2020; Schilz et al. 2023; Walther et al. 2020). However, its simplicity comes with limitations, as linear regression requires strict model assumptions such as the existence of the exact linear relationship between the response and predictor variables. Furthermore, the model also requires the assumption of normally distributed residuals, coupled with homoscedasticity, wherein the variance of the residuals remains constant across all values of the independent variables. A linear regression thus fails to capture complex, nonlinear trends among variables, thereby oversimplifying the intricate associations present in real-life scenarios. In the context of migration research, where multiple intersecting factors influence outcomes, such as socioeconomic status, cultural adaptation, family dynamics and trauma exposure, the linear regression model almost certainly does not completely capture the true dynamics. To address this challenge, we implement a machine learning/artificial intelligence (ML/AI) method, namely, the gradient-boosted Generalized Linear Model (`glmboost`) to construct a predictive model for refugee mental health and to determine factors that have a significant effect on refugee mental health. Gradient Boosting is a machine learning technique for regression that produces more accurate prediction models in the form of ensemble weak prediction models. It is an iterative algorithm that combines simple parameterized functions with weak performance (high prediction error) in order to produce a highly accurate prediction by minimizing the errors (Adamu et al. 2019). The gradient-boosted GLM constructs generalized models that are highly robust, model agnostic, and have interpretability similar to linear regression. Gradient boosted methods have been shown to outperform classical linear regression for insurance claims data in Greberg and Rylander (2022); Henckaerts et al. (2021). We implement the `glmboost` algorithm in `R` using package `mboost` (Hothorn et al. 2013), and a hands-on tutorial for the package is described in Hofner et al. (2014).

We examine data collected from Sri Lankan camp refugees in Tamil Nadu, India. Over 125,000 Sri Lankan refugees live in India after a civil war in their native country caused them to migrate to different areas of the globe (George 2010). Given the scarcity of information concerning the adaptation experiences of Sri Lankan Tamil refugees residing in Indian camps (Kuttikat et al. 2018), this study looks at data collected from Sri Lankan refugees residing in refugee camps in Tamil Nadu, India. The objective of this study is to identify stressors adversely affecting the mental health of refugees, and develop a predictive model for the mental health of the refugees, taking into account parental daily stressors, mental well-being, family functioning and the utilization of formal and informal resources by refugees. The gradient-boosted model implemented in this study is expected to improve predictions of refugee mental health scores compared to linear regression in terms of higher $R^2$ values, lower root mean squared error (RMSE) values, and the selection of the set of most important predictor variables that can capture more intricate (nonlinear) relationships with the mental health scores. Given the extensive literature highlighting the impact of migration stress on individual and family well-being (De Vries 2001; Siriwardhana and Wickramage 2014; Steel et al. 2006), it is imperative to investigate similar trends among Sri Lankan refugees and ultimately better inform the implementation of potential interventions to alleviate these associations.

## 2. Materials and Methods

### *2.1. Setting*

Approximately 300,000 Sri Lankan Tamil refugees have been displaced to India since the onset of the Sri Lankan civil war in the 1980s (Maneesh and Muniyandi 2016), which continued until 2009. As of 2019, more than 58,000 Sri Lankan refugees reside in 107 refugee camps in Tamil Nadu—a state in southern India with cultural affinities to the ethnic Tamil refugees (Newman 2022; Valcárcel Silvela 2019). An additional 37,000 refugees are also displaced in Tamil Nadu, with many financially resourced urban Tamil refugees opting for non-camp settings. The flow of refugees into India over the years has been influenced by various factors, including India's changing refugee policies and the de-escalation of violent conflicts in Sri Lanka (Goreau-Ponceaud and Madavan 2022). Tamil refugees living in India have continued to experience statelessness, discrimination, and minimal access to resources (Acharya 2007; George 2013; Hellmann-Rajanayagam 2007; Rogers and Sweeney 1998). The migration stressors coupled with economic hardships further contribute to family conflicts and poor mental health (Betancourt et al. 2017; George 2012; Lindert et al. 2018; Papola et al. 2020; Ponnet 2014).

During the different migration waves in 1984, 1999 and 2006, approximately 20,000 Sri Lankan Tamil refugees came to Southern India every year (Valatheeswaran and Rajan 2011). The southern Indian state of Tamil Nadu has 115 of the 123 refugee camps due to the linguistic and ethnic kinship that exists between Sri Lankan Tamils and the native residents (George 2009). The present study was conducted in partnership with the Organization for Eelam Refugee Rehabilitation, or OfERR, a non-profit group founded in 1984. The organization's mission is to help and provide resources to Sri Lankan refugees in India by working to ensure sustainable development inside refugee camps. Participants were recruited at a refugee camp located in Trichy, a city in India's southern state of Tamil Nadu. As one of several 'special' camps initially set up to house Sri Lankan refugees deemed high-security threats (Kodiyath and Padathu Veettil 2017), the camp houses about 1500 families. Recruitment and data collection at the Trichy camp lasted approximately one year, between June 2014 and August 2015. The institutional review board at the authors' university approved all practiced study procedures.

### 2.2. Sampling

At the time of data collection, the Trichy refugee camp had 1500 families with approximately 4500 individuals (George 2013). The researcher along with a team of 12 trained female healthcare workers, and current residents at Trichy refugee camp, conducted interviews among 120 parent-adolescent dyads (120 parents and 120 adolescents) from the Trichy refugee camp. The healthcare workers, responsible for conducting healthcare workshops within the refugee camps, undergo annual formal case management training facilitated by the Tamil Nadu Government. Their selection process was conducted through the community partner, OfERR. The research data collection team presented information about the study, such as inclusion criteria and notes about voluntary participation, at community events hosted by OfERR for the Sri Lankan refugee community. Stratified purposive sampling techniques were used to select participants in the study. The inclusion criteria for the study were as follows: 1. Sri Lankan refugee status; 2. Tamil ethnicity; 3. participation of one parent-adolescent dyad from a family and 4. adolescents were between the ages of 13 and 18 at the time of data collection. A specific process was used to ensure a representative sample of 40 families from each subdivision of the refugee camp. First, a number between 1 and 1500 was randomly generated to establish a starting point. Next, every eighth household was selected for the study. Assuming that families were homogeneous with respect to all variables except their residential subdivision, this sampling scheme provided a representative sample from the population, since the sampling scheme was an equal probability of selection sampling method (Mostafa and Ahmad 2018). The research team visited 180 homes, after which 120 families, with children and parents living together, contacted the team to inform them of their interest in participating in the study.

