BMJ Open

Hierarchy of demographic and social determinants of mental health: analysis of cross-sectional survey data from the Global Mind Project

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To cite: Bala J, Newson JJ, Thiagarajan TC. Hierarchy of demographic and social determinants of mental health: analysis of cross-sectional survey data from the Global Mind Project. *BMJ Open* 2024;**14**:e075095. doi:10.1136/bmjopen-2023-075095

► Prepublication history and additional supplemental material for this paper are available online. To view these files, please visit the journal online (https://doi.org/10.1136/bmjopen-2023-075095).

Received 02 May 2023
Accepted 16 February 2024

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ABSTRACT

Objectives To understand the extent to which various demographic and social determinants predict mental health status and their relative hierarchy of predictive power in order to prioritise and develop population-based preventative approaches.

Design Cross-sectional analysis of survey data.

Setting Internet-based survey from 32 countries across North America, Europe, Latin America, Middle East and North Africa, Sub-Saharan Africa, South Asia and Australia, collected between April 2020 and December 2021.

Participants 270 000 adults aged 18–85+ years who participated in the Global Mind Project.

Outcome measures We used 120+ demographic and social determinants to predict aggregate mental health status and scores of individuals (mental health quotient (MHQ)) and determine their relative predictive influence using various machine learning models including gradient boosting and random forest classification for various demographic stratifications by age, gender, geographical region and language. Outcomes reported include model performance metrics of accuracy, precision, recall, F1 scores and importance of individual factors determined by reduction in the squared error attributable to that factor.

Results Across all demographic classification models, 80% of those with negative MHQs were correctly identified, while regression models predicted specific MHQ scores within ±15% of the position on the scale. Predictions were higher for older ages (0.9+ accuracy, 0.9+ F1 Score; 65+ years) and poorer for younger ages (0.68 accuracy, 0.68 F1 Score; 18–24 years). Across all age groups, genders, regions and language groups, lack of social interaction and sufficient sleep were several times more important than all other factors. For younger ages (18–24 years), other highly predictive factors included cyberbullying and sexual abuse while not being able to work was high for ages 45–54 years.

Conclusion Social determinants of traumas, adversities and lifestyle can account for 60%–90% of mental health challenges. However, additional factors are at play, particularly for younger ages, that are not included in these data and need further investigation.

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ The findings are based on a very large-scale global data set (n=270 000) that encompasses comprehensive mental health profiles and a wide array of demographics and social determinants.

⇒ The MHQ outcome metric provides an aggregate, transdiagnostic metric of mental health and has been validated against metrics of productivity as well as clinical diagnoses.

⇒ Some potentially important factors have not been included here, such as internet behaviour, diet and factors of the physical environment that cannot be easily captured through survey.

⇒ The data are from a non-probability sample of the internet-enabled population, recruited via advertisements placed on Facebook and Google, with an unknown potential for sampling or non-response bias; although the USA sample has been reported to be demographically similar to the USA national population, the demographic representativeness of the samples from other countries is unknown.

⇒ Data are based on online self-report and therefore relevant only to an internet-enabled audience, and not likely to capture those with very severe mental illness who are not capable of accurate online self-assessment.

INTRODUCTION

The increased prevalence of mental health conditions as a consequence of the COVID-19 pandemic[1] and changing societal and generational dynamics[2–5] is placing increasing pressure on healthcare services.[6] This has created an urgent need to better understand the differential impact of various demographic and social determinants on mental health status. Such understanding can inform targeted preventative public health strategies at a population level to enhance societal mental health outcomes.

A number of determinants have been shown individually to contribute to mental health outcomes including socioeconomic status,[7–9] employment status,[10–12] educational attainment,[13–15] sexual abuse,[16–18] cyberbullying,[19–22] divorce,[23–26] physical exercise,[27–31] social interaction[32–37] and sleep quality.[38–41]

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However, studies to date have focused either on individual social determinants, individual mental health disorders or specific populations or clinical groups. Consequently, we presently lack an integrated understanding of the core determinants which are universally most influential to people's mental health status and their relative importance, across multiple determinants, mental health disorders and population groups.[42–44] This understanding will provide guidance on how resources and public health strategies and initiatives can be deployed at a population level for maximal impact, and contribute to the ongoing debate on the extent to which mental health challenges can be addressed through societal rather than medical means.[45–47]

Supervised and unsupervised machine learning approaches using large-scale data offer considerable opportunities for the advancement of mental healthcare and research,[42 48–52] and have been increasingly used to understand how multiple factors come together to predict health outcomes and their relative importance. This approach has been used with success in other fields such as cardiology.[53–55] However, data that aggregate many social determinants into a single study across a large population are rare. While medical records contain information on social determinants, what is available tends to be unstructured and incomplete and must be mined from physician notes.[56 57] Furthermore, medical records exclude the well population and therefore the ability to understand those social determinants that separate those with challenges from the well. Another challenge in mental health is that assessments are generally at the level of particular disorders and therefore do not provide an outcome of overall mental distress that aggregates across symptoms and disorders that tend to have high comorbidity.[58–63] Thus, while these techniques have been used to understand the social determinants of health generally,[51 64–66] they have not, to our knowledge, been used to predict mental health status from a large number of demographic and social determinants.

In this study, we used a unique global sample of 270 000 records spanning 32 countries and four languages taken from the Global Mind Project, a dynamic repository of global mental health data.[67] These data are obtained through the online mental health quotient (MHQ) assessment that includes self-assessment of 47 different elements of mental health on a life-impact scale, covering symptoms of 10 mental health disorders, as well as self-report of over 120 potential determinants including demographics, lifestyle, trauma and adversity, substance use and medical conditions.[58] An aggregate score of mental health, the MHQ, positions individuals on a spectrum from distressed to thriving, and decreases systematically with loss of work productivity and increasing number of clinical symptoms.[68 69] Here we used gradient boosting (XGBoost) and random forest (RF) supervised learning approaches to identify how well these demographic and social determinants could predict mental health status, as captured by the MHQ, and reveal the relative hierarchy of influence across these determinants across various demographic stratifications including age, gender and geographical region.

METHODS

Data source and structure

The data used in this study were from the Global Mind Project (previously called the Mental Health Million Project), a dynamic, ongoing repository of global mental health and life context data that is openly available to the research community[67] and is acquired through the online MHQ assessment. This free and anonymous assessment captures ratings of 47 mental health elements on a life impact scale spanning symptoms of major mental health disorders and elements from the Research Domain Criteria, as well as numerous life context factors including demographics, lifestyle factors, trauma experiences, medical conditions and substance use.[67–69] It takes approximately 15 min to complete and returns a detailed personalised report to respondents. Participants take the assessment anonymously for the purpose of getting their mental health scores and personalised report and consent by clicking on a start button after reading a detailed privacy policy. Data for the Global Mind Project are acquired by recruiting participants through advertisements placed on Facebook and Google that systematically target all age-gender groups and regions across broad-based interests and key words.

