Genome-wide interaction study of a proxy for stress-sensitivity and its

prediction of major depressive disorder

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Abstract

Individual response to stress is correlated with neuroticism and is an important predictor of both neuroticism and the onset of major depressive disorder (MDD). Identification of the genetics underpinning individual differences in response to negative events (stress-sensitivity) may improve our understanding of the molecular pathways involved, and its association with stress-related illnesses. We sought to generate a proxy for stress-sensitivity through modelling the interaction between SNP allele and MDD status on neuroticism score in order to identify genetic variants that contribute to the higher neuroticism seen in individuals with a lifetime diagnosis of depression compared to unaffected individuals. Meta-analysis of genome-wide interaction studies (GWIS) in UK Biobank (N = 23,092) and Generation Scotland: Scottish Family Health Study (N = 7,155) identified no genome-wide significance SNP interaction. However, gene-based tests identified a genome-wide significant gene, *ZNF366*, a negative regulator of glucocorticoid receptor function implicated in alcohol dependence ($p = 1.48 \times 10^{-7}$; Bonferroni-corrected significance threshold $p < 2.79 \times 10^{-6}$). Using summary statistics from the stress-sensitivity term of the GWIS, SNP heritability for stress-sensitivity was estimated at 5.0%. In models fitting polygenic risk scores of both MDD and neuroticism derived from independent GWAS, we show that polygenic risk scores derived from the UK Biobank stress-sensitivity GWIS significantly improved the prediction of MDD in Generation Scotland. This study may improve interpretation of larger genome-wide association studies of MDD and other stress-related illnesses, and the understanding of the etiological mechanisms underpinning stress-sensitivity.

Introduction

Stressful life events are known to increase liability to mental illness and disease-related traits [1] including neuroticism [2-4], major depressive disorder (MDD) [5-7], autoimmune diseases [8] and some cancers [9, 10]. A greater understanding of the causal mechanism by which negative events affect disease risk or outcome may be beneficial in identifying individuals for targeted support. However, it has been proposed that sensitivity to stress may be an important predictor of response to stress [11, 12]. In particular, the effect on an individual may result more from the perceived stress than the event itself, and may be dependent on individual differences in stress-sensitivity [13-18]. Studies of 5-HTT and twin studies suggest that stress-sensitivity may, at least in part, be heritable [19-22]. Despite a complex interaction between MDD, neuroticism and stress, multivariate structural equation models have confirmed a genetic effect on perceived stress, overlapping that on MDD or neuroticism, but with a specific genetic component [21]. The inter-relatedness of these traits may offer an approach to identify the genetic variation that affects an individual's stress-sensitivity, and improve genetic prediction of an individual's liability to negative outcomes. By modelling the interaction between SNP allele and MDD status on neuroticism score through genome-wide interaction studies (GWIS), we sought to investigate the genetics of stress-sensitivity.

The personality trait neuroticism is moderately heritable (30–50% estimates from twin studies) [23-26], is higher in individuals with depression compared to controls [27, 28] and is known to have shared genetic aetiology with depression [29-32]. Neuroticism is strongly correlated with measures of sensitivity to punishment but not reward [33], positively correlated with perceived personal relevance of a stressor [34, 35] and has been used

previously as a proxy measure of stress-sensitivity [36]. Neuroticism is thought to mediate or

interact with the effects of adverse life events on risk of depression [5, 37]. It has a

substantial stable component [38], however, there is evidence for change, as well as stability,

across the life span [2-4, 39]. Individual differences in neuroticism are enduringly influenced

by both genetic and environmental factors [40]. Whereas the stable component of

neuroticism is strongly determined by genetics, change in neuroticism score is attributed to

the effects of unshared environment [39]. Persistent change in neuroticism score has been

shown in response to life events [2-4]. Negative life events lead to small persistent increases

in neuroticism over time [3]. Recent stressful life events (β = 0.14 95%CI 0.13 - 0.15, p <

0.001) have a stronger effect than distant stressful life events suggesting a reduction of effect

over time [3]. Long-lasting increases in neuroticism associated with distant negative life

events are mediated by depression [4].

Major depressive disorder (MDD) is a complex disorder influenced by both genetic

contributions and environmental risk factors, with heritability estimates from twin and family

studies of between 31-42% [41, 42]. Confirmed environmental risk factors for MDD include

maternal infections, childhood maltreatment and negative life events [5-7, 43, 44]. However,

few genetic studies have such information and even fewer prospective studies exist.

Incorporation of stressful life events has been shown to improve the ability to predict

MDD [45, 46] and, although stress is an environmental risk factor, it may have an

independent genetic contribution to risk of depression [46-50].

These studies suggest that a genetic variable derived from the difference in neuroticism

levels seen in individuals with MDD compared to controls may allow us to identify genetic

loci important for stress-sensitivity. We sought to identify the genetic underpinnings of

individual's sensitivity to stress response (stress-sensitivity) by identifying variants that

contribute to the higher neuroticism levels seen in individuals with a lifetime diagnosis of

MDD. Further, polygenic risk scores (PRS) derived from this stress-sensitivity variable may

improve prediction of MDD over that based on MDD or neuroticism PRS alone.

Using unrelated individuals from two large population-based samples, UK Biobank (UKB; N =

23,092) and Generation Scotland: Scottish Family Health Study (GS:SFHS; N = 7,155), we

sought to identify genes involved in stress-sensitivity by performing GWIS for the interaction

between MDD status and SNP allele on neuroticism score. We identified a gene significantly

associated with stress-sensitivity and show that a PRS derived from the interaction term of

the GWIS, significantly predicts liability to depression independently of the PRS for MDD

and/or neuroticism.

108 Materials and methods

109 UK Biobank (UKB) Participants

UKB is a major national health resource that aims to improve the prevention,

diagnosis and treatment of a wide range of illnesses. It recruited more than 500,000

participants aged from middle to older age who visited 22 assessment centres across the UK

between 2006 and 2010. Data were collected on background and lifestyle, cognitive and

physical assessments, sociodemographic factors and medical history. The scientific rationale,

study design, ethical approval, survey methods, and limitations are reported elsewhere [51,

52]. UKB received ethical approval from the NHS National Research Ethics Service North West

(Research Ethics Committee Reference Number: 11/NW/0382). All participants provided

informed consent. The present study was conducted on genome-wide genotyping data

available from the initial release of UKB data (released 2015). Details of sample processing

specific   to   UKB   project   are   available   at

http://biobank.ctsu.ox.ac.uk/crystal/refer.cgi?id=155583   and   the   Axiom   array   at

http://media.affymetrix.com/support/downloads/manuals/axiom_2_assay_auto_workflow_

user_guide.pdf. UKB genotyping and the stringent QC protocol applied to UKB data before it

was released can be found at http://biobank.ctsu.ox.ac.uk/crystal/refer.cgi?id=155580. SNPs

genotyped on GS:SFHS were extracted from the imputed UKB genotype data [53] (imputed

by UKB using a merged panel of the UK10K haplotype reference panel and the 1000

Genomes Phase 3 reference panel) with quality > 0.9 was hard-called using PLINK v1.9 [54].

Individuals were removed based on UKB genomic analysis exclusion (UKB Data Dictionary

item #22010), non-white British ancestry (#22006: genetic ethnic grouping; from those

individuals who self-identified as British, PCs analysis was used to remove outliers), high

genotype missingness (#22005), genetic relatedness (#22012; no pair of individuals have a

KING-estimated kinship coefficient > 0.0442), QC failure in UK BiLEVE study (#22050 and

#22051: UK BiLEVE Affymetrix and UK BiLEVE genotype quality controls for samples) and

gender mismatch (#22001: genetic sex). Further, from the initial release of UKB data and

using PLINK pi-hat < 0.05, individuals who were also participants of GS:SFHS and their

relatives were excluded to remove any overlap of individuals between discovery and target

samples. A dataset of 109,283 individuals with 557,813 SNPs remained for further analysis,

aged 40-79 (57,328 female, 51,954 male; mean age = 57.1 years, s.d. = 7.99), of which

109,282 had data available for neuroticism score and 23,092 had data available on MDD

status (n_{cases} = 7,834, $n_{controls}$ = 15,258, n_{female} = 11,510, n_{male} = 11,582; mean age = 57.7 years,

s.d. = 8.04). Thus, the final dataset comprised 23,092 unrelated individuals.

Generation Scotland Scottish Family Health Study (GS:SFHS)

Participants

GS:SFHS is a family-based genetic epidemiology study which includes 23,960 participants from ~ 7,000 Scottish family groups collected by a cross-disciplinary collaboration of Scottish medical schools and the National Health Service (NHS) from Feb 2006 to Mar 2011. Participants were interviewed and clinically assessed for a wide range of health-related traits (including high-fidelity phenotyping for Major Depressive Disorder and related endophenotypes), environmental covariates and linked to routine health records [55, 56]. All components of GS:SFHS obtained ethical approval from the Tayside Committee on Medical Research Ethics on behalf of the NHS (Research Ethics Committee Reference Number: 05/S1401/89) and participants provided written consent. The protocol for recruitment is described in detail in previous publications [57, 58]. GS:SFHS genotyping and quality control is detailed elsewhere [59]. Briefly, individuals with more than 2% missing genotypes and sex discrepancies were removed, as well as population outliers. SNPs with genotype missingness > 2%, minor allele frequency < 1% and a Hardy-Weinberg Equilibrium test $p < 1 \times 10^{-6}$ were exclude. Finally, individuals were removed based on relatedness (pi-hat < 0.05), maximizing retention of case individuals, using PLINK v1.9 [54]. Genome-wide SNP data for further analysis comprised 7,233 unrelated individuals genotyped for 560,698 SNPs (n_{female} = 3,476, n_{male} = 3,757; PLINK v1.9 [54]), aged 18-92 (mean age = 50.4 years, s.d. = 12.06) of which: 7,190 had clinical data on MDD; 7,196 individuals had data on neuroticism; and 7,155 had data on both neuroticism and MDD.