A posthoc power analysis was conducted using Cohen's effect size $f^2$ for multiple linear regression (Cohen 1988),

$$f^2 = \frac{R^2}{1 + R^2},$$

where $R^2$ is the coefficient of determination. A sample size of $n = 120$ was found to detect a small effect size of 0.02 with 34% power; a medium effect size of 0.15 with 98.7% power and a large effect size of 0.35 with 99.9% power. All power computations were performed using G-Power v3.1 software (Faul et al. 2007).

### 2.3. Data Collection

The research team explained the study to and screened interested participants. They then provided a participation information letter in Tamil or English based on the preference of the potential participant. The researchers then contacted selected participants to arrange a date and time when the participants would sign the Tamil-translated consent form and attend a face-to-face interview. The researchers confirmed that refugee parents were volunteering to participate in this study during participant screenings. The team explained the study to all participants, describing the purpose of the study and how data were being collected to gain informed consent. For those who may distrust authority figures or differing cultural traditions, oral consent was allowed as an alternative to written consent. The research team only collected data and did not collect any identifying information; all demographic information stayed with the referral agency.

Participants' mental and cognitive status was assessed using the MINI Mental Health exam. Pilot studies with the refugee families were facilitated, and frequent visits were made to the Trichy camp through OfERR community events to help ensure trust and build rapport with families. The research team also received training in linguistic and social interaction to best communicate with families. Visiting and spending time with families outside of data collection allowed families to engage with the research team and build their comfort before data collection.

Interviews were conducted at the OfERR office due to its proximity to the study participants. Each parent completed their interviews independently, and the team ensured that parents were comfortable throughout the interview process. Following cultural traditions, an elderly woman was present when men were interviewed to ensure safety. The research team concluded each interview with a debrief session, allowing an opportunity for participants to ask any follow-up questions before receiving their compensation of $50 (2500 Indian Rupees).

### *2.4. Measurements*

In our study, Cronbach's alpha was calculated for each variable as a measure of internal consistency and reliability, reflecting the degree of intercorrelation (or homogeneity) among items within a multi-item scale (Shultz et al. 2020). All values demonstrated acceptable to high internal consistency.

*Mental Health*: Parental mental health was measured using the Brief Symptoms Inventory Scale (BSI; Derogatis and Melisaratos (1983)). The BSI consists of a total of nine dimensions, however, this study utilized four domains including depressive symptoms (six items), hostility (five items), anxiety symptoms (six items), and somatization (seven items). Using a 5-point Likert Scale ranging from 1 (not at all) to 5 (extremely), participants were asked how often they experienced an item in the last seven days. Responses were then summed to arrive at a total score, with higher scores indicating higher levels of mental distress. Reliability was assessed for each subscale. Cronbach's alpha was calculated at 0.700 for the somatization subscale, 0.818 for the depressive symptoms, 0.776 for anxiety symptoms, and 0.664 for hostility subscales.

*Sleep Quality*: To assess the presence of sleep problems among the adolescent sample, researchers administered the Pittsburgh Sleep Quality Index (Buysse et al. 1989). The scale includes a total of 15 items pertaining to respondent's sleeping patterns in the past two weeks. Higher total scores indicate poor sleep quality. Cronbach's alpha for this sample was calculated at 0.811, indicating high reliability.

*Strengths and Difficulties*: The Strengths and Difficulties Questionnaire (Goodman 1997) was used to assess behavioral and emotional challenges adults faced from their children. Cronbach's alpha for this sample was calculated to be 0.747, indicating acceptable internal consistency reliability.

*Postmigration stressors*: Postmigration stressors were assessed utilizing the Post-Migration Living Difficulties Checklist (PMLDC; Silove et al. (1997)), which has been effectively used in prior studies to assess transmigration and post-migration stressors in diverse refugee populations, including Tamils (Momartin et al. 2006; Sengoelge et al. 2022). Originally comprising 24 items, the PMLDC asks respondents to indicate the extent to which they are troubled by various living difficulties, utilizing a five-point scale ranging from "no problem at all" to "a very serious problem". In collaboration with the Tamil Community Collaborative Board (TCCB), an additional eight items were incorporated into the original scale, resulting in a 32-item scale. This revised scale was translated into Tamil and content comparability was ascertained through blind back-translation procedures. The revised scale, presented in Table 1, gauged the total transmigration stressor score. This tool has also been successfully employed in previous research George and Jettner (2015). Cronbach's alpha for this sample was calculated to be 0.814, which indicated high internal consistency and reliability.

**Table 1.** Post-Migration Living Difficulty Checklist/Questionnaire (PMLDC) Items. Means and standard deviations (SD) have been calculated for the post-migration stressors, based on the response scale ranging from 1 = no problem to 5 = serious problem. 'Percentage endorsing as a problem' is the percentage of valid responses that indicated the issue was at least a little problem (i.e., rated 2 or higher on a scale of 1 to 5). Adapted items added to scale are denoted with *.

| Items | % Endorsing | Mean (SD) |
|---|---|---|
| Communication difficulties | 66.1 | 2.79 (1.52) |
| Discrimination | 48.3 | 2.09 (1.40) |
| Separation from family | 18.1 | 1.53 (1.23) |
| Worries about family back home | 94.9 | 3.78 (1.24) |
| Unable to return home in an emergency | 48.3 | 2.08 (1.37) |
| No permission to work | 50.4 | 2.22(1.39) |
| Not being able to find work | 42.5 | 2.03 (1.35) |
| Bad job conditions | 41.2 | 1.91 (1.29) |
| Being in detention | 41.1 | 2.16 (1.51) |
| Interview by immigration | 52.1 | 2.30 (1.46) |
| Delays in processing your application | 61.6 | 2.53(1.51) |
| Conflict with immigration officials | 61.3 | 1.73 (1.12) |
| Fears of being sent home | 55.5 | 2.50 (1.56) |
| Worries about not getting treatment for health problems | 42.9 | 2.01 (1.44) |
| Poor access to emergency medical care | 34.5 | 1.84 (1.33) |
| Poor access to dentistry care | 42.7 | 2.07 (1.45) |
| Poor access to counseling services | 38.3 | 1.75 (1.11) |
| Little government help with welfare | 59.3 | 2.34 (1.35) |
| Little help with welfare from charities | 60.4 | 2.29 (1.32) |
| Poverty | 91.6 | 3.43 (1.32) |
| Loneliness and boredom | 71.4 | 2.87 (1.53) |
| Isolation | 58.0 | 2.52 (1.57) |
| Poor access to foods you like | 72.3 | 2.82 (1.39) |
| * Being uncertain about Sri Lanka's Future | 87.5 | 3.88 (1.42) |
| * The security situation in Sri Lanka | 93.3 | 3.87 (1.20) |
| * Not achieving the goals I have for my life | 84.6 | 3.47 (1.34) |
| * Feel reconstruction in Sri Lanka is not making things better | 91.5 | 3.71 (1.27) |
| * Not owning my own home | 89.9 | 4.19 (1.33) |
| * Too many children living in the house | 66.7 | 2.85 (1.57) |
| * Physical condition of my house | 83.9 | 3.13 (1.39) |
| * Overcrowding in my home | 64.4 | 2.53 (1.45) |