In addition, advertisements are continually and dynamically managed (using Google and Facebook Analytics) in response to feedback on the demographic composition of respondents to further ensure sufficient representation across age and gender groups.[70] The data are therefore from a non-probability sample of the internet-enabled population, with an unknown potential for sampling or non-response bias. However, trends from the Global Mind data for the USA have been shown to broadly mirror various trends of marital status, educational attainment and mental health treatment status acquired by the American Community Survey and Household Pulse Surveys conducted by the United States Census Bureau. Biases in the representativeness of the data included a relatively small bias (~7%) towards single versus married respondents, 5%–7% higher percentage of people not seeking treatment between the ages of 25 years and 54 years, and lower percentage of people seeking treatment among the older age groups (4%–5%).[70] The demographic representativeness of samples from other countries is unknown.

The sample population for this study included 284 000 respondents, aged 18+ years, who completed the MHQ between April 2020 and December 2021. This sample population spanned 32 countries and four languages (English, Spanish, French, Arabic; see online supplemental table 1 for full list of countries and N values and online supplemental table 2 for N values by regions and languages). The sample was 58% female and 41% male, with each age group 18–24 years to 75+ years containing

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13%–21% of the data. 39% was from the Core Anglosphere and 59% was from English-speaking respondents. Records were removed if time to completion was <7 min, if the same option was selected for all rating questions (SD of answers <0.5), or if the respondent provided incorrect or impossible answers (eg, 500 hours since the last meal). 270 000 records were included in the final analysis.

The mental health quotient

The MHQ is an aggregate score that positions individuals on a spectrum from distressed to thriving.[69] The score is based on an algorithm that thresholds ratings as negative and positive based on the impact to function and applies a non-linear transformation of the scale such that increasing negative impact to function is amplified.[69 71] The resulting MHQ Scores fall on a positive-negative continuum. The positive scores range from 0 to 200 and are scaled to a mean of 100 based on sample data from 2019 (obtained from USA, the UK and India, English-speaking population pre-COVID-19 pandemic). The negative side of the scale has the structure of a long tail that has been linearly re-scaled to compress values within a range of −1 to −100 (to mitigate the impact of negative scores on the individual; see online supplemental figure 1 for re-scaled and original distributions of these data). 42.8% of those with negative MHQ Scores (<0) mapped to one or more Diagnostic and Statistical Manual of Mental Disorders (DSM) disorder diagnoses, while 86% reported at least five severe symptoms that spanned multiple diagnostic criteria. In contrast, 0.7% with positive MHQ Scores (>0) mapped to a clinical diagnostic profile and only 5% had five or more severe symptoms indicating that positive scores generally represent normal functioning.[68]

The MHQ Score has been shown to have strong sample-to-sample consistency as well as criterion validity using data from 179 298 people across eight English-speaking countries.[68] This includes demonstration that, in the aggregate, average number of clinical symptoms and clinical diagnoses increase systematically as MHQ Scores decrease, and that MHQ Scores are linearly related to work productivity, including absenteeism and presenteeism.[68 71] Population MHQ Scores also align with well-established trends relating to age, employment, education, physical exercise, sleep and social engagement, as well as being generally higher in men than women.[72]

Encoding of demographic and social determinants

The various demographics and social determinants captured are shown in table 1 and online supplemental table 3 and the questionnaire used to capture this information is shown in the online supplemental materials. Household income and ethnicity were not used since they were only obtained for select countries. Furthermore, household income could not be easily normalised across countries due to differences in currencies and purchasing power parity.

Within the MHQ, these determinants or factors could be represented by two categories of data: categorical or numerical. For the supervised learning approaches described below, a multiple-choice encoding method was used where items in multiple-choice lists (eg, different types of trauma experiences) were each considered as individual factors coded as either 1 (if selected) or 0 (if not selected). Overall, this coding resulted in a factor set of 121 elements (online supplemental table 4). All factors were not independent and the correlations/collinearity are shown in online supplemental figure 2.

Classification of positive and negative MHQ Scores

To determine how well contextual factors could be used to distinguish those with normal (positive MHQ Score) versus distressed (negative MHQ Score) mental health status, we used the following supervised learning models: RF,[73] gradient-boosting (XGBoost),[74] Naïve bayes[75] and logistic regression.[76]

3-fold, 5-fold and 10-fold cross-validation was performed with five evaluation metrics (area under the receiver operating characteristic (ROC) curve, AUC; classification accuracy; precision, recall and F1 Score (harmonic mean of precision and recall) to evaluate and compare the algorithms. Cross-validation results on each metric were averaged across folds to obtain intermediate benchmark performance estimates. Final reported results were obtained using a 70/30 train/test split, randomly generated five times, to evaluate performance on the unseen (test) data. Results were reported as the average performance across the positive and negative MHQ prediction models over the five test sets. Lift scores were calculated as the ratio between the true positive rate of the model and the positive rate in the population.[77]

Table 1 Elements captured within each determinant category (see online supplemental table 3 for full list)

Determinant	Elements captured
Demographics	Age; Gender; Country; Language; Educational attainment, Employment status
Lifestyle	Frequency of sleeping well; Frequency of exercise, Frequency of in-person socialising with friends
Traumas and adversities	Experience of sexual abuse; Cyberbullying; Divorce; Breakdown of romantic relationships; Sudden or premature death of a family member; Extreme poverty and homelessness; Loss of a job; Debilitating or life-threatening injury; Loss due to natural disaster; Participant or witness to war
Substances used	Tobacco; Alcohol; Cannabis; Vaping products; Sedatives or sleeping pills; Amphetamines; Opioids
Medical conditions	31 common medical conditions including diabetes (type II), cancer, heart disease, hypertension, arthritis, migraine and traumatic brain injury

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Separately, linear regression as well as XGBoost and RF regressor models[78–80] were used to predict specific MHQ Scores across the −100 to +200 score range. The prediction performance was evaluated using root mean squared error (RMSE), mean absolute error (MAE) and *R*-squared (coefficient of determination). The RMSE measures the amount of error in a model's predictions compared with the actual values observed and has been used. A lower RMSE indicates better model performance and less deviation from actuals, with 0 meaning no error.

All analysis was carried out using Python (V.3.8) including the scikit-learn, pandas, seaborn and shap libraries. Orange (V.3.32), an open-source Python library with a hierarchically organised toolbox of data mining components, was used to simplify data manipulation, transformation, visualisation and modelling workflows.

