Suppl. Methods

A sample ED mental health assessment form

GIG CYMRU NHS WALES | Bwrdd Iechyd Prifysgol Abertawe Bro Morgannwg University Health Board

ED Mental Health Assessment Form

ED Dr ____________________ **Date** ____________________ **Time** ________ : ________

ED No ____________________
Surname ____________________
First Name ____________________
DOB ____________________
Address ____________________
____
Telephone: ____________________
Mobile: ____________________

Use sticky label

GP Name ____________________
Practice ____________________
Fax No ____________________

NOK: ____________________
Relationship: ____________________
Contact No: ____________________

History

____

Previous history ☐ **Known to Ψ services** ☐ **None** ☐ **Unknown**

Details *(method/date of previous self harm, details of mental health input, substance use etc)*

____

Social circumstances

☐ Single ☐ Separated/divorced ☐ Partnered/married ☐ Widowed

☐ Lives alone ☐ With partner/spouse ☐ With parents
☐ Lone parent ☐ With friends/relatives ☐ Homeless

☐ Dependent adult(s) ☐ Dependent child(ren) ☐ No dependents

Notes

____

Medication, drug/substance/alcohol use

____

Allergies ____________________

rev 30 July 2014

Patient's full name ______________________________ DOB ______________________

SAD PERSONS SCORE

- Sex (M = 1, F = 0) ☐
- Age (<19 or >45 =1) ☐
- Depression/Hopelessness (present = 2) ☐
- Previous attempts or in-pt care (yes = 1) ☐
- Excessive alcohol/drug use (yes = 1) ☐
- Rational thinking (organic illness or psychosis = 2) ☐
- Separated/divorced/widowed (yes = 1) ☐
- Organised/serious attempt (yes = 2) ☐
- No social supports (No support = 1) ☐
- Stated future intent (Yes = 2) ☐

TOTAL ☐

(0 – 5 : consider discharge, 6 – 8: ref psych, 9 – 14 : likely needs admission... **THIS IS ONLY A GUIDE!**

Mental State Examination *(Appearance/Behaviour, Mood (subj/obj), Speech (vol/rate/flow), Thought (content/ process), Perception (hallucinations), Orientation, Cognitive function, Insight)*

Does the patient have capacity to give informed consent to any intervention that may be necessary? YES/NO

If YES and the patient is declining treatment, senior or psychiatric review is MANDATORY before the patient is allowed to leave the hospital.

Impression

Plan (Completion mandatory). **All patients age ≥ 65 MUST be referred for formal MH assessment**)

☐ Admit Physicians ☐ Admit ITU ☐ Admit Surgical specialty

☐ Refer Psychiatry
Time of referral: ________

☐ Home, notes faxed to Crisis Resolution Team on ext 2673, **give patient information sheet so they can contact CRHTT**

☐ Home, Ψ F/U already arranged (ie patient already known to MH services)

☐ Home, notes faxed to GP for GP F/U (this should be the default option for most patients)

Other Covariates

We used sex, age (as group: 0-14, 15-34, 35-54, and 55 years or above), marital status (single, separated/divorced/widowed, partnered/married, and unknown), household status (lives alone, with lone parent, with parents, with partner/spouse, with friends/relatives, and Others & unknown), area deprivation, and urban/rural indicator as sociodemographic variables. Area deprivation was categorized according to quintiles of Welsh Index of Multiple Deprivation (WIMD) 2011 score for all lower-layer super-output areas (LSOAs) in Wales (Welsh Government, 2011), with the first quintile (Q1) represents the least and the fifth (Q5) the most deprived areas. The urban/rural indicator for England and Wales was used to categorize urban and rural LSOAs (Barham & Begum, 2006). LSOAs with unknown WIMD quintile or urban/rural indicator were grouped as "unknown LSOA" category. Please note that marital and household status were not used for the enhanced dataset due to the data unavailability in SAIL databank.

Apart from demographic variables, we included the following variables from the SAIL datasets (primary and secondary care), as shown in a previous study on premature mortality following self-harm (Carr et al., 2017).

Physical comorbidity: We used the Charlson comorbidity index (CCI) to measure individuals' physical comorbidity (Charlson et al., 1987). The CCI is based on 17 binary scores for the presence of any of the 17 physical illnesses. We used both Read (for primary care dataset) and International Classification of Diseases version 10 (ICD-10, for secondary care dataset) codes to identify each of these illnesses based on previous studies (Bottle & Aylin, 2011; Khan et al., 2010). The unweighted CCI, i.e., summing the binary score for an individual was calculated and categorized into two groups: CCI =0 and CCI ≥1.

Previous self-harm events as a binary variable: Self-harm events were extracted using previously used Read and ICD-10 code lists (Carr et al., 2017; Marchant et al., 2020; Thomas et al., 2013).

Any mental health diagnoses as a binary variable: Mental health diagnoses were extracted according to the definitions used in a previous study (Ann John et al., 2020). All Read codes within the category of mental disorders (E…. and all associated subcodes) and ICD-10 codes within the category of mental and behavioural disorders (F00-F99) were used for this variable.

Common mental disorders (CMDs) as a binary variable: We used previously used code lists (John et al., 2015; John, Marchant, et al., 2016; John, McGregor, et al., 2016) to identify individuals with CMDs, including mainly depression and anxiety, from both SAIL datasets.

Severe mental illness (SMI) as a binary variable: We adopted the definition and the code lists of SMI used in previous studies (Economou et al., 2012; Ford et al., 2009; John et al., 2018; Lloyd et al., 2015). This included schizophrenia, schizotypal, delusional, and schizoaffective disorders, bipolar disorder, and other psychotic disorders.