*Family functioning*: Family functioning was assessed using the Self-Report of Family Inventory (SFI; Beavers et al. (1985)). The SFI consists of 17 items, with participants rating how much each item fits their family from 1 (= yes, fits our family well) to 5 (no, does not fit our family well). Items were summed to create a total score, with higher scores indicating lower family functioning. Internal consistency of the sample was good, with a Cronbach's alpha of 0.784.

*Short Form—12 Item Version* (SF-12): The evaluation of physical health levels was conducted through the utilization of a standardized self-report medical questionnaire (Ware et al. 1996), which has been employed in various studies involving refugee populations (e.g., Xu and Borders (2008)). The scoring method employed was norm-based. This entailed generating separate summary scores for both physical and mental domains by aggregating responses across all 12 items within each domain. Higher scores signify greater levels of health. Internal consistency of the sample was acceptable, with a Cronbach's alpha of 0.739.

*Longitudinal Immigrant Student Adaptation study* (LISA): A standardized questionnaire (Suárez-Orozco and Qin 2006) was used to record parental behavior, parental activities and parental approval score. Once again, Cronbach's alpha was calculated at 0.736 for LISA parental behavioral score, 0.758 for LISA parental activities score and 0.752 for LISA parental approval score, indicating acceptable/good internal consistency and reliability in the sample.

*Resource utilization*: Resource utilization was evaluated via structured interviews regarding both formal and informal family support. During these interviews, participants were prompted to identify significant support figures, delineate their location, relationships, institutional affiliations, types of support offered, accessibility, and the frequency of utilization.

### 2.5. Data Analysis—'glmboost' Prediction Model

In this paper, we implement a machine learning/artificial intelligence version of a generalized linear model via component-wise gradient boosting. The algorithm fits a non-linear prediction model by fitting component-wise simple linear models to obtain statistical estimates of the predictive model parameters by optimizing the squared error loss function through functional gradient descent (FGD; Bühlmann and Hothorn (2007)). The fitted `glmboost` prediction model has the same interpretation as a classical linear regression. Moreover, variable selection is conducted simultaneously by shrinking coefficients corresponding to non-important predictors to zero. This model is implemented using the `glmboost` function in the `mboost` package (Hothorn et al. 2013) in `R` (R Core Team 2021) version 4.2.1 (2022-06-23 ucrt)—"Funny-Looking Kid".

The tuning parameters involved in the `glmboost` model include the number of iterations (`mstop`) and the step size or shrinkage parameter ($\nu$). It has been shown that boosting algorithms, if run till convergence, usually result in overfitting and results in suboptimal prediction models (Bühlmann and Hothorn 2007). Hence, the number of iterations (`mstop`) becomes a critical tuning parameter in the boosted generalized linear model algorithm. While there are several techniques to accurately tune parameters in a model, the cross-validation technique was implemented in our application, as suggested in Hofner et al. (2014). In general, $k$-fold cross-validation techniques have been known to be effective while fitting machine learning models on a limited data sample. Typically, there is a bias-variance trade-off associated with the choice of $k$ in the $k$-fold cross-validation. Given these considerations, performing $k$-fold cross-validation using $k = 5$ or $k = 10$ has been shown empirically to yield test error estimates that suffer neither from excessively high bias nor from very high variance (James et al. 2013). We implemented a 10-fold repeated cross-validation technique to optimize the tuning parameter in terms of the lowest root mean squared error (RMSE). The optimal number of iterations used in the final model was `mstop` = 79. This step was implemented using the `train` function in the `caret` package in `R` (Kuhn 2008). Also, the predictive performance of a boosting algorithm has been shown to vary insignificantly with the choice of the step size, $\nu$. Hence, we chose the default value of $\nu = 0.1$ for our implementation.

*Advantages over Linear Regression*: Unlike linear regression, the proposed model accounts for non-linear relationships between the response and predictor variables, which are often present in such complex dynamics. Moreover, linear regression models are interpretable models that require strict model assumptions such as normality and homoscedasticity of residuals, which are not consistently met in real-world scenarios, especially in datasets arising from social science research. A big disadvantage of such models is the potential loss of predictive performance when compared to other machine learning models, coupled with the limitation of model interpretation to a singular model type (Molnar 2020). However, the proposed framework is model agnostic, that is, it is not reliant on any specific statistical model and hence is applicable to a wide range of datasets. The proposed modeling framework is flexible and allows users to freely integrate different structural and distributional assumptions to suit the specific requirements of their estimation tasks (Hofner et al. 2014). Finally, the proposed model performs automated variable selection without relying on heuristic techniques like stepwise variable selection, which is implemented under the linear regression framework.

*Computation*: Since the proposed `glmboost` method is a gradient-boosted algorithm, the model is fit through several iterations to achieve an "optimal" prediction of response $y$ given the set of predictors $\boldsymbol{x}$ by minimizing the squared error loss function within each boosting iteration. Thus, the computational time required to fit the `glmboost` model is usually more than the time taken to fit a traditional linear regression model using the `lm` function in `R`. In our application, for a sample of size $n = 111$, it takes approximately 33 s to fit the `glmboost` model, while the `lm` function takes only approximately 0.06 s to fit the linear regression model. These computations have been executed on a Dell XPS 15 7590 computer equipped with 32 GB RAM, an Intel(R) Core(TM) i7-9750H CPU, and a Windows 10 Enterprise 64-bit operating system.