Assessing the impact of factor categories and individual factors

The relative importance of individual factors were determined for the XGBoost and RF models by how often the factor was selected to split the tree during learning, and how much it contributed to reducing the squared error over all trees in the model.[79 81] The reduction in squared error attributable to that factor was computed based on the difference in squared error between that node and its children and normalised to the highest value. Thus, the larger the difference in squared error between the node and its children across the tree, the greater the influence of the factor. The factor selection process added predefined categories of conceptually related factors sequentially rather than individually. The process focused on entire categories rather than individual factors within each group. This is because the groupings represent concepts where many individual factors would likely have collinearity (online supplemental figure 2). Adding factor groups helped mitigate issues like redundancy in evaluating factor contributions. The order of adding factor categories was determined by the average factor importance score of each category, assessed using XGBoost and Shapley additive explanations (SHAP) methods, helping to guide sequence priority. The primary goal was to evaluate the marginal contribution of each factor group regardless of sequence order. Along with isolated category contribution, sequential addition aimed to uncover if certain factor types incrementally boosted performance earlier versus later in the model build process.

Naive bayes and logistic regression were not used for determination of factor importance. Naive bayes assumes independence, making its factor importance unreliable while logistic regression provides coefficients for individual factors but overlooks interactions. In contrast, XGBoost and RF automatically select important factors, considering interactions and non-linear patterns. RF assesses factors by their impact on reducing variance and handling complex relationships across many trees while XGBoost calculates factor importance based on how useful or valuable each factor was in the construction of the decision trees within the model. It is known for its precision in identifying the most important factors due to its built-in factor selection capabilities as well as bias-resistance and stability.[81]

We also used the SHAP method to compute Shapley values, to assess how specific factors affect prediction outcomes through additive factor attribution, thereby providing a view of both the magnitude and direction of each factor's contribution.[82]

Comparisons by age, region and language

All analysis carried out for the entire global data was similarly repeated for groups stratified by age, gender, region and language. For analysis within these stratified groups, we considered only the XGBoost model. Age groups used were 18–24 years, 25–35 years, 35–44 years, 45–54 years, 55–64 years, 65–74 years, 75–84 years. Countries were regionally grouped into Core Anglosphere, Latin America, Europe, Middle East, North Africa, West Africa, Sub-Saharan Africa and South Asia (see online supplemental table 2). Language groups were English, Spanish, French and Arabic.

Patient and public involvement

Patients and the public were not involved in the design or conduct of the study. Findings from the Global Mind Project will be disseminated through appropriate public channels.

RESULTS

Prediction of mental health status and scores from demographics and social determinants

All classification models (XGBoost, RF, Naïve bayes and logistic regression) were able to classify mental health status as negative or positive in the global data using demographic and social determinants with high accuracy ranging from 0.75 to 0.8 across models and F1 Scores ranging from 0.73 to 0.79 (online supplemental table 5A). Negative status refers to MHQ Scores <0 which typically represent ≥5 symptoms and functional impact of ≥3 days of work loss per month while positive refers to a normal range of function with typically <3 days of loss of work per month.[68] ROC curves for model prediction of MHQ scores <0 (figure 1A) and of MHQ scores ≥0 (figure 1B) show that performance was similar for all models (AUC ranging from 0.76 for Naïve bayes to 0.83 for XGBoost and logistic regression; online supplemental table 5A). Going forward, we further characterised performance, robustness and factor importance for the XGBoost model alone.

Overall, the XGBoost classification model was able to correctly identify 80% of those who were struggling with their mental health (ie, MHQ Scores <0) with a precision of 79% (table 2). Across the range of scores, 85% of those with the most severe mental health challenges (lowest 5% of MHQ Scores), typically corresponding to the presence of one or more clinical disorders[68 69] could

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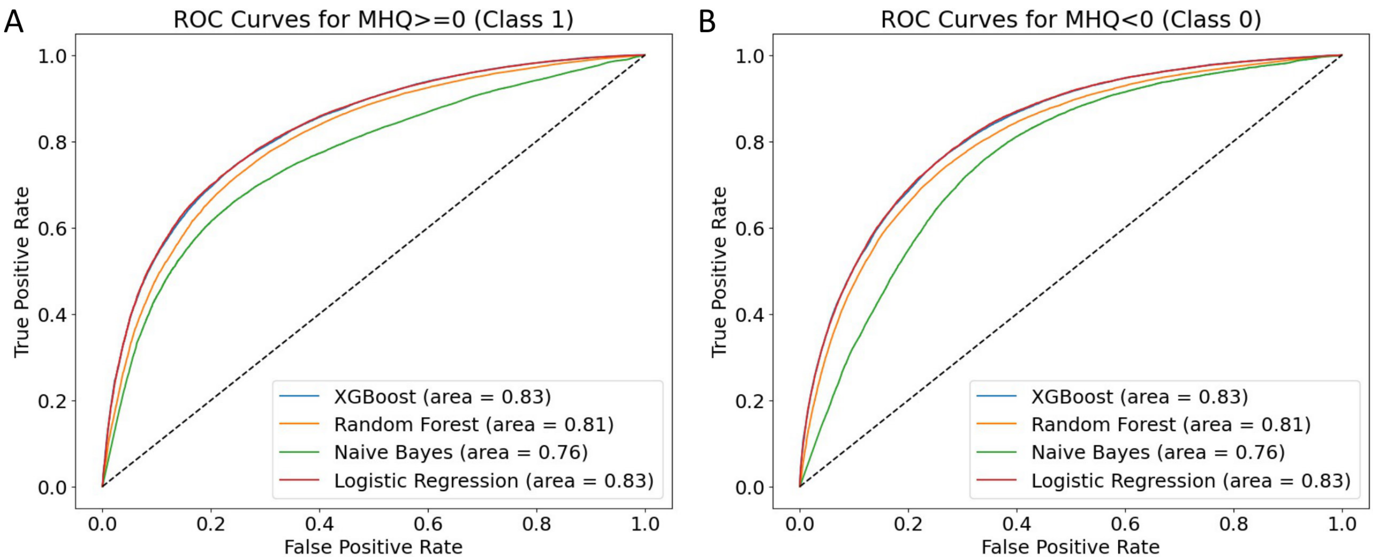

Figure 1 ROC curves for four types of classification models predicting (A) MHQ <0 and (B) MHQ ≥0. MHQ, mental health quotient.

be accurately identified as having negative mental health status (table 3). Conversely, 96% of those within the top 20% of MHQ Scores (typically MHQ Scores >120) could be correctly identified as having positive mental health status. The lift of the model (a measure of how much prediction is improved by the model relative to random classification) was 2.1 for the lowest 50% of negative scores and 2.7 for the lowest 5% (table 3).

Using XGBoost and RF regressor models as well as linear regression, an individual's specific MHQ Score could be predicted with an average error of ±18%–19% of the 300-point MHQ Scale using the RMSE methods and ±15%–15.3% using the MAE method (table 4). Models had R^2 between the actual and predicted MHQ values ranging from 0.4 for RF to 0.44 for linear regression.