Phenotype assessment

Neuroticism score (EPQN)

Participants in both UKB and GS:SFHS cohorts were assessed for neuroticism using 12

questions from the Eysenck Personality Questionnaire-Revised Short Form's Neuroticism

Scale (EPQN) [60-63]. Neuroticism can be scored by adding up the number of "Yes" responses

on EPQN. This short scale has a reliability of more than 0.8 [64]. EPQN distributions were

found to be sufficiently "normal" after assessment for skewness and kurtosis to be analysed

using linear regression (both coefficients were between -1 and 1).

MDD diagnoses

In UKB depressive symptoms were assessed by items relating to the lifetime experience of

minor and major depression [60], items from the Patient Health Questionnaire [65] and items

on help-seeking for mental health [63]. Controls were defined as those who a) answered

"No" to the question "Ever depressed for a whole week" or b) who reported symptoms but

duration was too short (< 2 weeks) or who did not report having seen a GP or psychiatrist for

nerves, anxiety, tension or depression. In our unrelated sample, 7,834 participants were

diagnosed with MDD (with single, moderate or recurrent episodes) and 15,258 were controls

(N = 23,092).

In GS:SFHS, participants who answered yes to either of two screening questions were

assessed for psychiatric, mood state/psychological distress, personality and cognitive

assessment by trained researchers using the Structured Clinical Interview for DSM-IV Non-

Patient Version (SCID) [66]. In our unrelated GWIS sample (N = 7,155), 2,010 had a lifetime

diagnosis of MDD and 5,145 were controls.

Statistical Methods

GWIS and derivation of a genetic stress-sensitivity effect

The effect size of an stress-sensitivity effect (β_{SS}) was derived by performing a GWIS

for the effect of the MDD status and SNP allele on EPQN (dependent variable) in both UKB

and GS:SFHS cohorts using PLINK 1.90 (PLINK-command --gxe; fitting MDD diagnosis as a

binary "group" effect) [54]. PLINK-command --gxe estimates the difference in allelic

association with a quantitative trait (EPQN) between two groups (MDD cases vs. controls)

producing effect estimates on each group and a test of significance for the interaction

between SNP allele and MDD status. The interaction p value reflects the difference between

the regression coefficient of the allelic effect in a linear model for EPQN in MDD cases (β_A)

and the same regression coefficient in a linear model for EPQN in controls (β_B). The stress-

sensitivity interaction effect was defined as the difference in allele effect between MDD

cases and control groups.

Considering one SNP, the effect it confers to EPQN can be modelled by MDD status (control =

0, MDD case = 1) as follows:

$$\begin{cases} MDD = 0; \ EPQN = \beta_0 + \beta_B SNP + \beta_{0c} COV + \varepsilon \\ MDD = 1; \ EPQN = \beta_1 + \beta_A SNP + \beta_{1c} COV + \varepsilon \end{cases}$$

204 This is equivalent to modelling the effect on MDD cases as follows:

$$\begin{cases} MDD = 0; \ EPQN = \beta_0 + \beta_B SNP + \beta_{0c} COV + \varepsilon \\ MDD = 1; \ EPQN = \beta_1 + \beta_B SNP + (\beta_A - \beta_B)SNP + \beta_{1c} COV + \varepsilon \end{cases}$$

205 Or, it can be modelled as a whole as:

$$EPQN = \beta_0 + \beta_2 MDD + \beta_B SNP + (\beta_A - \beta_B)SNP * MDD + \beta_{0c} COV + \beta_{2c} COV * MDD + \varepsilon$$

206 Where COV stands for covariates, β_2 stands for $\beta_1 - \beta_0$, and β_{2c} stands for $\beta_{1c} - \beta_{0c}$.

207 Thus, the interaction effect (β_{SS}) can be estimated as the difference in allelic effect on EPQN

208 between MDD cases (β_A) and controls (β_B) as follows,

$$\hat{\beta}_{SS} = \hat{\beta}_A - \hat{\beta}_B$$

$\hat{\beta}_{SS}$ is therefore defined as the effect size reflecting the genetic stress-sensitivity effect on

MDD cases compared to controls (S1 Fig).

Stress-sensitivity GWIS, main additive effect GWASs, meta-analysis and gene-

set analysis.

For GWIS and subsequent analyses, sample specific covariates were applied as

follows: *UKB.* All phenotypes were adjusted for centre, array and batch as random effects

prior to analyses. Analyses were adjusted for age, sex and 15 informative principal

components (PCs; UKB Data Dictionary items #22009.01 to #22009.15) as fixed effects to

take account of possible population stratification. *GS:SFHS.* All the analyses were adjusted for

age, sex and 20 PCs.

GWAS for MDD and neuroticism, using logistic and linear models of additive allelic effects

respectively, were conducted on the same sample sets for comparison and generation of

matched PRS using PRSice-2 [67].

Results from the GWIS of UKB and GS:SFHS were combined in a sample size weighted meta-

analysis performed using METAL [68]. While the use of standard error weighting is more

common, the different diagnostic scheme and MDD prevalence between the two cohorts

(GS:SFHS; 12.2%, UKB: 25.8%) [57, 63] may indicate systematic differences in the

measurement of MDD. Generalized gene-based analysis of the meta-analysis was performed

using MAGMA [69] implemented through FUMA [70] (http://fuma.ctglab.nl). Briefly, SNP

summary statistics were mapped to 17,931 protein-coding genes. Individual SNP *p* values

from a gene were combined into a gene test-statistic using a SNP-wise model and a known

approximation of the sampling distribution used to obtain a gene-based *p* value. Genome-

wide significance was defined at $p = 0.05/17,931 = 2.79 \times 10^{-6}$.

LD Score regression

The summary statistics from the meta-analysis were used to examine the genetic

overlap between the polygenic architecture of stress-sensitivity, MDD and neuroticism. LD

score regression was used to derive the genetic correlations (r_G) between these traits [71, 72]

using meta-analysed GWAS and GWIS summary statistics. SNP-based heritability was also

estimated using LD score regression, which only requires summary statistics from single-SNP

analyses.

Pathway, functional and gene expression analyses

Lead SNPs, independently associated with the phenotype, were identified using PLINK

1.90 by clumping (*p* threshold $< 2 \times 10^{-5}$; LD r2 > 0.1; physical kb threshold = 500kb; 1000

Genomes Project Phase 1 CEU, GBR, TSI genotype data), and analysed using DEPICT [73].

Further detail is given in 'DEPICT analyses' in S1 Supporting Information.

Genes associated with lead SNPs were investigated for evidence of: phenotypic association in

the   NCBI   dbGaP   database   of   genotypes   and   phenotypes [74]

(https://www.ncbi.nlm.nih.gov/gap/phegeni), regulatory DNA elements in normal cell lines

and association with expression quantitative trait loci (eQTLs) using the RegulomeDB

database [75] (http://www.regulomedb.org) and the Genotype-Tissue Expression (GTEx)

Portal [76] (http://www.gtexportal.org).

Polygenic profiling

PRS were produced using PRSice-2 [67], permuted 10,000 times and standardized to a mean of 0 and a standard deviation of 1. Using GWIS summary statistics, we created PRS for stress-sensitivity (PRS_{SS}) by weighting the sum of the reference alleles in an individual by the stress-sensitivity effect (β_{SS}). Additional PRS were generated weighting by MDD main additive effects (PRS_D) and neuroticism main additive effects (PRS_N) using GWAS summary statistics from GS:SFHS or UKB. In addition, PRS_D and PRS_N were also generated using summary statistics from the most recent Psychiatric Genetic Consortium (PGC) MDD meta-analysis [42] (excluding GS:SFHS, and UKB individuals when required; N = 155,866 & 138,884) and the Genetics of Personality Consortium (GPC) neuroticism meta-analysis [24, 77] (N = 63,661). Generalized linear models were implemented in R 3.1.3 [78]. The direct effect of PRS_{SS} (model 1), PRS_D (model 2) and PRS_N (model 3) on MDD risk were assessed in independent logistic regression models on GS:SFHS (target cohort) using GWAS and GWIS statistics from UKB (the largest cohort) as the discovery sample to weight PRS. Multiple regression models fitting both PRS_D and PRS_N (model 4) and fitting each of them separately with PRS_{SS} (models 5 and 6) were also calculated. Finally, full additive multiple regression models fitting PRS weighted by all three effects (full model) was assessed using both PRS_{SS}, PRS_D and PRS_N at their best-fit in independent models. Further, results were also assessed using PRS_D and PRS_N weighted by PGC2 MDD [42] and GPC neuroticism [77] summary statistics. Further detail is given in 'Polygenic Profiling' in S1 Supporting Information. All models were adjusted by sex, age and 20 PCs. A null model was estimated from the direct effects of all covariates on MDD. 10,000 permutations were used to assess significance of each PRS. The predictive improvement of combining the effects of multiple PRS over a single PRS alone was tested for significance using the likelihood-ratio test.