## 3. Results

**Sample Characteristics and Descriptive Statistics:** Parents selected for the study were overwhelmingly female (96%) and married (87%). The average age for parents was 38 years old. The average number of children per parent was about three (2.86), and their average time spent in the camp was 22.67 years. Table 2 summarizes the characteristics of the response variable (BSI score) and the predictor variables/covariates used in the study.

**Table 2.** A comprehensive overview of response and covariates from the Sri Lankan adult refugee data. Means and standard deviations have been computed for the responses obtained from a sample size of n = 111 adult refugees, for whom complete observed data were available.

| Variables | Mean (SD) |
|---|---|
| BSI score | 27.16 (18.86) |
| PTSD score | 26.74 (16.65) |
| Sleep quality score | 12.67 (8.0) |
| Strength and difficulty score | 14.50 (6.07) |
| PMLDC score | 37.37 (12.48) |
| Family functioning | 54.86 (12.37) |
| Physical health score | 6.49 (2.99) |
| Longitudinal Immigrant Student Adaptation study (LISA) | |
| LISA behavioral score | 38.41 (14.87) |
| LISA activity score | 10.05 (2.67) |
| LISA approve score | 2.099 (1.65) |
| Resource Utilization | |
| NGO support | 1.95 (1.96) |
| Government support | 0.38 (0.75) |
| Informal support from family | 1.51 (1.61) |
| Informal support from friends | 0.39 (1.65) |

*GLMBOOST*: In the subsequent results, 'beta' ($\beta$) represents the unstandardized coefficients associated with the respective covariates. As previously noted, the interpretation of the estimated coefficients within the `glmboost` model aligns with that of linear regression. That is, $\beta$ is the change in the average amount of the response variable BSI score, when the corresponding covariate changes by one unit, while other covariates are held constant. Consequently, in the subsequent interpretation of a particular covariate, it is assumed that all other covariates remain constant. Also, all covariates with estimated non-zero $\beta$ coefficients are deemed to be statistically significant in the study, while covariates with estimated $\beta = 0.00$ are not important. Thus, for the Sri Lankan adult refugees, the PMLDC score ($\beta = 0.18$), PTSD score ($\beta = 0.62$), Sleep difficulty score ($\beta = 0.24$), Family functioning ($\beta = 0.02$), Strength and difficulties score ($\beta = 0.75$) and Physical health score ($\beta = 0.14$) were found to be important predictors of mental health scores. The positive estimated coefficients indicate that higher levels of these predictor variables are associated with deterioration in an individual's mental health since higher values on the BSI scale indicate worse mental health conditions.

Among the Intergenerational conflict variables, higher LISA approval ($\beta = 0.27$) and LISA behavior ($\beta = 0.12$) scores were linked to more severe mental health conditions, while the LISA activity ($\beta = 0.00$) variable was not important while predicting the mental health of refugees. That is, higher parental endorsement of children's adherence to rules (LISA approval) and higher parental endorsement of children's conduct (LISA behavior) had a negative impact on the parents' mental health, while parental approval of children's activities (LISA activity) did not impact parental mental health. Additionally, employment ($\beta = 0.00$), utilization of NGO ($\beta = 0.00$), government resources ($\beta = 0.00$) and support from friends ($\beta = 0.00$) were not important in predicting mental health, while refugees experiencing greater familial support ($\beta = -0.71$) reported improved mental health scores, suggesting a protective effect of family support on mental well-being. The fitted `glmboost` model yielded a notable $R^2$ value of 77.1%, accompanied by an RMSE of 9.05, demonstrates its efficacy in capturing the variance in the data and their predictive accuracy.

*Comparison with Linear Regression*: After ensuring approximate normality and homoscedasticity of BSI scores by using the square root transformation, and checking for multicollinearity, the linear regression model was also fit to the data. The linear regression model was only able to identify a subset of the important predictors, namely, PMLDC score ($\beta = 0.03, p < 0.01$), PTSD score ($\beta = 0.06, p < 0.001$), Sleep difficulty score ($\beta = 0.05$, $p < 0.01$), Strength and difficulty score ($\beta = 0.11, p < 0.001$) and LISA behavior score ($\beta = 0.02, p < 0.05$). The signs of the estimated coefficients align with those derived from the `glmboost` model, indicating that the interpretations of these significant covariates in linear regression mirror those within the `glmboost` framework. Predictors such as family functioning ($\beta = 0.27, p > 0.2$), physical health score ($\beta = 0.01, p > 0.5$), employment ($\beta = -0.35, p > 0.1$), support from family ($\beta = -0.13, p > 0.05$), NGO ($\beta = -0.03, p > 0.5$), and government resources ($\beta = 0.01, p > 0.5$) were deemed not important in predicting mental health for the Sri Lankan adult refugee population by the regression analysis. Also, Intergenerational conflict variables such as LISA approval ($\beta = 0.04, p > 0.4$) and LISA activity ($\beta = 0.02, p > 0.5$) were not significant in predicting the mental health of adult refugees. Moreover, post adjustment for normality and homoscedasticity, the fitted regression model demonstrated an $R^2$ value of 74%, coupled with an RMSE of 9.11.

In comparison, the proposed `glmboost` model suggested that refugees experiencing lower family functioning reported deteriorated mental health status, while great family support reported alleviated mental health status. Moreover, the `glmboost` model highlights elevated physical health scores and increased parental endorsement of children's adherence to rules (LISA approval) as potential markers of mental disorders among Sri Lankan refugees. This is counterintuitive, and suggests the possible presence of certain confounding effects, warranting further investigation, which would have remained undetected if solely relying on the linear regression model. Consequently, utilizing linear regression alone in this study would have overlooked significant relationships between mental health scores and crucial predictor variables such as family functioning and familial support. Although the difference in RMSE values between the `glmboost` and the linear regression model was relatively minor, the `glmboost` model demonstrated a noteworthy 3.1% increase in explained variance within the dataset. This difference bears significance, particularly within the context of the study and considering the sample size.

## 4. Discussion

The plight of Tamil refugees in Indian camps, characterized by their sudden departure from Sri Lanka without adequate resources (George 2013; Kunz 1973, 1981), exposes them to a myriad of unique stressors, including post-traumatic stress, physical health ailments, sleep disturbances, post-migration challenges, familial discord, and joblessness (Kuttikat et al. 2018; Miller and Rasmussen 2010). Through data analysis employing the `glmboost` and linear regression prediction models, this study has identified several key markers of declining mental health among Tamil refugee participants, namely, PMLDC score, PTSD score, sleep difficulties score, Strengths and Difficulties score, and LISA behavior and approval scores. Elevated levels of these predictor variables are associated with a decline in the mental well-being of refugee participants, a finding consistent with numerous prior studies establishing the link between specific migration stressors and refugee mental health (Betancourt et al. 2017; George and Jettner 2016; Miller and Rasmussen 2010; Rasmussen and Annan 2010).