We next looked at how model performance changed with sample size for both the XGBoost classification and regression models (figure 2). Increasing sample size from 5000 to 10 000 records provided the steepest gains in classification model performance and was relatively stable beyond a sample size of 50 000. For the regression model, there were substantial performance gains as the sample size increased up to 40 000. Although not shown, we note that the standard deviation (SD) of performance metrics across iterations also decreased sharply as the sample size increased. This makes the case for the need for large-scale studies of at least 20 000 to 50 000 records for stable and robust results.

Model performance by age, gender, region and language

We next evaluated the XGBoost model performance for different groupings of the data—by age, by gender, by region and by language (table 2). Overall performance increased substantially from younger to older age groups. Accuracy increased systematically from just 0.68 for the age group 18–24 years to 0.94 for the age groups 75–84 years, while F1 Scores similarly increased from 0.68 to 0.92. Thus, the factor set captured in these data appears to be more relevant to the older age groups while additional factors not captured here (eg, age of first smartphone or social media use) may be more relevant for younger age groups and particularly those aged 18–24 years. On the other hand, model performance when splitting the data by specific regions and languages was more similar. Across regions, performance was poorest for South Asia and Sub-Saharan Africa (accuracy and F1 Scores 0.74 or 0.75 for all cases) and best for Europe (French-speaking and Spanish-speaking countries only; accuracy 0.85, F1 0.84). Split by language, performance was poorest for Arabic (accuracy: 0.76, F1: 0.74) and best for French (accuracy: 0.86, F1: 0.83).

Contribution and relative importance of categories of determinants to prediction of mental health status

Evaluation of the XGBoost classification model performance using the global data for different categories of factors or determinants (table 5) showed that a subset of demographic factors alone (age, gender and language) predicted the sign of the MHQ Score with an AUC of 0.74 and F1 of 0.72. Incorporating either traumas or education attainment and employment status into the model increased the AUC and F1 Scores to 0.77 and 0.74, respectively. Similarly, lifestyle factors alone (frequency of getting a good night's sleep; frequency of exercise; frequency of in person socialising with friends) had an AUC of 0.72 and an F1 Score of 0.71, while trauma and adversities alone had a slightly lower AUC of 0.65 and an F1 Score of 0.68. Combining all demographic factors with all lifestyle factors increased the AUC from 0.77 to 0.82 and F1 Scores from 0.74 to 0.78. The further addition of traumas and adversities yielded no additional model improvement, while the addition of medical conditions and substance use marginally improved performance to an AUC of 0.83 and an F1 Score of 0.79. A similar pattern of contribution

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Table 2 Performance metrics by age, gender, region and language using XGBoost

Data grouping	CA	Precision	Recall	F1	AUC
All	0.80	0.79	0.80	0.79	0.84
By age, years					
18–24	0.68	0.68	0.68	0.68	0.74
25–34	0.71	0.70	0.71	0.70	0.75
35–44	0.77	0.74	0.77	0.75	0.75
45–54	0.82	0.79	0.82	0.79	0.78
55–64	0.86	0.83	0.86	0.83	0.79
65–74	0.91	0.88	0.91	0.88	0.76
75–84	0.94	0.91	0.94	0.92	0.70
By gender					
Male	0.82	0.80	0.82	0.80	0.81
Female	0.79	0.77	0.79	0.78	0.83
By region					
Core Anglosphere	0.79	0.79	0.79	0.79	0.84
Latin America	0.82	0.80	0.82	0.80	0.82
Europe	0.85	0.84	0.85	0.84	0.84
Middle East	0.74	0.72	0.74	0.72	0.72
North Africa	0.81	0.78	0.81	0.78	0.72
West Africa	0.82	0.79	0.82	0.80	0.72
Sub-Saharan Africa	0.75	0.74	0.75	0.74	0.79
South Asia	0.75	0.75	0.75	0.75	0.81
South-East Asia	0.77	0.76	0.77	0.77	0.82
By language					
English	0.78	0.77	0.78	0.78	0.83
Spanish	0.83	0.81	0.83	0.81	0.84
French	0.86	0.83	0.86	0.83	0.72
Arabic	0.76	0.73	0.76	0.74	0.73

AUC, area under the ROC curve; CA, classification accuracy.

of these determinant categories to model performance was observed for prediction of specific MHQ Scores using regression (not shown). This redundancy of determinant categories reflects the interdependence of determinants and suggests that lifestyle and trauma experiences may derive in large part from demographic position.

Table 3 Lift characteristics of XGBoost classification model

	MHQ <0		MHQ ≥0	
Top* % of scores	Recall	Lift	Recall	Lift
5%	0.85	2.7	0.99	1.43
10%	0.79	2.5	0.98	1.42
15%	0.74	2.4	0.97	1.40
20%	0.69	2.2	0.96	1.39
50%	0.67	2.1	0.90	1.30

*Lowest in the case of MHQ <0 and highest in the case of MHQ ≥0.
MHQ, mental health quotient.

Relative importance of specific individual determinants in the prediction of mental health status

Using the global data, we evaluated the reduction in the squared error attributable to each individual factor to determine their relative importance in predicting mental health status in each of the XGBoost and RF classification and regressor models (figure 3, online supplemental tables 5B,C). This provided an estimate of how much each determinant contributed across all different trees of the model, each representing a different constellation of factors overall. Across all models, the most important factor for predicting MHQ sign or score was being in an 18–24 years age range (figure 3A,B), which contributed twice as much predictive power compared with the next most important factors, which were rarely or never socialising with friends in person and rarely getting a good night's sleep. This was followed by being in the 25–34 years age range, rarely engaging in physical exercise, and a higher number of lifetime traumas and adversities, all of which contributed only 30%–45% of the predictive power of rarely socialising with friends in person. Employment status also featured among the top 20. Among the various traumas and adversities, sexual abuse or assault and cyberbullying contributed most, while use of sedatives or sleeping pills contributed the most of all substances used. Notably, the experience of financial adversities were not individually prominent in prediction. We also note that between the RF and XGBoost classification models there was an overlap of 16 of the top 20 factors (online supplemental table 5B).

Given the dramatic impact of age in prediction outcome, and the systematic change in model performance with age, we similarly compared the contributions of these factors to the classification prediction within each age group using the XGBoost classification model (figure 3C,D; online supplemental table 6). Across all age groups, the top two most predictive factors were rarely socialising in person and hardly ever getting a good night's sleep. However, other factors differed substantially. Sexual abuse and cyberbullying were among the top five most important factors only for the 18–24 years age group, while an employment status of 'Not able to work' and taking sedatives or sleeping pills were among the top five for all age groups between 25 years and 64 years. Similarly, while the major factors were similar between both men and women, not being able to work and sexual abuse were much higher ranked for women (online supplemental table 7).