Cross-validation was performed using UKB as target sample and GS:SFHS as discovery

sample. Additional analyses using PRS_D and PRS_N weighted by PGC2 MDD [42] and GPC

neuroticism [77] summary statistics were also tested. MDD status on UKB was adjusted by

centre, array and genotyping batch as random effects and scaled (between 0 and 1) prior to

analysis, giving a quasi-binomial distribution of MDD status on UKB. Models implemented on

UKB (quasi-binomial regression) were adjusted by sex, age and 15 PCs. Nagelkerke's R^2

coefficients were estimated to quantify the proportion of MDD liability explained at the

observed scale by each model and converted into R^2 coefficients at the liability scale

(prevalence: 12.2% in GS:SFHS [57] and 25.8% in UKB [63]) using Hong Lee's

transformation [79] available from GEAR: GEnetic Analysis Repository [80].

Using stress-sensitivity to stratify depression

GS:SFHS MDD cases (n_{cases} = 2,016; n_{female} = 1,345, n_{male} = 671) have data available on

MDD course (single or recurrent), age of onset (n = 1,964) and episode count (n = 2,016), as

well as on neuroticism (n = 2,010). In addition, a subset were evaluated by Mood Disorder

Questionnaire [81] (MDQ; n = 1,022) and Schizotypal Personality Questionnaire [82] (SPQ; n =

1,093). The reduced sample number of MDQ and SPQ reflects the later addition of these

questionnaires to the study and does not reflect a particular subgroup of GS:SFHS.

Difference in PRS_{SS} and PRS_D between MDD cases and controls on GS:SFHS were tested using

a Student's two sample t-test (two tailed). Cases of MDD on GS:SFHS with data available on

each trait analyzed were stratified by quintiles based on PRS_{SS} and PRS_D (5x5 groups). Post

hoc, the effects on each trait of quintiles based on PRS_{SS} and its interaction effect with

quintiles based on PRS_D were assessed using linear regression models adjusting by sex and

age in an attempt to identify a characteristic subtype of MDD patients with differential

stress-sensitivity levels. The same analysis was reproduced using PRSs as continuous

variables.

Results

We confirmed the elevated neuroticism score in MDD cases in our samples.

Individuals with a diagnosis of MDD had significantly higher EPQN scores compared to

healthy controls (all $p < 1.9 \times 10^{-279}$) in both GS:SFHS (mean$_{controls}$ = 3.16; mean$_{cases}$ = 6.42) and

UKB (mean$_{controls}$ = 2.79; mean$_{cases}$ = 5.64). Neuroticism levels differ significantly between

males and females. To control for this and any age/polygenic effects, which may account for

differences in the prevalence of MDD, we created a matched set of cases and controls. The

difference in neuroticism levels between cases and controls remained significant after

matching for PGC PRS$_D$, sex and age. (GS:SFHS: mean$_{controls}$ = 3.51; UKB: mean$_{controls}$ = 2.97; all

$p < 2.7 \times 10^{-158}$; S1 Table).

Meta-analysis of stress-sensitivity in UKB and GS:SFHS

No SNPs were associated with stress-sensitivity at the genome-wide significant

threshold ($p < 5 \times 10^{-8}$, Fig 1). However, 14 SNPs from 8 loci achieved suggestive p value ($p <$

1×10^{-5}) ranging between $p = 8.9 \times 10^{-6}$-5.1×10^{-7} (Meta-analysis: Table 1; UKB and GS:SFHS: S2

and S3 Tables; Meta-analysis QQ-plot with λ: S2 Fig; UKB and GS:SFHS QQ-plots: S3 Fig).

Traits with prior evidence of association with the nearest genes to the 8 lead SNPs were

identified using dbGap and are shown in S4 Table. Comparison between the SNP association

profile along the genome between stress-sensitivity GWIS and MDD GWAS meta-analyses is

shown in Miami plots filtering for the most significant stress-sensitivity or MDD SNPs ($p <$

0.001; Meta-analysis: Fig 2; UKB and GS:SFHS: S4 Fig). No SNP with a *p*-value < 0.01 had a

corresponding p-value in the alternate trait, suggesting that different variants contribute to

depression and stress-sensitivity. Gene-based test identified *ZNF366* as the only gene

achieving genome-wide significance ($p = 1.48 \times 10^{-7}$; Bonferroni-corrected significance

threshold $p < 2.79 \times 10^{-6}$; S5 Table and S5 Fig). Using summary statistics from meta-analysis

GWIS results, stress-sensitivity SNP-based heritability was estimated from LD score

regression at 5.0% ($h^2 = 0.0499$, s.e. = 0.017, $p = 1.67 \times 10^{-3}$). Conversely, the SNP-based

heritability for MDD and neuroticism were estimated at 9.6% ($h^2 = 0.0962$, s.e. = 0.0179, $p =$

3.87×10^{-8}) and 10.1% ($h^2 = 0.1006$, s.e. = 0.0076, $p = 3.47 \times 10^{-40}$) respectively, using summary

statistics from the meta-analysed GWAS of UKB and GS:SFHS.

Fig 1. Manhattan plots showing stress-sensitivity associations.

Manhattan plots of the GWIS from (A) UKB, (B) GS:SFHS and (C) sample size weighted meta-

analysis of UKB and GS:SFHS. The x-axis is chromosomal position and y-axis is the *p* value (-

log10 *p* value) of association with stress-sensitivity effect. Suggestive genome-wide

significance threshold ($p = 1 \times 10^{-5}$) is shown by solid line at y = 5. Genes or closest gene up-

and down-stream from SNP position (/) are annotated. "-": No gene within 100kb of the SNP.

Fig 2. Miami plots showing comparison between association profile between stress-

sensitivity GWIS and MDD GWAS.

Miami plots from meta-analysis filter at $p = 1 \times 10^{-3}$: (A) filtering for stress-sensitivity *p* values

(•), (B) filtering for MDD *p* values (×). The x-axis is chromosomal position and y-axis is the *p*

value (-log10 *p* value) of association with stress-sensitivity (up; red dots) and MDD *p* value

(down; blue crosses). Dot line: genome-wide suggestive threshold ($p = 1\mathrm{x}10^{-5}$) at the filtered

effect; dashed lines: $p = 0.01$ and 0.05 at unfiltered effect.

Table 1. Top 25 SNPs from meta-analysis of GWISs.

Rank	CHR	SNP	BP	A1	Z-score	Effect[a]	p[b]	p (EPQN)[c]	p (MDD)[d]	GENE	POSITION[e]
1	6	rs319924	64487247	A	5.024	++	5.05×10^{-7}	0.376	0.637	EYS	Intronic
2	5	rs246565	71809247	A	-4.684	--	2.82×10^{-6}	0.248	0.589	ZNF366	5998bp 5'
3	10	rs2265265	24854876	A	4.604	++	4.15×10^{-6}	0.035	0.084	KIAA1217 / ARHGAP21	18104bp 3' / 17662bp 3'
4	6	rs1057530	64427095	A	-4.556	--	5.21×10^{-6}	0.636	0.840	PHF3/EYS	1677bp 3' / 2781bp 3'
5	16	rs7199110	78790765	A	-4.553	--	5.29×10^{-6}	0.661	0.741	WWOX	Intronic
6	6	rs10485358	64386060	A	-4.546	--	5.46×10^{-6}	0.390	0.902	PHF3	Intronic
7	12	rs10778077	101193988	A	4.54	++	5.62×10^{-6}	0.614	0.430	ANO4	Intronic
8	5	rs13358894	71803446	A	4.527	++	5.99×10^{-6}	0.257	0.651	ZNF366	197bp 5'
9	10	rs2256220	24856314	A	-4.524	--	6.06×10^{-6}	0.134	0.129	KIAA1217 / ARHGAP21	19542bp 3' / 16224bp 3'
10	10	rs3762096	98136250	A	-4.521	--	6.15×10^{-6}	0.437	0.149	TLL2	Intronic
11	11	rs2221540	132716369	A	-4.492	--	7.05×10^{-6}	0.468	0.364	OPCML	Intronic
12	5	rs10043659	71781839	A	4.483	++	7.37×10^{-6}	0.339	0.808	ZNF366	Intronic
13	12	rs10778078	101195088	A	-4.45	--	8.58×10^{-6}	0.599	0.456	ANO4	Intronic
14	9	rs10987199	128968987	A	-4.442	--	8.91×10^{-6}	0.199	0.026	LOC101929116	63416bp 3'
15	5	rs10042132	71789021	A	-4.416	--	1.01×10^{-5}	0.418	0.538	ZNF366	Intronic
16	11	rs10894606	132671611	A	-4.404	--	1.06×10^{-5}	0.438	0.587	OPCML	Intronic
17	12	rs7295089	2440464	A	4.372	++	1.23×10^{-5}	0.266	0.212	CACNA1C	Intronic
18	5	rs9293292	71696942	A	-4.351	--	1.36×10^{-5}	0.126	0.731	PTCD2/ZNF366	41762bp 3' / 42292bp 3'
19	15	rs3097437	27872136	A	4.346	++	1.38×10^{-5}	0.970	0.226	GABRG3	93762bp 3'
20	9	rs1999377	11919732	A	4.344	++	1.40×10^{-5}	0.436	0.064	-	Intragenic
21	5	rs6862221	71754962	A	4.342	++	1.41×10^{-5}	0.543	0.823	ZNF366	Intronic
22	5	rs9293289	71683885	A	-4.323	--	1.54×10^{-5}	0.395	0.510	PTCD2/ZNF366	28705bp 3' / 55349bp 3'
23	11	rs4575282	132719646	A	-4.313	--	1.61×10^{-5}	0.598	0.514	OPCML	Intronic
24	9	rs2417008	128970219	A	-4.3	--	1.71×10^{-5}	0.208	0.026	LOC101929116	62184bp 3'
25	9	rs7021461	128972210	A	4.299	++	1.72×10^{-5}	0.202	0.025	LOC101929116	60193bp 3'