The refugee journey is fraught with a series of traumatic experiences, both in their country of origin and during migration, underscoring the significance of PTSD in predicting mental health outcomes (Carlsson and Sonne 2018). Consistent with our findings, the PTSD score emerges as a significant contributor to overall mental health, particularly among adult refugees (Chung and Teo 2022; Fazel et al. 2005; Marshall et al. 2005; Saraceno et al. 2002; Steel et al. 2009). Research by Lies et al. (2019) establishes a positive correlation between sleep difficulties and the severity of mental health issues, while Lies et al. (2019); Schweitzer et al. (2011); Somasundaram (2007) highlight sleep disturbances as a contributing factor to poor mental health. These insights from existing literature align closely with the results obtained from our `glmboost` and linear regression analyses.

Moreover, existing research underscores the significant influence of family functioning on the mental health of not only the Sri Lankan refugee population (George and Jettner 2016; Scharpf et al. 2021), but also other refugee communities (Liddell et al. 2021). When confronted with challenges in family functioning, mental health tends to deteriorate, establishing a positive correlation between higher levels of family functioning and improved mental health scores. This observation aligns with the outcomes derived from our `glmboost` model. Furthermore, studies emphasize the pivotal role of family support in enhancing the mental well-being of the Sri Lankan refugee population (George and Jettner 2016). Consequently, increased support from families is associated with an amelioration of the mental health conditions of refugees, a trend consistent with the results obtained from our `glmboost` model. It is noteworthy that both family functioning and family support did not exhibit significance in the linear regression analysis. However, they emerged as important factors in predicting mental health scores within the `glmboost` model. This disparity stems from the nonlinear relationship between these predictor variables and mental health scores, a relationship inherently ignored by linear regression, but effectively captured by the `glmboost` model.

Finally, it is essential for researchers to delve into how refugees utilize resources to effectively cope with their stressors and establish pathways for resource utilization that can enhance refugee health outcomes. Most refugees in our study belong to the category of acute refugees, lacking essential resources such as familial and social support networks. Instead, all of them rely heavily on government-mandated provisions like temporary housing, fuel, and NGO assistance, which may include aid for children's education and school supplies. As a result, these support variables had no discernible effect on the mental health scores of the participants (George 2017).

## 5. Conclusions

Despite the limitations inherent in linear regression models, their appeal lies in the ease of model applicability and interpretability, making them popular in social work research. In this study, we propose the `glmboost` model as a flexible alternative to the restrictive linear regression model, due to its easy implementation and similar interpretation to linear regression, recognizing the importance of model interpretability in applied statistical research. Our study aims to provide social work researchers with a generalized approach to constructing predictive models for mental health, offering an alternative to the linear regression method. Our focus is not on conducting a comparative analysis of multiple statistical models to determine the "best" model for a specific dataset. Instead, we endeavor to furnish researchers with a user-friendly, readily implementable, and interpretable alternative to linear regression, designed to be applicable across a wide range of datasets.

Based on the results, this study underscores the critical need for community-based interventions aimed at enhancing family functioning and support network systems and addressing mental health challenges among refugee populations. Our findings highlight the significant impacts of post-traumatic stress disorder (PTSD), post-migration stressors, parental concerns regarding child care, and sleeping difficulties on refugee mental health. The data-driven, model-agnostic `glmboost` approach provides a nuanced understanding of these impacts, surpassing the capabilities of traditional linear regression models. This is evident in the 3.1% higher $R^2$ value achieved by the `glmboost` model compared to the linear regression model, which is a significant difference considering the sample size. These insights emphasize the importance of targeted mental health interventions tailored to address specific stressors within refugee communities, ultimately reducing the burden on public healthcare systems and enhancing overall refugee well-being.

In conclusion, this research underscores the importance of exploring resource utilization among refugees to effectively address stressors and improve health outcomes. By identifying the pivotal role of family support and the impact of PTSD, post-migration living difficulties, family functioning and other stressors on mental health, our study provides the means to formalize the conceptual refugee mental health framework for Sri Lankan Tamil refugees residing in India. This can, in turn, offer valuable insights for policymakers, mental health professionals, and NGOs working with refugee populations. Moving forward, developing tailored interventions that strengthen family support systems and address identified stressors is crucial. Moreover, our study highlights the significance of employing advanced statistical techniques to comprehend complex social and psychological phenomena, enabling more effective and tailored interventions for refugee populations.

**Author Contributions:** Conceptualization, I.S., M.K. and D.C.; methodology, I.S.; software, I.S.; validation, I.S. and E.A.; formal analysis, I.S. and E.A.; investigation, I.S. and E.A.; resources, I.S. and M.K.; data curation, M.K.; writing—original draft preparation, I.S., E.A., M.K. and D.C.; writing—review and editing, I.S.; supervision, D.C.; project administration, M.K. and D.C.; funding acquisition, M.K. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the National Institute of Health (NIH) Fogarty International Center (FIC) grant number K01 TW009648: "Testing a refugee family dynamics model: A study with Sri Lankan Tamils in camps". The APC was funded by Dr. Kuttikat's professional development grant, sponsored by the School of Social Work, Virginia Commonwealth University.

**Institutional Review Board Statement:** The study was conducted in accordance with the Declaration of Helsinki, and was approved by the Institutional Review Board of Virginia Commonwealth University, with the protocol number HM20000475 (date of approval: 11 March 2014).

**Informed Consent Statement:** Informed consent was obtained from all participants involved in the study.

**Data Availability Statement:** The data set used for this project can be found at https://github.com/indranil09/SLRefugees_MHPred (accessed on 4 May 2024).

**Acknowledgments:** The authors would like to acknowledge Marianne Lund from the School of Social Work at Virginia Commonwealth University for her discussions on the introduction of this paper.

**Conflicts of Interest:** The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

## References

Acharya, Arun Kumar. 2007. Ethnic conflict and refugees in Sri Lanka. *Antropología Experimental* 7: 107–21.

Adamu, Hamid A., Murtala Muhammad, and Abdullahi Mohammed Jingi. 2019. Application of gradient boosting algorithm in statistical modelling. *Research & Reviews: Journal of Statistics and Mathematical Sciences* 5: 11–18.