We similarly evaluated factor importance by region and language (with all age groups included and age included as a factor; online supplemental tables 8,9). In this case, age between 18 years and 24 years and hardly ever socialising in person were the two most important factors in all regions, while hardly ever getting a good night's sleep was among the top five for all regions. However, a few

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Table 4 Performance metrics of regression models

Regression method	RMSE MHQ points	RMSE % of scale	MAE MHQ points	MAE % of scale	*R*-squared
XGBoost regressor	57	19%	46	15.3%	0.42
Random forest regressor	57	19%	46	15.3%	0.40
Linear regression	55	18%	45	15.0%	0.44

MAE, mean absolute error; MHQ, mental health quotient; RMSE, root mean squared error.

dramatic differences between regions were noted. First, non-binary gender was within the top 20 in Core Anglosphere and Europe but irrelevant as a predictor in all African regions as well as South Asia where alternative genders are not common. Second, use of cannabis was within the top 25 in Core Anglosphere, Latin America and Sub-Saharan Africa but irrelevant as a predictor in the Middle East where it is generally illegal with severe penalties.

Using the entire data we also assessed whether a particular factor predicted a more negative or positive MHQ using SHAP values (figure 4). The dominant factors were consistent with findings from the squared error method. Age under 35 years, lack of in person socialising, poor sleep, lack of physical exercise, excessive work stress, sexual abuse, and use of sedatives or sleeping pills contributed strongly to negative or low MHQ Scores, while regular in person socialising, exercising, getting a good night's sleep and older age contributed to positive MHQ Scores.

Risk and prevalence of factors in negative mental health

Finally, we provide a perspective of the risk probability of negative mental health (MHQ <0) for each of the top 20 factors, as well as the statistical prevalence by factor among those with negative mental health for all the data together as well as for age groups 18–24 years and 45–54 years separately (table 6). This provides an additional perspective as factor importance in the prediction models incorporates information on both prevalence of a factor as well as relative risk of other factors such as inter-relationships. Many factors with low prevalence overall, if present, have substantial risk of negative mental health. For example, 53% of those who took opioids had negative mental health although only 1.1% of those with negative mental health in the sample consumed opioids, a 3.2 times higher prevalence compared with the fraction with positive mental health. Similarly, among those who had traumatic brain injury, the risk of negative mental health was 49.4%. However, only 0.8% of those who had negative mental health had traumatic brain injury which represents a 2.7 times higher prevalence compared with the percentage of those who had positive mental health. In contrast, poor sleep, rarely/never socialising and rarely/never exercising carried a high risk of negative mental health (51.5%, 44.6% and 37.7%, respectively), and also had high prevalence (24.8%, 40% and 46.7%, respectively, among those with negative mental health). Finally, the factors that carried the highest risk were cyberbullying

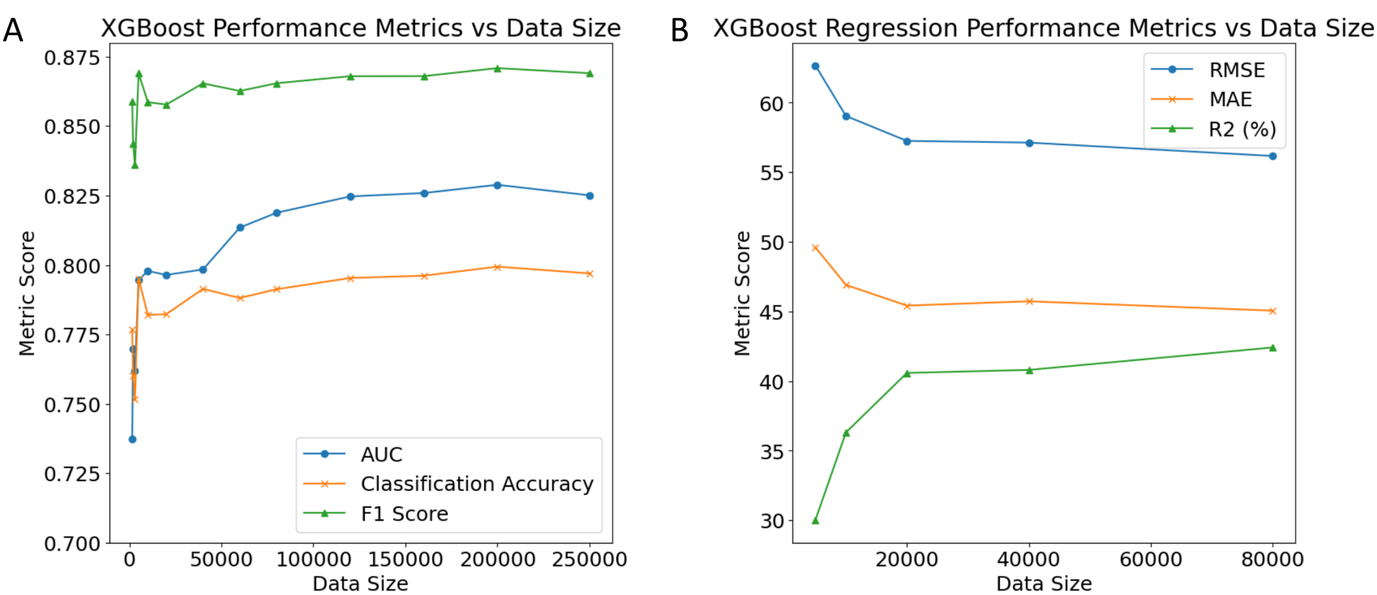

Figure 2 Performance characteristics of the XGBoost models. (A) Classification model performance characteristics increase with data sample size. (B) Regression model performance characteristics increase with data sample size. AUC, area under the ROC curve; MAE, mean absolute error; RMSE, root mean squared error.

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Table 5 Performance characteristics by categories of determinants used

Combination	AUC	CA	F1 Score	Precision	Recall
Demographic1 (age, gender, language)	0.74	0.75	0.72	0.72	0.75
Demographic1+Traumas	0.77	0.76	0.74	0.74	0.76
Demographics2 (age; gender, language; education; employment)	0.77	0.76	0.74	0.74	0.76
Demographics2 Lifestyle (exercise, sleep, socialising)	0.82	0.79	0.78	0.78	0.79
Demographics2+Lifestyle + Traumas	0.82	0.80	0.78	0.78	0.80
Demographics2+Lifestyle + Traumas+Medical Conditions	0.83	0.80	0.78	0.78	0.80
Demographics2+Lifestyle + Traumas+Medical Conditions+Substance Use	0.83	0.80	0.79	0.79	0.80
Lifestyle	0.72	0.75	0.71	0.72	0.75
Lifestyle+Traumas	0.75	0.76	0.73	0.74	0.76
Lifestyle+Number of Traumas	0.73	0.75	0.71	0.73	0.75
Lifestyle+Number of Traumas+Traumas	0.75	0.76	0.73	0.74	0.76
Traumas	0.65	0.74	0.68	0.71	0.74
Traumas+Lifestyle (exercise)	0.69	0.75	0.69	0.72	0.75
Traumas+Lifestyle (exercise+sleep)	0.73	0.76	0.72	0.73	0.76
Traumas+Lifestyle (exercise+sleep + socialising)	0.75	0.76	0.73	0.74	0.76

AUC, area under the ROC curve; CA, classification accuracy.