[a]Effect direction in GS:SFHS and UK Biobank. [b,c,d]Significances of: [b]GWIS stress-sensitivity effect; [c]SNP main effect on neuroticism derived from GWAS meta-analysis of EPQN between UK Biobank and Generation Scotland; [d]SNP main effect on MDD derived from GWAS meta-analysis of MDD between UK Biobank and Generation Scotland. [e]Position of the SNP respect to closest gene transcripts within 100kb (including UTRs) from 5 prime (5') or 3prime (3').

LD score regression was performed to obtain genetic correlations between stress-sensitivity,

MDD and neuroticism. As previously shown, there was a significant genetic correlation

between MDD and neuroticism (r_G = 0.637, s.e. = 0.0704, p = 1.39x10^{-19}). However, we found

no evidence for a genetic correlation between stress-sensitivity and MDD (rG = -0.099, s.e. =

0.182, p = 0.585) or between stress-sensitivity and neuroticism (r_G = 0.114, s.e. = 0.107, p =

0.285).

Pathway enrichment, functional annotation and gene expression analyses

Lead SNPs from the GWIS meta-analysis were investigated using DEPICT. No gene

showed statistically significant links to stress-sensitivity at a DEPICT false discovery rate (FDR)

< 0.05. No significant result was found for either gene set analysis or tissue enrichment

analysis at FDR < 0.05. Evidence of regulatory elements on normal cell lines/tissues was

identified for 5 of the 12 lead SNPs (i.e. rs3762096, rs10987199, rs2221540, rs246565,

rs319924). Two lead SNPs were associated with eQTLs: rs319924 (an intronic SNP in *EYS*) and

rs9509508 (an intronic SNP in *LATS2*) and potentially regulate *LGSN/RP3-407E4.3* (p =

6.31x10^{-12}/ p = 1.15x10^{-5}) and *LATS2* (p = 3.74x10^{-8}), respectively.

Polygenic risk scores for stress-sensitivity predict MDD liability

PRS were used to investigate whether common variants affecting stress-sensitivity

predict MDD risk. We generated PRS (PRS$_{SS}$) for stress-sensitivity based on the summary

statistics from the GWIS. After 10,000 permutations, PRS$_{SS}$ significantly predicted MDD risk in

GS:SFHS using weights from the larger UKB summary data (Empirical-p = 0.04; p = 5.2x10^{-3}; β

= 0.078, s.e. = 0.028; best-fit p threshold = 0.005; S6 Table). On the liability scale, the MDD

variance explained in GS:SFHS by PRS_{SS} was modest (R^2 = 0.195%). This was less than

predicted by PRS weighted by the genetic main effects of MDD or neuroticism (PRS_D: R^2 =

0.368%; PRS_N: R^2 = 0.459%; Table 2 and S6 Table). However, this association was not cross-

validated in UKB using summary data from the smaller GS:SFHS GWIS (Empirical-p = 0.68; p =

0.23; β = 0.004, s.e. = 0.003; best-fit p threshold = 0.005; PRS_{SS} R^2 = 0.013%; S6 Table), likely

due to lack of power as a result of the small discovery sample size. PRS_D (R^2 = 0.204%) and

PRS_N (R^2 = 0.166%) derived from GS:SFHS also significantly predicted MDD in UKB (Table 2

and S6 Table).

Table 2. MDD risk prediction at best fits.

UKB predicting on GS:SFHS

Weighted effect	Best fit threshold	# SNPs	R^2 (%)[d]	R^2 (%)[e]	p	Empirical-p
Stress-sensitivity	0.005	1,626	0.141	0.195	5.2×10^{-3}	0.0399
MDD[a]	0.1	22,771	0.265	0.368	1.3×10^{-4}	0.0015
EPQN[b]	0.4	65,276	0.330	0.459	1.8×10^{-5}	0.0002
MDD[a] + EPQN[b]	-	-	0.503	0.699	8.0×10^{-7}	-
joint models[c]	-	-	0.627	0.871	1.2×10^{-7}	-

PGC2 & GPC predicting on GS:SFHS

PGC2 MDD[a]	1	92,248	0.993	1.378	1.4×10^{-13}	≤0.0001
GPC EPQN[b]	0.01	3,521	0.108	0.149	0.014	0.1038
PGC2 MDD + GPC EPQN[b]	-	-	1.052	1.461	1.7×10^{-13}	-
joint models[c]	-	-	1.203	1.671	1.6×10^{-14}	-

GS:SFHS predicting on UKB

Weighted effect	Best fit threshold	# SNPs	R^2 (%)[a]	R^2 (%)[b]	p	Empirical-p
Stress-sensitivity	0.005	1,526	0.008	0.013	0.231	0.6841
MDD[a]	0.03	7,725	0.130	0.204	1.6×10^{-6}	≤0.0001
EPQN[b]	0.05	12,296	0.106	0.166	1.6×10^{-5}	0.0005
MDD[a] + EPQN[b]	-	-	0.197	0.309	2.8×10^{-8}	-
joint models[c]	-	-	0.206	0.322	6.6×10^{-8}	-

PGC2 & GPC predicting on UKB

PGC2 MDD[a]	0.5	64,113	0.919	1.440	3.4×10^{-37}	<0.0001
GPC EPQN[b]	0.03	8,761	0.066	0.104	6.5×10^{-4}	0.006
PGC2 MDD[a] + GPC EPQN[b]	-	-	0.950	1.488	2.9×10^{-37}	-
joint models[c]	-	-	0.958	1.501	1.5×10^{-36}	-

[a]major depressive disorder, [b]neuroticism score, [c]combined effect fitting all 3 PRS weighted by all the effects (i.e. stress-sensitivity, MDD and EPQN), [d]Nagelkerke's R^2 at observed scale, [e]R^2 on the liability scale.

Due to the known genetic correlations between MDD, neuroticism and stressful life events [21],

models jointly fitting the effects of multiple PRS were analysed. Multiple regression analyses in

GS:SFHS showed that, compared to PRS_D effects alone, stress-sensitivity effect derived from the

UKB GWIS effects significantly explains an additional 0.195% (a predictive improvement of 53.1%,

$p = 5.1 \times 10^{-3}$; PRS_D: β = 0.112, s.e. = 0.029; PRS_{SS} : β = 0.078, s.e. = 0.028). The inclusion of PRS_{SS} in

the full model, where PRS_{SS} was fitted along with both PRS_D and PRS_N weighted by GWAS summary

statistics derived from UKB remained significant; explaining an additional 0.172% (a predictive

improvement of 24.6%, $p = 8.5 \times 10^{-3}$; PRS_D: β = 0.093, s.e. = 0.029; PRS_N: β = 0.107, s.e. = 0.030;

PRS_{SS}: β = 0.073, s.e. = 0.028). In models fitting PRS_D and PRS_N, the variances explained were non-

additive, demonstrating the partial overlap between MDD risk prediction from PRS_D and PRS_N main

additive effects. This is consistent with the known genetic correlation between these two traits. An

overlap was not seen between the variance explained by PRS_{SS} effect and the variance explained

by PRS_D and/or PRS_N. Multiple regression analyses fitting PRS_D and PRS_N derived from worldwide

consortiums (Fig 3) showed that the increased sample size from GWAS used to derive PRS_D

resulted in an increment of MDD variance explained in GS:SFHS by PRS_D (from 0.368% to 1.378%).

However, there was no change in the proportion of the variance explained by the PRS_{SS} in the full

model (PRS_{SS} $p = 3.5 \times 10^{-3}$). These results suggest that PRS_{SS} explains a proportion of MDD risk not

accounted for by PRS_D or PRS_N at current sample sizes. However, these findings were not cross-

validated in UKB using PRS_{SS} derived from GS:SFHS GWIS, likely due to lack of power as a result of

the small discovery sample size (S6 Fig).

Fig 3. MDD is best predicted using multiple PRS.