Alemi, Qais, Sigrid James, Hafifa Siddiq, and Susanne Montgomery. 2015. Correlates and predictors of psychological distress among afghan refugees in san diego county. *International Journal of Culture and Mental Health* 8: 274–88. [CrossRef] [PubMed]

Al-Simadi, Fayez, and Adnan Atoum. 2000. Family environment and self-concept of palestinian youth living in jordanian refugee camps. *Social Behavior and Personality: An International Journal* 28: 377–85. [CrossRef]

Amrutkar, Prashant. 2012. Ethnic conflict and conflict management process in Sri Lanka. *The Indian Journal of Political Science* 73: 745–56.

Beavers, W. Robert, Robert B. Hampson, and Yosef F. Hulgus. 1985. Commentary: The beavers systems approach to family assessment. *Family Process* 24: 398–405. [CrossRef]

Betancourt, Theresa S., Lauren C. Ng, Catherine M. Kirk, Robert T. Brennan, William R. Beardslee, Sara Stulac, Christine Mushashi, Estella Nduwimana, Sylvere Mukunzi, Beatha Nyirandagijimana, and et al. 2017. Family-based promotion of mental health in children affected by hiv: a pilot randomized controlled trial. *Journal of Child Psychology and Psychiatry* 58: 922–30. [CrossRef]

Bhui, Kamaldeep, Abdisalama Abdi, Mahad Abdi, Stephen Pereira, Mohammed Dualeh, David Robertson, Ganesh Sathyamoorthy, and Hellena Ismail. 2003. Traumatic events, migration characteristics and psychiatric symptoms among somali refugees: Preliminary communication. *Social Psychiatry and Psychiatric Epidemiology* 38: 35–43. [CrossRef]

Buysse, Daniel J., Charles F. Reynolds, III, Timothy H. Monk, Susan R. Berman, and David J. Kupfer. 1989. The pittsburgh sleep quality index: A new instrument for psychiatric practice and research. *Psychiatry Research* 28: 193–213. [CrossRef]

Bühlmann, Peter, and Torsten Hothorn. 2007. Boosting algorithms: Regularization, prediction and model fitting. *Statistical Science* 22: 477–505.

Carlsson, Jessica, and Charlotte Sonne. 2018. Mental health, pre-migratory trauma and post-migratory stressors among adult refugees. In *Mental Health of Refugee and Conflict-Affected Populations: Theory, Research and Clinical Practice*. Cham: Springer International Publishing. pp. 15–35.

Chattoraj, Diotima. 2022. *Displacement among Sri Lankan Tamil Migrants: The Diasporic Search for Home in the Aftermath of War*. Singapore: Springer Nature.

Chung, Jetli, and Jason Teo. 2022. Mental health prediction using machine learning: Taxonomy, applications, and challenges. *Applied Computational Intelligence and Soft Computing* 2022: 9970363 . [CrossRef]

Cohen, Jacob. 1988. *Statistical Power Analysis for the Behavioral Sciences*. Hillsdale: Lawrence Earlbaum Associates.

Costa, Diogo, Louise Biddle, Catharina Mühling, and Kayvan Bozorgmehr. 2020. Subjective social status mobility and mental health of asylum seekers and refugees: Population-based, cross-sectional study in a german federal state. *Journal of Migration and Health* 1: 100020. [CrossRef]

Derogatis, Leonard R., and Nick Melisaratos. 1983. The brief symptom inventory: An introductory report. *Psychological Medicine* 13: 595–605. [CrossRef]

De Vries, Jolanda. 2001. Mental health issues in tamil refugees and displaced persons. counselling implications. *Patient Education and Counseling* 42: 15–24. [CrossRef] [PubMed]

Fadhlia, Tengku Nila. 2023. The socio-ecological factors associated with resilience in refugees: A systematic scoping review. *PsyArXiv* 1–60. [CrossRef]

Faul, Franz, Edgar Erdfelder, Albert-Georg Lang, and Axel Buchner. 2007. G* power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods* 39: 175–91. [CrossRef] [PubMed]

Fazel, Mina, Jeremy Wheeler, and John Danesh. 2005. Prevalence of serious mental disorder in 7000 refugees resettled in western countries: A systematic review. *The Lancet* 365: 1309–14. [CrossRef] [PubMed]

George, Miriam. 2009. *Sri Lankan Tamil Diaspora: Contextualizing Pre-Migration and Post-Migration Traumatic Events and Psychological Distress*. Toronto: University of Toronto.

George, Miriam. 2010. A theoretical understanding of refugee trauma. *Clinical Social Work Journal* 38: 379–87. [CrossRef]

George, Miriam. 2012. Migration traumatic experiences and refugee distress: Implications for social work practice. *Clinical Social Work Journal* 40: 429–37. [CrossRef]

George, Miriam. 2013. Sri Lankan Tamil refugee experiences: A qualitative analysis. *International Journal of Culture and Mental Health* 6: 170–82. [CrossRef]

George, Miriam. 2017. Application of conservation of resource theory with camp refugees. *Migration and Development* 6: 460–78. [CrossRef]

George, Miriam, and Jennifer Jettner. 2015. Demographic characteristics, migration traumatic events and psychological distress among Sri Lankan tamil refugees: A preliminary analysis. *Migration and Development* 4: 125–42. [CrossRef]

George, Miriam, and Jennifer Jettner. 2016. Migration stressors, psychological distress, and family—A Sri Lankan tamil refugee analysis. *Journal of International Migration and Integration* 17: 341–53. [CrossRef]

Goodman, Robert. 1997. The strengths and difficulties questionnaire: A research note. *Journal of Child Psychology and Psychiatry* 38: 581–86. [CrossRef] [PubMed]

Goreau-Ponceaud, Anthony, and Delon Madavan. 2022. Sri Lanka: An island in turmoil. a look back at a multifaceted crisis. *EchoGéo*. [CrossRef]

Greberg, Felix, and Andreas Rylander. 2022. Using Gradient Boosting to Identify Pricing Errors in Glm-Based Tariffs for Non-Life Insurance. Stockholm, Sweden. Available online: https://www.diva-portal.org/smash/get/diva2:1669166/FULLTEXT01.pdf (accessed on 4 May 2024).