(58.9% negative mental health), not able to work (55.5%) and sexual abuse (53.9%) and had moderate prevalence. Cyberbullying and sexual abuse were substantially more prevalent among those aged 18–24 years with negative mental health compared with those aged 45–54 years with negative mental health (cyberbullying 16.4% for the 18–24 years age group compared with 3.0% for the 45–54 years age group; sexual abuse 12.2% for the 18–24 years age group compared with 9.3% for the 45–54 years age group). Conversely 'Not able to work' was substantially more prevalent among those aged 45–54 years with negative mental health (13.0%) compared with those aged 18–24 years (2.9%).

DISCUSSION

Using a comprehensive set of 47 mental health symptoms and 120+ determinants from 270 000 adults, we have shown that with just a handful of demographic and social determinants, it is possible to predict mental health status with high accuracy and precision. Furthermore, we show the hierarchy of importance of individual determinants and highlight the dominance of being part of GenZ (18–24 years) along with infrequency of in person socialising with friends and hardly ever getting a good night's sleep as outsized predictors of mental health status across all demographics. Furthermore, we have shown that model performance is similar for four model types and that the top factors are consistently ranked highest while a certain set of 15–20 factors are of similarly high importance across all four model types amenable to this analysis. This demonstrates that the primary results are robust and not specific to model peculiarities.

Life context as the primary determinant of mental health status

We have shown here that 80% of people struggling with mental health challenges could be accurately identified from their demographic and social characteristics. Similarly, one's specific MHQ Score or position on a scale of mental health ranging from negative to positive could be predicted within an average error of ±15%. This suggests that our mental health status is largely dependent on the societal milieu in which we live; in essence an expected response of our brain and mind to ongoing life circumstances.[42 44 83–85] Understanding these demographic and social determinants provides an opportunity to substantially alter mental health outcomes at a population level through systemic societal shifts and delivers an impetus for individuals to take action to alter the circumstances of their own lives.

The relative impact of individual factors

This study furthers our understanding of the specific demographic and social determinants that are most influential in driving population mental health status. While all demographic factors together were effective at classifying MHQ as negative or positive, young age (ie, being 18–24 years followed by 25–34 years) was disproportionately powerful as a predictor of negative mental health. This is supported by other evidence that shows overall mental health status is worse for each younger age group: data from the Global Mind Project has shown that in 2021, 44% of young adults (18–24 years) were mentally distressed or struggling compared with 7% among those aged 65 years and above,[72] while other studies also highlight the increase in mental health problems in

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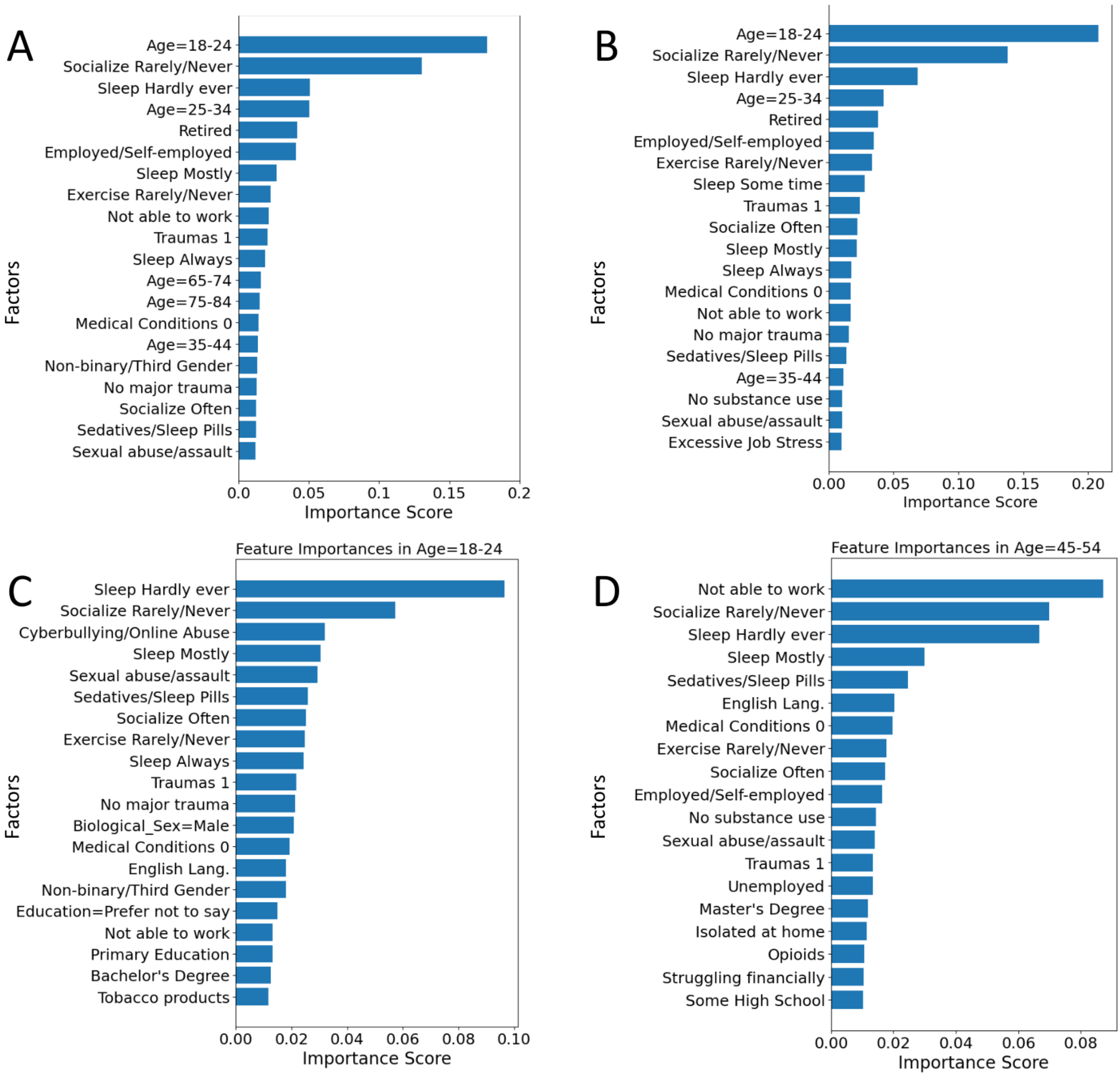