MDD risk explained (R^2 coefficient (%); top bar values) on the liability scale by each PRS in GS:SFHS;

weighted by GWAS main additive and GWIS stress-sensitivity effects independently and combined.

(A) Using summary statistics from UKB as discovery sample. There is an increment on MDD risk

prediction from adding PRS_{SS} to PRS_D model of 53.1% and 24.6% when combining PRS_{SS} with both

MDD and neuroticism PRS. (B) Replication of fitting PRS_D and PRS_N using summary statistics from

worldwide consortiums (i.e. PGC &GPC). Significance codes: p values *** < 0.001 < ** < 0.01 < * <

0.05 < • < 0.1; derived from likelihood ratio tests. *SS* stands for stress-sensitivity.

Using stress-sensitivity to stratify MDD in GS:SFHS

MDD cases show significantly higher PRS_{SS} (p = $2x10^{-3}$) and PRS_D (p = $1.8x10^{-4}$) than

controls. Association between MDD-related traits and stress-sensitivity risk quintiles was assessed

on MDD cases in order to identify a subgroup of MDD patients, perhaps defining a characteristic

aetiological subtype of MDD. However, stratification analysis failed, and no quintile based on PRS_{SS}

nor its interaction with quintiles based on PRS_D showed statistically significant effects on any trait

analyzed. Individuals with high PRS_{SS} were not significantly different from other cases for sex, MDD

course, age of onset or episode count, nor neuroticism, mood disorder or schizotypal personality

scores (p > 0.05; S7 table). Results remained non significant when PRSs were fitted as continuous

variables (p > 0.05).

Discussion

The existence of genetic variants affecting an individual's risk of depression in response to stress has been predicted previously [46, 49, 50] and is consistent with the departure from a simple additive genetic model seen in twin-studies of recurrent depressive disorder [83]. Through international research efforts such as the PGC and UK Biobank, there are ever-increasing sample sizes available for understanding the genetics of MDD. These resources are beginning, and will continue to, identify genome-wide significant loci [42, 84, 85]. However, the lack of environmental data and/or their reliability, makes the study of genetic individual's response to their negative effects, and their contribution to the onset of MDD and other stress-related disorders, difficult. As a way to address this limitation, we generated a proxy for stress-sensitivity through modelling the interaction between SNP allele and MDD status on neuroticism score in a GWIS approach. Thus, we sought to identify the genetic underpinnings of individual's sensitivity to stress response (stress-sensitivity) through those variants that contribute to higher neuroticism levels only in individuals with a lifetime diagnosis of MDD but not in healthy controls.

We performed a GWIS to identify loci showing differential effects on neuroticism scores in individuals with and without MDD (so called stress-sensitivity proxy). No SNPs reached genome-wide significance, but 14 SNPs from 8 loci reached suggestive significance levels (see S4 Table for prior evidence of associated phenotypes). Enrichment analysis showed no evidence for enrichment of specific pathways or tissues. The top two loci, *PTP4A1-PHF3-EYS* and *ZNF366* have been previously associated with alcohol dependence [86-90], alcohol intake (dbGaP: phs000342) and glucocorticoid receptor function [91-93]. The most significant SNP in this study, rs319924, is an intronic variant in *EYS* that is a potential eQTL for *LGSN* [76], a gene previously associated with male-specific depression [94]. This is of particular interest given previous studies linking alcohol

consumption, stress and the risk of depression [95-100]. However, findings should be interpreted

with caution, as these loci did not reach genome-wide significance at current sample size.

Evidence of an eQTL effect was predicted for a lead SNP in *LATS2*, a positive regulator of histone

methyltransferase activity [101] a process important in anxiety-related behaviours [102]. The prior

association of the top two loci in this study with alcohol related-phenotypes suggests that genes

involved in the sensitivity to stress may mediate the effects of stress on alcohol consumption.

Some *PHF3* paralogs have been shown to be linked with depression and modulate stress

response [103, 104].

Gene-based analysis identified a genome-wide significant association between *ZNF366* and stress-

sensitivity. *ZNF366* (also known as *DC-SCRIPT*) is a corepressor of transcription found in nuclear

receptor complexes including the glucocorticoid receptor. *ZNF366* represses glucocorticoid

receptor-mediated transcription in monocyte-derived dendritic cells [91]; and may act through

histone deacetylases to modulate immune response [92]. There is evidence from a large-scale

mRNA display study that *PHF3*, in the region underlying the most significant peak in the single SNP

analysis, may also interact, directly or indirectly, with the glucocorticoid receptor (IntAct

database [93]) but this has not been confirmed. These results reinforce the hypothesis that our

proxy for stress-sensitivity truly reflects the genetic architecture of sensitivity to respond to stress.

We estimated a significant lower bound on common SNP-based heritability for stress-sensitivity of

5%. Whilst the known genetic overlap between MDD and neuroticism was detectable, the lack of

genetic correlation with stress-sensitivity, reinforced by results from multiple regression analyses,

indicated a lack of significant overlap in the genetics factors underpinning stress-sensitivity and

MDD or neuroticism. This analysis may be limited by our sample size, although using the largest

available meta-analyses of MDD and neuroticism [42, 77] did not decrease the proportion of

liability explained by the PRS_{SS}. We note, that as such meta-analyses increase in size it is likely, as

with the effects of smoking in schizophrenia [105, 106], that the indirect genetic effects of the

environment on the risk of depression will be detected by GWAS. However, through studies such

as ours, or similar, the mechanism for the effect of the risk alleles may be clarified.

Further, we show that such genetic information in stress-sensitivity could significantly improve the

proportion of liability to MDD predicted by PRS based only on additive genetic effects on MDD

identified by large GWAS. The summary results from the GWIS were used to derive a PRS

reflecting the genetic difference in stress-sensitivity. This variable significantly predicted liability to

MDD in GS:SFHS (p = 5.2x10^{-3}, Empirical-p = 0.04 after 10,000 permutations), although this finding

could not be replicated in UKB (Empirical-p = 0.68), likely due to lack of power. This is consistent

with the expectation that the larger the discovery sample (i.e. UKB), the greater the accuracy of

the weighting and the more predictive the PRS [107]. Multiple regression models in GS:SFHS

suggest that inclusion of PRS weighted by stress-sensitivity significantly improves MDD prediction

over use of either MDD and/or neuroticism weighted PRS alone (improvement in full model p =

8.5x10^{-3}). However, we were unable to identify a subgroup of MDD cases with higher PRS_{ss}. The

polygenic interaction approach used in our study may, therefore, improve the interpretation of

both positive and negative findings from GWAS studies (i.e. pathways and mechanisms involved,

lack of replication, or negative findings in variants mediating environmental effects). Added to

paralleling recent developments in GWAS analyses, it may maximize our power to detect gene-by-

environment effects in this heterogeneous disorder.

Future studies will be required to further investigate the effects of adverse life events in

individuals with high or low polygenic risk scores for stress-sensitivity. However, the methodology

presented allows addressing the genetic response to negative outcomes via proxy in the absence

of prospective environmental data.

Here we identify an independent set of risk variants for an individual's response to negative

outcomes and show that incorporating information across many loci provides clear and replicable

evidence for a genetic effect of stress-sensitivity on MDD risk; identifying a potential genetic link

with alcohol intake. These results require further study, but may inform treatment of comorbid

alcohol dependency and depression.

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References

1.   Monroe SM. Modern approaches to conceptualizing and measuring human life stress. Annu Rev Clin Psychol. 2008;4:33-52. doi: 10.1146/annurev.clinpsy.4.022007.141207. PubMed PMID: 17716038.

2.   Jeronimus BF, Riese H, Sanderman R, Ormel J. Mutual reinforcement between neuroticism and life experiences: a five-wave, 16-year study to test reciprocal causation. Journal of personality and social psychology. 2014;107(4):751-64. doi: 10.1037/a0037009. PubMed PMID: 25111305.

3.   Riese H, Snieder H, Jeronimus BF, Korhonen T, Rose RJ, Kaprio J, et al. Timing of Stressful Life Events Affects Stability and Change of Neuroticism. European Journal of Personality. 2014;28(2):193-200. doi: 10.1002/per.1929.

4.   Jeronimus BF, Ormel J, Aleman A, Penninx BW, Riese H. Negative and positive life events are associated with small but lasting change in neuroticism. Psychol Med. 2013;43(11):2403-15. doi: 10.1017/S0033291713000159. PubMed PMID: 23410535.

5.   Kendler KS, Kuhn J, Prescott CA. The interrelationship of neuroticism, sex, and stressful life events in the prediction of episodes of major depression. Am J Psychiatry. 2004;161(4):631-6. doi: 10.1176/appi.ajp.161.4.631. PubMed PMID: 15056508.

6.   Kessler RC. The effects of stressful life events on depression. Annu Rev Psychol. 1997;48:191-214. doi: 10.1146/annurev.psych.48.1.191. PubMed PMID: 9046559.

7.   Tennant C. Life events, stress and depression: a review of recent findings. Aust N Z J Psychiatry. 2002;36(2):173-82. doi: 10.1046/j.1440-1614.2002.01007.x. PubMed PMID: 11982537.