Hellmann-Rajanayagam, Dagmar. 2007. From rpgs to mous: The lite and the media. perceptions of a 'terrorist'movement among the Sri Lankan tamil diaspora. *Diaspora Studies* 1: 85–104. [CrossRef]

Henckaerts, Roel, Marie-Pier Côté, Katrien Antonio, and Roel Verbelen. 2021. Boosting insights in insurance tariff plans with tree-based machine learning methods. *North American Actuarial Journal* 25: 255–85. [CrossRef]

Herath, Dhammika, Kalinga Tudor Silva, and International Centre for Ethnic Studies (Sri Lanka). 2012. *Healing the Wounds: Rebuilding Sri Lanka after the War*. Colombo: International Centre for Ethnic Studies Colombo.

Hofner, Benjamin, Andreas Mayr, Nikolay Robinzonov, and Matthias Schmid. 2014. Model-based boosting in R: A hands-on tutorial using the R package mboost. *Computational Statistics* 29: 3–35. [CrossRef]

Hothorn, Torsten, Peter Buehlmann, Thomas Kneib, Matthias Schmid, Benjamin Hofner, Fabian Sobotka, and Fabian Scheipl. 2013. Package 'mboost'. Available online: https://cran.uib.no/web/packages/mboost/mboost.pdf (accessed on 4 May 2024).

James, Gareth, Daniela Witten, Trevor Hastie, and Robert Tibshirani. 2013. *An Introduction to Statistical Learning*. New York: Springer, vol. 112.

Kodiyath, Sreekumar Panicker, and Sheethal Padathu Veettil. 2017. Invisible people: Suspected ltte members in the special refugee camps of tamil nadu. *Refugee Survey Quarterly* 36: 126–45. [CrossRef]

Kuhn, Max. 2008. Building predictive models in r using the caret package. *Journal of Statistical Software* 28: 1–26. [CrossRef]

Kulandai, Arockiam. 2021. *Camp Life of Sri Lankan Refugees in India*. Routledge India.

Kunz, Egon F. 1973. The refugee in flight: Kinetic models and forms of displacement. *International Migration Review* 7: 125–46. [CrossRef]

Kunz, Egon F. 1981. Part II: The analytic framework: Exile and resettlement: Refugee theory. *International Migration Review* 15: 42–51. [CrossRef]

Kuttikat, Miriam, Hannah George, and Daya George. 2022. Proverbs and gender: The interface between proverbs and human relations in a refugee camp. *International Journal of Social Science Studies* 10: 67. [CrossRef]

Kuttikat, Miriam, Anita Vaillancourt, and Michael Massey. 2018. Battered but bold: Sri Lankan tamil refugee war experiences, camp challenges and resilience. *International Journal of Migration, Health and Social Care* 14: 245–59. [CrossRef]

Liddell, Belinda J, Yulisha Byrow, Meaghan O'Donnell, Vicki Mau, Nicole Batch, Tadgh McMahon, Richard Bryant, and Angela Nickerson. 2021. Mechanisms underlying the mental health impact of family separation on resettled refugees. *Australian & New Zealand Journal of Psychiatry* 55: 699–710.

Lies, July, Alix Mellor, Laura Jobson, and Sean P. A. Drummond. 2019. Prevalence of sleep disturbance and its relationships with mental health and psychosocial issues in refugees and asylum seekers attending psychological services in Australia. *Sleep Health* 5: 335–43. [CrossRef]

Lies, July, Lester Jones, and Roger Ho. 2019. The management of post-traumatic stress disorder and associated pain and sleep disturbance in refugees. *BJPsych Advances* 25: 196–206. [CrossRef]

Lindert, Jutta, Ondine S. von Ehrenstein, Annette Wehrwein, Elmar Brähler, and Ingo Schäfer. 2018. Angst, depressionen und posttraumatische belastungsstörungen bei flüchtlingen–eine bestandsaufnahme. *PPmP-Psychotherapie· Psychosomatik· Medizinische Psychologie* 68: 22–29. [CrossRef]

Lustig, Stuart L., Maryam Kia-Keating, Wanda Grant Knight, Paul Geltman, Heidi Ellis, John David Kinzie, Terence Keane, and Glenn N. Saxe. 2004. Review of child and adolescent refugee mental health. *Journal of the American Academy of Child & Adolescent Psychiatry* 43: 24–36.

Maneesh, P., and C. Muniyandi. 2016. Deprived outlander in India: An analysis of Sri Lankan-tamil refugees. *International Journal of Applied Research* 2: 219–24.

Marshall, Grant N., Terry L. Schell, Marc N. Elliott, S. Megan Berthold, and Chi-Ah Chun. 2005. Mental health of Cambodian refugees 2 decades after resettlement in the United States. *JAMA* 294: 571–79. [CrossRef]

Miller, Kenneth E., and Andrew Rasmussen. 2010. War exposure, daily stressors, and mental health in conflict and post-conflict settings: Bridging the divide between trauma-focused and psychosocial frameworks. *Social Science & Medicine* 70: 7–16.

Molnar, Christoph. 2020. *Interpretable Machine Learning*. Morrisville: Lulu Press.

Momartin, Shakeh, Zachary Steel, Marianio Coello, Jorge Aroche, Derrick M Silove, and Robert Brooks. 2006. A comparison of the mental health of refugees with temporary versus permanent protection visas. *Medical Journal of Australia* 185: 357–61. [CrossRef] [PubMed]

Morantz, Gillian, Cecile Rousseau, and Jody Heymann. 2012. The divergent experiences of children and adults in the relocation process: Perspectives of child and parent refugee claimants in montreal. *Journal of Refugee Studies* 25: 71–92. [CrossRef]

Mostafa, Sayed A., and Ibrahim A. Ahmad. 2018. Recent developments in systematic sampling: A review. *Journal of Statistical Theory and Practice* 12: 290–310. [CrossRef]

Nesterko, Yuriy, David Jäckle, Michael Friedrich, Laura Holzapfel, and Heide Glaesmer. 2020. Factors predicting symptoms of somatization, depression, anxiety, post-traumatic stress disorder, self-rated mental and physical health among recently arrived refugees in germany. *Conflict and Health* 14: 1–12. [CrossRef] [PubMed]

Newman, Paul. 2022. Sri Lankan tamil refugees: A voiceless, undignified existence. In *The Routledge Handbook of Refugees in India*. Delhi: Routledge, pp. 628–41.