Figure 3 Top 20 factors ranked in order of importance for model performance for (A) XGBoost classification using all data, (B) XGBoost regression using all data, (C) XGBoost classification using the 18–24 yeas age group only, (D) XGBoost classification using the 45–54 years age group only. Factor importance is computed as the normalised sum of the contributions to squared error reduction.

teens.[2 3] This is in sharp contrast to psychological well-being patterns observed prior to 2010 where young adults were typically at the higher end of well-being scales.[86 87] The timeline of this decline of younger generations is also highlighted by a recent Centers for Disease Control and Prevention (CDC) report that shows a sharp rise in feelings of sadness reported by teens only in this last decade.[88]

Given that age is immutable, this trend suggests that age stands as a proxy for global changes in the environment and life context with each generation that are not currently captured in these data. This is further evidenced by the worse prediction performance for younger age groups, and in particular those aged 18–24 years or Gen Z. One factor that stands out as important is the considerable shift in the sociotechnological environment across generations with the introduction of the internet in the 1990s and smartphones (eg, iPhones) in 2007. A growing body of evidence suggests that this shift, and in particular the unhealthy use of social media, is having a negative effect on mental health within the GenZ population who are the first generation of digital natives.[89–92] However,

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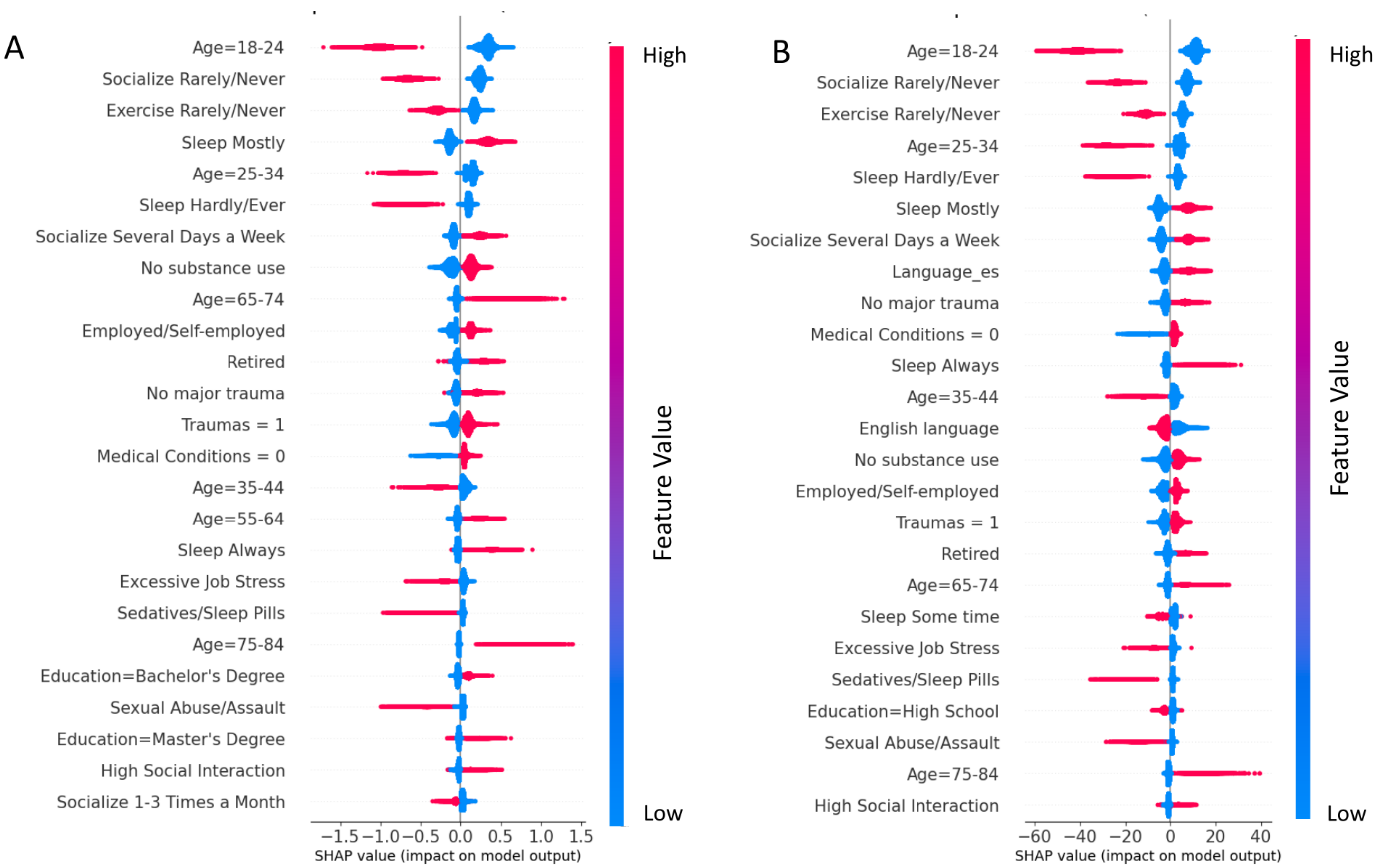

Figure 4 SHAP values for the top 25 factors for (A) XGBoost classification and (B) XGBoost regression.

we cannot rule out other possibilities that may also contribute. For example, plastic production has doubled in the last 20 years[93 94] and microplastics and phthalates which have been shown to be neuroendocrine disruptors and neurotoxic substances are increasingly present in our food and water,[95–97] and blood,[98–100] potentially having a disproportionate impact on younger generations.

Among lifestyle or life experience factors, lack of in person socialising with friends, poor sleep, lack of physical exercise, and a larger number of traumatic experiences were key predictors of negative mental health across all age groups, genders, regions and languages. Interestingly, lack of in person socialising with friends was two to four times as important as all the other factors other than sleep and is supported by other evidence highlighting the importance of in person socialising.[33 101] The reasons behind low levels of in person socialising are complex, calling for the need to evaluate deeply the sociological factors that drive it. Similarly, hardly ever getting a good night's sleep was two or more times as important as all other factors other than lack of in person socialising, particularly for younger adults. The impact of sleep on mental health is also well documented[38 39] and challenges for young people have also been studied in the context of schoolwork pressure in schools, smartphone ownership and social media.[102–104] Given its high level of importance at a population level, this is another area that should be of high priority. It is also of interest that cyberbullying, which is far more prevalent among younger adults, was one of the key trauma factors along with sexual abuse for the 18–24 years group, and aligns with other research.[105–107] On the other hand, the experience of financial traumas and adversities such as homelessness and difficulty making ends meet were relatively less predictive and did not make it into the top 25, although inability to work was a major factor particularly for those age 45 years and above. Together, this hierarchy of influence across demographic and social determinants provides an initial framework to approach population mental health at a preventative level and points to where efforts should be focused for the greatest impact. Solutions that enable greater frequency of in person social interaction, for instance, could have a much greater impact on population mental health compared with financial programmes while a combination of increased in person social interaction and physical exercise may enhance population mental health more significantly than tackling the prevalence of a host of traumas and adversities.