8.   Porcelli B, Pozza A, Bizzaro N, Fagiolini A, Costantini MC, Terzuoli L, et al. Association between stressful life events and autoimmune diseases: A systematic review and meta-analysis of retrospective case-control studies. Autoimmun Rev. 2016;15(4):325-34. doi: 10.1016/j.autrev.2015.12.005. PubMed PMID: 26708168.

9.   Lin Y, Wang C, Zhong Y, Huang X, Peng L, Shan G, et al. Striking life events associated with primary breast cancer susceptibility in women: a meta-analysis study. J Exp Clin Cancer Res. 2013;32(1):53. doi: 10.1186/1756-9966-32-53. PubMed PMID: 23941600; PubMed Central PMCID: PMCPMC3751759.

10.   Jafri SHR, Ali F, Mollaeian A, Hasan SM, Hussain R, Akkanti BH, et al. Major stressful life events and risk of developing lung cancer. Journal of Clinical Oncology. 2017;35(15_suppl):1575-. doi: 10.1200/JCO.2017.35.15_suppl.1575.

11.   Hasler G, Drevets WC, Manji HK, Charney DS. Discovering endophenotypes for major depression. Neuropsychopharmacology. 2004;29(10):1765-81. doi: 10.1038/sj.npp.1300506. PubMed PMID: 15213704.

12.   Bogdan R, Nikolova YS, Pizzagalli DA. Neurogenetics of depression: a focus on reward processing and stress sensitivity. Neurobiol Dis. 2013;52:12-23. doi: 10.1016/j.nbd.2012.05.007. PubMed PMID: 22659304; PubMed Central PMCID: PMCPMC3570616.

13.   Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. European Journal of Personality. 1987;1(3):141-69. doi: 10.1002/per.2410010304.

14.   Smith MA, Riccalton VC, Kelly-Hughes DH, Craw OA, Allen SF, O'Connor DB, et al. The relationship between Type D personality and physical health complaints is mediated by perceived stress and anxiety but not diurnal cortisol secretion. Stress. 2018:1-8. doi: 10.1080/10253890.2018.1435637. PubMed PMID: 29402161.

15.   Herr RM, Barrech A, Riedel N, Gundel H, Angerer P, Li J. Long-Term Effectiveness of
Stress Management at Work: Effects of the Changes in Perceived Stress Reactivity on Mental
Health and Sleep Problems Seven Years Later. Int J Environ Res Public Health. 2018;15(2).
doi: 10.3390/ijerph15020255. PubMed PMID: 29401657.
16.   Moore RC, Eyler LT, Mausbach BT, Zlatar ZZ, Thompson WK, Peavy G, et al. Complex
interplay between health and successful aging: role of perceived stress, resilience, and social
support. Am J Geriatr Psychiatry. 2015;23(6):622-32. doi: 10.1016/j.jagp.2014.08.004.
PubMed PMID: 25217186; PubMed Central PMCID: PMCPMC4329284.
17.   Hayman LW, Jr., Lucas T, Porcerelli JH. Cognitive appraisal vs. exposure-based stress
measures: links to perceived mental and physical health in low-income black women. J Nerv
Ment Dis. 2014;202(11):807-12. doi: 10.1097/NMD.0000000000000198. PubMed PMID:
25275345.
18.   Harris ML, Loxton D, Sibbritt DW, Byles JE. The influence of perceived stress on the
onset of arthritis in women: findings from the Australian Longitudinal Study on women's
health. Ann Behav Med. 2013;46(1):9-18. doi: 10.1007/s12160-013-9478-6. PubMed PMID:
23436274.
19.   Caspi A, Hariri AR, Holmes A, Uher R, Moffitt TE. Genetic sensitivity to the
environment: the case of the serotonin transporter gene and its implications for studying
complex diseases and traits. Am J Psychiatry. 2010;167(5):509-27. doi:
10.1176/appi.ajp.2010.09101452. PubMed PMID: 20231323; PubMed Central PMCID:
PMCPMC2943341.
20.   Bleys D, Luyten P, Soenens B, Claes S. Gene-environment interactions between stress
and 5-HTTLPR in depression: A meta-analytic update. J Affect Disord. 2018;226:339-45. doi:
10.1016/j.jad.2017.09.050. PubMed PMID: 29031184.
21.   Rietschel L, Zhu G, Kirschbaum C, Strohmaier J, Wust S, Rietschel M, et al. Perceived
stress has genetic influences distinct from neuroticism and depression. Behav Genet.
2014;44(6):639-45. doi: 10.1007/s10519-013-9636-4. PubMed PMID: 24366676.
22.   Rietschel L, Streit F, Zhu G, McAloney K, Frank J, Couvy-Duchesne B, et al. Hair Cortisol
in Twins: Heritability and Genetic Overlap with Psychological Variables and Stress-System
Genes. Sci Rep. 2017;7(1):15351. doi: 10.1038/s41598-017-11852-3. PubMed PMID:
29127340; PubMed Central PMCID: PMCPMC5703444.
23.   Glahn DC, Curran JE, Winkler AM, Carless MA, Kent JW, Jr., Charlesworth JC, et al. High
dimensional endophenotype ranking in the search for major depression risk genes. Biol
Psychiatry. 2012;71(1):6-14. doi: 10.1016/j.biopsych.2011.08.022. PubMed PMID: 21982424;
PubMed Central PMCID: PMCPMC3230692.
24.   van den Berg SM, de Moor MH, McGue M, Pettersson E, Terracciano A, Verweij KJ, et al.
Harmonization of Neuroticism and Extraversion phenotypes across inventories and cohorts in
the Genetics of Personality Consortium: an application of Item Response Theory. Behav Genet.
2014;44(4):295-313. doi: 10.1007/s10519-014-9654-x. PubMed PMID: 24828478; PubMed
Central PMCID: PMCPMC4057636.
25.   Wray NR, Birley AJ, Sullivan PF, Visscher PM, Martin NG. Genetic and phenotypic
stability of measures of neuroticism over 22 years. Twin Res Hum Genet. 2007;10(5):695-702.
doi: 10.1375/twin.10.5.695. PubMed PMID: 17903109.
26.   Vukasovic T, Bratko D. Heritability of personality: A meta-analysis of behavior genetic
studies. Psychol Bull. 2015;141(4):769-85. doi: 10.1037/bul0000017. PubMed PMID:
25961374.
27.   Hirschfeld RM, Klerman GL. Personality attributes and affective disorders. Am J
Psychiatry. 1979;136(1):67-70. doi: 10.1176/ajp.136.1.67. PubMed PMID: 758831.

28.   Hirschfeld RM, Klerman GL, Clayton PJ, Keller MB, McDonald-Scott P, Larkin BH.
Assessing personality: effects of the depressive state on trait measurement. Am J Psychiatry.
1983;140(6):695-9. doi: 10.1176/ajp.140.6.695. PubMed PMID: 6846626.
29.   Levinson DF. The genetics of depression: a review. Biol Psychiatry. 2006;60(2):84-92.
doi: 10.1016/j.biopsych.2005.08.024. PubMed PMID: 16300747.
30.   Middeldorp CM, Cath DC, Van Dyck R, Boomsma DI. The co-morbidity of anxiety and
depression in the perspective of genetic epidemiology. A review of twin and family studies.
Psychol Med. 2005;35(5):611-24. PubMed PMID: 15918338.
31.   Smith DJ, Escott-Price V, Davies G, Bailey ME, Colodro-Conde L, Ward J, et al. Genome-
wide analysis of over 106 000 individuals identifies 9 neuroticism-associated loci. Mol
Psychiatry. 2016;21(6):749-57. doi: 10.1038/mp.2016.49. PubMed PMID: 27067015; PubMed
Central PMCID: PMCPMC4879189.
32.   Luciano M, Hagenaars SP, Davies G, Hill WD, Clarke TK, Shirali M, et al. Association
analysis in over 329,000 individuals identifies 116 independent variants influencing
neuroticism. Nat Genet. 2018;50(1):6-11. doi: 10.1038/s41588-017-0013-8. PubMed PMID:
29255261.
33.   Smits DJM, Boeck PD. From BIS/BAS to the big five. European Journal of Personality.
2006;20(4):255-70. doi: 10.1002/per.583.
34.   Schneider TR, Rench TA, Lyons JB, Riffle RR. The influence of neuroticism, extraversion
and openness on stress responses. Stress Health. 2012;28(2):102-10. doi: 10.1002/smi.1409.
PubMed PMID: 22281953.
35.   Kim SE, Kim HN, Cho J, Kwon MJ, Chang Y, Ryu S, et al. Direct and Indirect Effects of
Five Factor Personality and Gender on Depressive Symptoms Mediated by Perceived Stress.
PLoS One. 2016;11(4):e0154140. doi: 10.1371/journal.pone.0154140. PubMed PMID:
27120051; PubMed Central PMCID: PMCPMC4847785.
36.   Tak LM, Kingma EM, van Ockenburg SL, Ormel J, Rosmalen JG. Age- and sex-specific
associations between adverse life events and functional bodily symptoms in the general
population. J Psychosom Res. 2015;79(2):112-6. doi: 10.1016/j.jpsychores.2015.05.013.
PubMed PMID: 26052060.
37.   Hovens JG, Giltay EJ, van Hemert AM, Penninx BW. Childhood Maltreatment and the
Course of Depressive and Anxiety Disorders: The Contribution of Personality Characteristics.
Depress Anxiety. 2016;33(1):27-34. doi: 10.1002/da.22429. PubMed PMID: 26418232.
38.   Bazana PG, Stelmack RM. Chapter 8 - Stability of Personality Across the Life Span: A
Meta-Analysis. On the Psychobiology of Personality. Oxford: Elsevier; 2004. p. 113-44.
39.   McGue M, Bacon S, Lykken DT. Personality Stability and Change in Early Adulthood.
Developmental Psychology. 1993;29(1):96-109.
40.   Nivard MG, Middeldorp CM, Dolan CV, Boomsma DI. Genetic and Environmental
Stability of Neuroticism From Adolescence to Adulthood. Twin Res Hum Genet.
2015;18(6):746-54. doi: 10.1017/thg.2015.80. PubMed PMID: 26678053.
41.   Sullivan PF, Neale MC, Kendler KS. Genetic epidemiology of major depression: review
and   meta-analysis.   Am   J   Psychiatry.   2000;157(10):1552-62.   doi:
10.1176/appi.ajp.157.10.1552. PubMed PMID: 11007705.
42.   Wray NR, Ripke S, Mattheisen M, Trzaskowski M, Byrne EM, Abdellaoui A, et al.
Genome-wide association analyses identify 44 risk variants and refine the genetic
architecture of major depression. Nat Genet. 2018;50(5):668-81. doi: 10.1038/s41588-018-
0090-3. PubMed PMID: 29700475; PubMed Central PMCID: PMCPMC5934326.
43.   Loret de Mola C, de Franca GV, Quevedo Lde A, Horta BL. Low birth weight, preterm
birth and small for gestational age association with adult depression: systematic review and