Pandalangat, Nalini, Joanna Anneke Rummens, Charmaine Williams, and Mary V. Seeman. 2013. The social dimensions of health and illness in the Sri Lankan tamil diaspora: Implications for mental health service delivery. *Journal of Preventive Medicine* 1: 36–42.

Papola, Davide, Marianna Purgato, Chiara Gastaldon, Chiara Bovo, Mark van Ommeren, Corrado Barbui, and Wietse A. Tol. 2020. Psychological and social interventions for the prevention of mental disorders in people living in low-and middle-income countries affected by humanitarian crises. *Cochrane Database of Systematic Reviews* 9: CD012417.

Ponnet, Koen. 2014. Financial stress, parent functioning and adolescent problem behavior: An actor–partner interdependence approach to family stress processes in low-, middle-, and high-income families. *Journal of Youth and Adolescence* 43: 1752–69. [CrossRef]

Porter, Matt, and Nick Haslam. 2001. Forced displacement in yugoslavia: A meta-analysis of psychological consequences and their moderators. *Journal of Traumatic Stress* 14: 817–34. [CrossRef]

Rasmussen, Andrew, and Jeannie Annan. 2010. Predicting stress related to basic needs and safety in darfur refugee camps: A structural and social ecological analysis. *Journal of Refugee Studies* 23: 23–40. [CrossRef]

R Core Team. 2021. *R: A Language and Environment for Statistical Computing*. Vienna: R Foundation for Statistical Computing.

Rogers, Andrei, and Stuart Sweeney. 1998. Measuring the spatial focus of migration patterns. *The Professional Geographer* 50: 232–42. [CrossRef]

Saraceno, Benedetto, Shekhar Saxena, and Pallab K. Maulik. 2002. Mental health problems in refugees. In *Psychiatry in Society*. Hoboken: Wiley, pp. 193–220.

Scharpf, Florian, Elisa Kaltenbach, Angela Nickerson, and Tobias Hecker. 2021. A systematic review of socio-ecological factors contributing to risk and protection of the mental health of refugee children and adolescents. *Clinical Psychology Review* 83: 101930. [CrossRef]

Schilz, Laura, Solveig Kemna, Carine Karnouk, Kerem Böge, Nico Lindheimer, Lena Walther, Sara Mohamad, Amani Suboh, Alkomiet Hasan, Edgar Höhne, and et al. 2023. A house is not a home: A network model perspective on the dynamics between subjective quality of living conditions, social support, and mental health of refugees and asylum seekers. *Social Psychiatry and Psychiatric Epidemiology* 58: 757–68. [CrossRef] [PubMed]

Schweitzer, Robert D, Mark Brough, Lyn Vromans, and Mary Asic-Kobe. 2011. Mental health of newly arrived Burmese refugees in Australia: Contributions of pre-migration and post-migration experience. *Australian & New Zealand Journal of Psychiatry* 45: 299–307.

Sengoelge, Mathilde, Alexander Nissen, and Øivind Solberg. 2022. Post-migration stressors and health-related quality of life in refugees from syria resettled in sweden. *International Journal of Environmental Research and Public Health* 19: 2509. [CrossRef]

Shultz, Kenneth S., David Whitney, and Michael J. Zickar. 2020. *Measurement Theory in Action: Case Studies and Exercises*. London: Routledge.

Silove, Derrick, Ingrid Sinnerbrink, Annette Field, Vijaya Manicavasagar, and Zachary Steel. 1997. Anxiety, depression and ptsd in asylum-seekers: Associations with pre-migration trauma and post-migration stressors. *The British Journal of Psychiatry* 170: 351. [CrossRef] [PubMed]

Siriwardhana, Chesmal, and Kolitha Wickramage. 2014. Conflict, forced displacement and health in Sri Lanka: A review of the research landscape. *Conflict and Health* 8: 22. [CrossRef] [PubMed]

Somasundaram, Daya. 2007. Collective trauma in northern Sri Lanka: A qualitative psychosocial-ecological study. *International Journal of Mental Health Systems* 1: 5. [CrossRef]

Somasundaram, Daya. 2010. Collective trauma in the vanni-a qualitative inquiry into the mental health of the internally displaced due to the civil war in Sri Lanka. *International Journal of Mental Health Systems* 4: 22. [CrossRef]

Steel, Zachary, Derrick Silove, Robert Brooks, Shakeh Momartin, Bushra Alzuhairi, and INA Susljik. 2006. Impact of immigration detention and temporary protection on the mental health of refugees. *The British Journal of Psychiatry* 188: 58–64. [CrossRef]

Steel, Zachary, Tien Chey, Derrick Silove, Claire Marnane, Richard A Bryant, and Mark Van Ommeren. 2009. Association of torture and other potentially traumatic events with mental health outcomes among populations exposed to mass conflict and displacement: A systematic review and meta-analysis. *JAMA* 302: 537–49. [CrossRef] [PubMed]

Suárez-Orozco, Carola, and Desirée Baolian Qin. 2006. Gendered perspectives in psychology: Immigrant origin youth. *International Migration Review* 40: 165–98. [CrossRef]

Valatheeswaran, C., and S. Irudaya Rajan. 2011. Sri Lankan tamil refugees in India: Rehabilitation mechanisms, livelihood strategies, and lasting solutions. *Refugee Survey Quarterly* 30: 24–44. [CrossRef]

Valcárcel Silvela, A. 2019. Sri Lankan tamil refugees in India: Return or integration? *Forced Migration Review* 62: 13–15. Available online: https://www.fmreview.org/sites/fmr/files/FMRdownloads/en/return/valcarcelsilvela.pdf (accessed on 4 May 2024).

Walther, Lena, Lukas M. Fuchs, Jürgen Schupp, and Christian Von Scheve. 2020. Living conditions and the mental health and well-being of refugees: evidence from a large-scale german survey. *Journal of Immigrant and Minority Health* 22: 903–13. [CrossRef]

Ware, John E., Mark Kosinski, and Susan D. Keller. 1996. A 12-item short-form health survey: Construction of scales and preliminary tests of reliability and validity. *Medical Care* 34: 220–33. [CrossRef] [PubMed]

Weaver, Hilary N. 2016. Developing a culturally appropriate assessment tool: Reflections on process considerations. *Journal of Ethnic & Cultural Diversity in Social Work* 25: 270–81.

Xu, Ke Tom, and Tyrone F Borders. 2008. Does being an immigrant make a difference in seeking physician services? *Journal of Health Care for the Poor and Underserved* 19: 380–90. [CrossRef]