Alcohol and drug misuse: We used the previously defined code lists for alcohol (Carr et al., 2017; John et al., 2020; McKenzie et al., 2010; Quan et al., 2005) and drug misuse (John et al., 2020; Quan et al., 2005; Thompson et al., 2004). Alcohol and drug misuse were separately represented by two binary variables.

Prescription of psychotropic and opiates drug medications: Prescription of drug medications could be extracted from the primary care dataset only. For psychotropic medications including antidepressants, anxiolytics, hypnotics, and antipsychotics, we used the code definition from others (Dennis et al., 2017; John et al., 2015; John et al., 2020). Code lists adopted by (John et al., 2020) were used for opiates medication. We used two separate binary variables for psychotropic and opiates drug medications.

All described variables were time-fixed and age, marital status, household status, area deprivation, and urbanicity were measured as at the date of the index self-harm event. Other variables were measured from January 01, 2000 to the date before the date of index self-harm event (defined as history period, see Suppl. Fig. 1 in ESM 3).

Analysis and statistical methods

Linked data in SAIL were interrogated using structured query language (SQL DB2). Statistical analyses were conducted using Stata 17 and R. Level of statistical significance was set at $p = 0.05$. We compared individuals' characteristics and outcomes between DC and BC groups. Number of individuals who self-harmed and the methods of self-harm used were compared between DC and BC group during their two respective ascertainment periods as well as during the 10-year follow-up period. All descriptive statistics were summarized as person counts and percentages or group means for continuous variables with 95% confidence intervals (CIs). CIs for proportions were estimated by Wilson score with continuity correction (Newcombe, 1998).

Due to the issue of small sample size, we used both frequentist and Bayesian approaches (Jamil et al., 2017; Oliveira et al., 2018), including Fisher's exact tests, likelihood ratio tests, and Bayes factors to examine independence of variables for contingency tables. While Fisher's exact and likelihood ratio tests are classical hypothesis tests for independence that associated with *p*-values, Bayes factors directly estimate the weights of evidence over two competing hypotheses, i.e., dependence vs. independence of variables in contingency tables. Bayes factor reflects the degree of shift of beliefs about the relative odds between the two hypotheses (Jeffreys, 1961). We reported Bayes factor as a ratio of the conditional probabilities associated with the alternative (dependence) to those with the null hypothesis (independence) given the observed data. Thus, Bayes factor >1 and <1 respectively represent evidence in favor of the alternative and null hypothesis and a Bayes factor of unity indicates no evidence towards any of the hypothesis. All Bayes factors for contingency tables were calculated using the 'BayesFactor' package in R (Morey et al., 2022) and we reported range of bayes factors based on the four available data sampling plans (Poisson, joint multinomial, independent multinomial, and hypergeometric) and used uninformative priors with concentration parameter of one.

Differences in means for continuous variables between groups were assessed by independent sample *t* test accompany with the corresponding Bayes factors of the *t* statistics. Similarly, Bayes factor >1 and <1 respectively provide evidence for and the presence (alternative hypothesis) and absence (null hypothesis) of mean differences between groups. All Bayes factors for *t* test were calculated using the 'BayesFactor' package in R (Morey et al., 2022) and we reported the range of bayes factors based on the Cauchy priors with scale parameters of √2/2, 1, and √2.

We interpreted all Bayes Factors in this study using the previously reported guidelines: 1-3 as providing anecdotal, 3-10 as moderate, 10-30 as strong, 30-100 as very strong, and >100 as extreme evidence for the alternative hypothesis (Jamil et al., 2017).

Effect modification of stratified cross-tabulation by sex and age was tested by the homogeneity of odds ratios (ORs) based on the Breslow-Day test adjusted by (Tarone, 1985). We also reported the effect sizes (as ratio of ORs) of the sex-by-age group interaction term from the Firth logistic regression of the probability of being in BC or DC group, with sex, age group, and the interaction term as predictors.

For the enhanced dataset, we built multivariable regression models for self-harm and mortality outcomes during the 10-year follow-up when significant difference between DC and BC group exists in the descriptive statistics. We stratified the DC and BC groups further by sex (BC-male, BC -female, DC-male and DC-female) and performed the adjusted analysis with two models. Model 1 adjusted for age group (≤34 vs. >34 years), area deprivation (WIMD quintile), and urban/rural indicator. Model 2 included all variables in Model 1 and further adjusted for the CCI, history of self-harm, any mental health diagnoses, CMD, SMI, alcohol misuse, drug misuse, prescription of psychotropic, and prescription of opiate medications. We performed Firth logistic regression (Firth, 1993) to circumvent biased estimates from conventional maximum likelihood estimation due to small sample size and separation issues (Heinze & Schemper, 2002). To evaluate the differences in all-cause mortality among the four sex-stratified DC and BC groups, we computed multiple pairwise comparisons following regression modelling and reported the Wald chi-square statistics and the corresponding unadjusted and Holm-adjusted p-values. While we reported estimates from the Firth logistic regression in the main text, results from conventional logistic regression were also shown in relevant supplementary tables for reference. We conducted diagnostic checks on multicollinearity by calculating the variance inflation factors (VIFs) of all independent variables in all adjusted models. We used the commonly adopted VIF threshold of three to determine if multicollinearity is an issue for each model (Miles & Shevlin, 2001).

References for Suppl. Methods

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