meta-analysis. Br J Psychiatry. 2014;205(5):340-7. doi: 10.1192/bjp.bp.113.139014. PubMed
PMID: 25368358.
44.   Peyrot WJ, Milaneschi Y, Abdellaoui A, Sullivan PF, Hottenga JJ, Boomsma DI, et al.
Effect of polygenic risk scores on depression in childhood trauma. Br J Psychiatry.
2014;205(2):113-9. doi: 10.1192/bjp.bp.113.143081. PubMed PMID: 24925986; PubMed
Central PMCID: PMCPMC4118052.
45.   Mullins N, Power RA, Fisher HL, Hanscombe KB, Euesden J, Iniesta R, et al. Polygenic
interactions with environmental adversity in the aetiology of major depressive disorder.
Psychol Med. 2016;46(4):759-70. doi: 10.1017/S0033291715002172. PubMed PMID:
26526099; PubMed Central PMCID: PMCPMC4754832.
46.   Colodro-Conde L, Couvy-Duchesne B, Zhu G, Coventry WL, Byrne EM, Gordon S, et al. A
direct test of the diathesis-stress model for depression. Mol Psychiatry. 2017. doi:
10.1038/mp.2017.130. PubMed PMID: 28696435.
47.   Kendler KS, Baker JH. Genetic influences on measures of the environment: a systematic
review. Psychol Med. 2007;37(5):615-26. doi: 10.1017/S0033291706009524. PubMed PMID:
17176502.
48.   Luciano M, Batty GD, McGilchrist M, Linksted P, Fitzpatrick B, Jackson C, et al. Shared
genetic aetiology between cognitive ability and cardiovascular disease risk factors:
Generation Scotland's Scottish family health study. Intelligence. 2010;38(3):304-13. doi:
http://dx.doi.org/10.1016/j.intell.2010.03.002.
49.   Silberg J, Rutter M, Neale M, Eaves L. Genetic moderation of environmental risk for
depression and anxiety in adolescent girls. Br J Psychiatry. 2001;179:116-21. PubMed PMID:
11483472.
50.   Kendler KS, Kessler RC, Walters EE, MacLean C, Neale MC, Heath AC, et al. Stressful life
events, genetic liability, and onset of an episode of major depression in women. Am J
Psychiatry. 1995;152(6):833-42. PubMed PMID: 7755111.
51.   Biobank U. UK Biobank: protocol for a large-scale prospective epidemiological
resource   2010.   Available   from: http://www.ukbiobank.ac.uk/wp-
content/uploads/2011/11/UK-Biobank-Protocol.pdf.
52.   Biobank U. UK Biobank ethics and governance framework, version 3.0 2007. Available
from: http://www.ukbiobank.ac.uk/wp-
content/uploads/2011/05/EGF20082.pdf?phpMyAdmin=trmKQlYdjjnQIgJ%2CfAzikMhEnx6.
53.   Biobank U. Genotype imputation and genetic association studies of UK Biobank. 2015.
54.   Purcell S, Neale B, Todd-Brown K, Thomas L, Ferreira MA, Bender D, et al. PLINK: a tool
set for whole-genome association and population-based linkage analyses. Am J Hum Genet.
2007;81(3):559-75. doi: 10.1086/519795. PubMed PMID: 17701901; PubMed Central PMCID:
PMCPMC1950838.
55.   Amador C, Huffman J, Trochet H, Campbell A, Porteous D, Generation S, et al. Recent
genomic heritage in Scotland. BMC Genomics. 2015;16:437. doi: 10.1186/s12864-015-1605-
2. PubMed PMID: 26048416; PubMed Central PMCID: PMCPMC4458001.
56.   Smith BH, Campbell A, Linksted P, Fitzpatrick B, Jackson C, Kerr SM, et al. Cohort
Profile: Generation Scotland: Scottish Family Health Study (GS:SFHS). The study, its
participants and their potential for genetic research on health and illness. Int J Epidemiol.
2013;42(3):689-700. doi: 10.1093/ije/dys084. PubMed PMID: 22786799.
57.   Fernandez-Pujals AM, Adams MJ, Thomson P, McKechanie AG, Blackwood DH, Smith
BH, et al. Epidemiology and Heritability of Major Depressive Disorder, Stratified by Age of
Onset, Sex, and Illness Course in Generation Scotland: Scottish Family Health Study (GS:SFHS).
PLoS One. 2015;10(11):e0142197. doi: 10.1371/journal.pone.0142197. PubMed PMID:
26571028; PubMed Central PMCID: PMCPMC4646689.

58.   Smith BH, Campbell H, Blackwood D, Connell J, Connor M, Deary IJ, et al. Generation
Scotland: the Scottish Family Health Study; a new resource for researching genes and
heritability. BMC medical genetics. 2006;7:74. doi: 10.1186/1471-2350-7-74. PubMed PMID:
17014726; PubMed Central PMCID: PMC1592477.
59.   Kerr SM, Campbell A, Murphy L, Hayward C, Jackson C, Wain LV, et al. Pedigree and
genotyping quality analyses of over 10,000 DNA samples from the Generation Scotland:
Scottish Family Health Study. BMC Med Genet. 2013;14:38. doi: 10.1186/1471-2350-14-38.
PubMed PMID: 23521772; PubMed Central PMCID: PMCPMC3614907.
60.   Biobank U. Touchscreen questionnaire 2012. Available from:
http://www.ukbiobank.ac.uk/wp-content/uploads/2011/06/Touch_screen_questionnaire.
pdf?phpMyAdmin = trmKQlYdjjnQIgJ%2CfAzikMhEnx6.
61.   Eysenck HJ ES. Manual of the Eysenck Personality Questionnaire. London: Hodder and
Stoughton; 1975.
62.   Kendler KS, Myers J. The genetic and environmental relationship between major
depression and the five-factor model of personality. Psychol Med. 2010;40(5):801-6. doi:
10.1017/S0033291709991140. PubMed PMID: 19732485.
63.   Smith DJ, Nicholl BI, Cullen B, Martin D, Ul-Haq Z, Evans J, et al. Prevalence and
characteristics of probable major depression and bipolar disorder within UK biobank: cross-
sectional study of 172,751 participants. PLoS One. 2013;8(11):e75362. doi:
10.1371/journal.pone.0075362. PubMed PMID: 24282498; PubMed Central PMCID:
PMCPMC3839907.
64.   Eysenck SBG, Eysenck, H.J. & Barrett, P. A revised version of the psychoticism scale.
Personality and Individual Differences. 1985;6:21-9.
65.   Spitzer RL, Kroenke K, Williams JB. Validation and utility of a self-report version of
PRIME-MD: the PHQ primary care study. Primary Care Evaluation of Mental Disorders. Patient
Health Questionnaire. JAMA. 1999;282(18):1737-44. PubMed PMID: 10568646.
66.   First MB SR, Gibbon M, Williams JB. Structured Clinical Interview for DSM-IV-TR Axis I
Disorders. New York: New York State Psychiatric Institute; 2002.
67.   Euesden J, Lewis CM, O'Reilly PF. PRSice: Polygenic Risk Score software.
Bioinformatics. 2015;31(9):1466-8. doi: 10.1093/bioinformatics/btu848. PubMed PMID:
25550326; PubMed Central PMCID: PMCPMC4410663.
68.   Willer CJ, Li Y, Abecasis GR. METAL: fast and efficient meta-analysis of genomewide
association scans. Bioinformatics. 2010;26(17):2190-1. doi: 10.1093/bioinformatics/btq340.
PubMed PMID: 20616382; PubMed Central PMCID: PMCPMC2922887.
69.   de Leeuw CA, Mooij JM, Heskes T, Posthuma D. MAGMA: generalized gene-set analysis
of GWAS data. PLoS Comput Biol. 2015;11(4):e1004219. doi: 10.1371/journal.pcbi.1004219.
PubMed PMID: 25885710; PubMed Central PMCID: PMCPMC4401657.
70.   Watanabe K, Taskesen E, van Bochoven A, Posthuma D. FUMA: Functional mapping and
annotation of genetic associations. bioRxiv. 2017. doi: 10.1101/110023.
71.   Bulik-Sullivan BK, Loh PR, Finucane HK, Ripke S, Yang J, Schizophrenia Working Group
of the Psychiatric Genomics C, et al. LD Score regression distinguishes confounding from
polygenicity in genome-wide association studies. Nat Genet. 2015;47(3):291-5. doi:
10.1038/ng.3211. PubMed PMID: 25642630; PubMed Central PMCID: PMCPMC4495769.
72.   Bulik-Sullivan B, Finucane HK, Anttila V, Gusev A, Day FR, Loh PR, et al. An atlas of
genetic correlations across human diseases and traits. Nat Genet. 2015;47(11):1236-41. doi:
10.1038/ng.3406. PubMed PMID: 26414676; PubMed Central PMCID: PMCPMC4797329.
73.   Pers TH, Karjalainen JM, Chan Y, Westra HJ, Wood AR, Yang J, et al. Biological
interpretation of genome-wide association studies using predicted gene functions. Nat