Implications, limitations and conclusions

The degree to which demographic and social determinants predict our mental health status attests to how intimately intertwined the struggles of mind are with

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Table 6 Statistical risk and prevalence of top 20 factors

No.	Factor	All data: Risk	All data: Prevalence MHQ <0	All data: Relative prevalence	18–24 years only: Prevalence MHQ <0	18–24 years only: Relative prevalence	45–54 years only: Prevalence MHQ <0	45–54 years only: Relative prevalence
1	Cyberbullying or online abuse	58.9%	9.4%	4.02	16.4%	2.28	3.0%	2.09
2	Employment = not able to work	55.5%	6.2%	3.49	2.9%	2.74	13.0%	5.90
3	Prolonged sexual abuse or severe sexual assault	53.9%	10.1%	3.27	12.2%	2.49	9.3%	2.96
4	Opioids	53.0%	1.1%	3.16	0.5%	4.68	2.0%	8.84
5	Sleep = hardly ever	51.5%	24.8%	2.97	21.5%	2.90	32.5%	3.17
6	Number of subtances_3	50.8%	3.3%	2.89	3.0%	2.60	3.2%	3.25
7	Age = 18–24 years	50.6%	42.5%	2.87	N/A		N/A	
8	Traumatic brain injury	49.4%	0.8%	2.73	0.4%	4.91	1.4%	4.78
9	Employment = studying	47.9%	31.5%	2.59	68.4%	1.00	1.3%	0.94
10	Vaping products	47.3%	4.4%	2.51	5.6%	1.99	3.2%	1.93
11	Extreme poverty leading to homelessness and/or hunger	44.9%	6.9%	2.28	5.2%	1.77	8.8%	2.41
12	Cannabis	44.7%	7.2%	2.27	7.4%	1.65	5.6%	2.49
13	How regularly do you socialise with friends in person? = rarely/never	44.6%	40.0%	2.26	31.2%	1.96	50.9%	2.35
14	Asthma	41.6%	4.3%	1.99	3.2%	2.37	6.2%	3.06
15	Employment = unemployed	41.3%	13.4%	1.97	11.5%	1.33	13.7%	1.79
16	I am unable to make ends meet for basic necessities	40.4%	8.8%	1.90	5.2%	1.54	12.9%	2.06
17	Sedatives or sleeping pills	39.1%	7.6%	1.80	7.6%	1.80	10.9%	2.87
18	How regularly do you engage in physical exercise (30 min or more)? = rarely/never	37.7%	46.7%	1.70	46.2%	1.48	45.9%	1.55
19	Education = some high school	37.4%	8.5%	1.67	9.8%	1.63	8.7%	1.94
20	Age = 25–34 years	37.3%	17.6%	1.67	N/A		N/A	

MHQ, mental health quotient.

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life circumstances. Practically, these findings are a first view of how analysis of large-scale global multidimensional cross-disorder data can provide insights into the relative impact of various demographic and social determinants on overall population mental health. An implication of understanding the full impact of these determinants is that it can enable the separation of mental health profiles that are predominantly socially driven from those that are predominantly biologically driven (ie, due to genetics, pathogens, toxins). This first iteration, however, identifies certain gaps. First, the disproportionate impact of age in the aggregate data, and the relatively poorer predictive performance for younger age groups, indicates that important factors exist that have not been included here. The most obvious and significant relates to use of smartphones and social media[89 91] which have been linked to poor mental health in younger age groups that are the first generation of digital natives. In addition, the importance of in person socialising suggests that it is important to probe social relationships in much more detail. This would then provide a clearer picture of social determinants to facilitate the design of effective interventions and policies.

We also acknowledge certain limitations that arise from the data. The Global Mind Project recruits participants using a dynamically adjustable online recruitment strategy which systematically targets predefined age-gender groups across a series of selected geographies, with the goal of broad representation across age, gender and regional groups. However, non-probability sampling approaches are subject to various sampling and non-response biases, and these are unknown in these data. However, the USA sample (n=25 124 for 2022) has been shown to mirror representative demographic and social trends captured in the American Community Survey and Household Pulse Surveys conducted by the United States Census Bureau and also the American Trends Panel conducted by the Pew Research Centre.[70] While this suggests that it may also be reasonably representative for those countries where internet penetration is high and sample sizes are large, this is unlikely to be the case for countries with low internet penetration or low sample sizes. Online recruitment excludes the poorest populations of the world for whom different factors may be more important. Altogether the generalisability across countries will have to be tested on a country-by-country basis as the representativeness of the sample is unknown outside the USA.

A further limitation of these data is that it is not likely to fully capture the negative extreme, that is, those with very severe mental illness who are not capable of accurate online self-assessment. However, while this approach may have these limitations, it provides a substantial view of the drivers of population mental health and adds a perspective to the debate on the extent to which mental health challenges can be addressed through societal rather than medical means.[45–47]

In summary, we provide an initial view of the aggregate impact of demographic and social determinants on mental health status, and a hierarchy of determinants that can inform and enhance our ability to impact population mental health.

Acknowledgements The authors thank members of the Sapien Labs team for their assistance with recruitment and data management. The authors also thank all survey respondents for their participation in the Global Mind Project.

Contributors TT and JB were responsible for the study concept, design and interpretation. JB was responsible for the analysis. TT, JB and JN drafted the manuscript. All the authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work. TT is responsible for the overall content as guarantor.

Funding This work was supported by funding from Sapien Labs. It did not receive any specific award/grant from funding agencies in the public, commercial or not-for-profit sectors.

Competing interests One author (TT) received a grant award from the National Institute of Mental Health (NIMH) to develop a commercial version of the MHQ tool referenced here for clinical use. There are no other commercial or financial relationships to declare.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval This study involves human participants. The data used in this study received ethics approval from the Health Media Lab Institutional Review Board (Office for Human Research Protections Institutional Review Board #00001211, Federal Wide Assurance #00001102, IORG #0000850). Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available upon reasonable request. Data are available via the online data repository Brainbase where data from the ongoing Global Mind Project are dynamically updated as respondents complete the MHQ. The anonymised data set, together with supporting information, is freely available for use for not-for profit purposes and access can be requested here: https://sapienlabs.org/global-mind-project/researcher-hub/

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