Commun. 2015;6:5890. doi: 10.1038/ncomms6890. PubMed PMID: 25597830; PubMed
Central PMCID: PMCPMC4420238.

74.   Mailman MD, Feolo M, Jin Y, Kimura M, Tryka K, Bagoutdinov R, et al. The NCBI dbGaP
database of genotypes and phenotypes. Nat Genet. 2007;39(10):1181-6. doi:
10.1038/ng1007-1181. PubMed PMID: 17898773; PubMed Central PMCID:
PMCPMC2031016.

75.   Boyle AP, Hong EL, Hariharan M, Cheng Y, Schaub MA, Kasowski M, et al. Annotation of
functional variation in personal genomes using RegulomeDB. Genome research.
2012;22(9):1790-7. doi: 10.1101/gr.137323.112. PubMed PMID: 22955989; PubMed Central
PMCID: PMC3431494.

76.   Consortium GT. Human genomics. The Genotype-Tissue Expression (GTEx) pilot
analysis: multitissue gene regulation in humans. Science. 2015;348(6235):648-60. doi:
10.1126/science.1262110. PubMed PMID: 25954001; PubMed Central PMCID:
PMCPMC4547484.

77.   Genetics of Personality C, de Moor MH, van den Berg SM, Verweij KJ, Krueger RF,
Luciano M, et al. Meta-analysis of Genome-wide Association Studies for Neuroticism, and the
Polygenic Association With Major Depressive Disorder. JAMA Psychiatry. 2015;72(7):642-50.
doi: 10.1001/jamapsychiatry.2015.0554. PubMed PMID: 25993607; PubMed Central PMCID:
PMCPMC4667957.

78.   Team RC. R: A language and environment for statistical computing. Vienna, Austria: R
Foundation for Statistical Computing; 2015.

79.   Lee SH, Wray NR, Goddard ME, Visscher PM. Estimating missing heritability for disease
from genome-wide association studies. Am J Hum Genet. 2011;88(3):294-305. doi:
10.1016/j.ajhg.2011.02.002. PubMed PMID: 21376301; PubMed Central PMCID:
PMCPMC3059431.

80.   Chen GB. Estimating heritability of complex traits from genome-wide association
studies using IBS-based Haseman-Elston regression. Front Genet. 2014;5:107. doi:
10.3389/fgene.2014.00107. PubMed PMID: 24817879; PubMed Central PMCID:
PMCPMC4012219.

81.   Hirschfeld RM, Williams JB, Spitzer RL, Calabrese JR, Flynn L, Keck PE, Jr., et al.
Development and validation of a screening instrument for bipolar spectrum disorder: the
Mood Disorder Questionnaire. Am J Psychiatry. 2000;157(11):1873-5. doi:
10.1176/appi.ajp.157.11.1873. PubMed PMID: 11058490.

82.   Raine A. The SPQ: a scale for the assessment of schizotypal personality based on DSM-
III-R criteria. Schizophr Bull. 1991;17(4):555-64. PubMed PMID: 1805349.

83.   Polderman TJ, Benyamin B, de Leeuw CA, Sullivan PF, van Bochoven A, Visscher PM, et
al. Meta-analysis of the heritability of human traits based on fifty years of twin studies. Nat
Genet. 2015;47(7):702-9. doi: 10.1038/ng.3285. PubMed PMID: 25985137.

84.   consortium C. Sparse whole-genome sequencing identifies two loci for major
depressive disorder. Nature. 2015;523(7562):588-91. doi: 10.1038/nature14659. PubMed
PMID: 26176920; PubMed Central PMCID: PMCPMC4522619.

85.   Hyde CL, Nagle MW, Tian C, Chen X, Paciga SA, Wendland JR, et al. Identification of 15
genetic loci associated with risk of major depression in individuals of European descent. Nat
Genet. 2016;48(9):1031-6. doi: 10.1038/ng.3623. PubMed PMID: 27479909.

86.   Zuo L, Tan Y, Zhang X, Wang X, Krystal J, Tabakoff B, et al. A New Genomewide
Association Meta-Analysis of Alcohol Dependence. Alcohol Clin Exp Res. 2015;39(8):1388-95.
doi: 10.1111/acer.12786. PubMed PMID: 26173551.

87.   Cook MN, Baker JA, Heldt SA, Williams RW, Hamre KM, Lu L. Identification of candidate
genes that underlie the QTL on chromosome 1 that mediates genetic differences in stress-

ethanol interactions. Physiol Genomics. 2015;47(8):308-17. doi:
10.1152/physiolgenomics.00114.2014. PubMed PMID: 25991709; PubMed Central PMCID:
PMCPMC4525077.
88. Zuo L, Wang K, Wang G, Pan X, Zhang X, Zhang H, et al. Common PTP4A1-PHF3-EYS
variants are specific for alcohol dependence. Am J Addict. 2014;23(4):411-4. doi:
10.1111/j.1521-0391.2013.12115.x. PubMed PMID: 24961364; PubMed Central PMCID:
PMCPMC4111256.
89. Zuo L, Zhang X, Deng HW, Luo X. Association of rare PTP4A1-PHF3-EYS variants with
alcohol dependence. J Hum Genet. 2013;58(3):178-9. doi: 10.1038/jhg.2012.153. PubMed
PMID: 23324950.
90. Zuo L, Zhang CK, Wang F, Li CS, Zhao H, Lu L, et al. A novel, functional and replicable
risk gene region for alcohol dependence identified by genome-wide association study. PLoS
One. 2011;6(11):e26726. doi: 10.1371/journal.pone.0026726. PubMed PMID: 22096494;
PubMed Central PMCID: PMCPMC3210123.
91. Hontelez S, Karthaus N, Looman MW, Ansems M, Adema GJ. DC-SCRIPT regulates
glucocorticoid receptor function and expression of its target GILZ in dendritic cells. J Immunol.
2013;190(7):3172-9. doi: 10.4049/jimmunol.1201776. PubMed PMID: 23440419.
92. Lopez-Garcia J, Periyasamy M, Thomas RS, Christian M, Leao M, Jat P, et al. ZNF366 is
an estrogen receptor corepressor that acts through CtBP and histone deacetylases. Nucleic
Acids Res. 2006;34(21):6126-36. doi: 10.1093/nar/gkl875. PubMed PMID: 17085477;
PubMed Central PMCID: PMCPMC1693901.
93. Miyamoto-Sato E, Fujimori S, Ishizaka M, Hirai N, Masuoka K, Saito R, et al. A
comprehensive resource of interacting protein regions for refining human transcription factor
networks. PLoS One. 2010;5(2):e9289. doi: 10.1371/journal.pone.0009289. PubMed PMID:
20195357; PubMed Central PMCID: PMCPMC2827538.
94. Aragam N, Wang KS, Pan Y. Genome-wide association analysis of gender differences in
major depressive disorder in the Netherlands NESDA and NTR population-based samples. J
Affect Disord. 2011;133(3):516-21. doi: 10.1016/j.jad.2011.04.054. PubMed PMID: 21621269.
95. Fidalgo TM, da Silveira ED, da Silveira DX. Psychiatric comorbidity related to alcohol
use among adolescents. Am J Drug Alcohol Abuse. 2008;34(1):83-9. doi:
10.1080/00952990701764664. PubMed PMID: 18161646.
96. Lopez B, Turner RJ, Saavedra LM. Anxiety and risk for substance dependence among
late adolescents/young adults. J Anxiety Disord. 2005;19(3):275-94. doi:
10.1016/j.janxdis.2004.03.001. PubMed PMID: 15686857.
97. Low NC, Lee SS, Johnson JG, Williams JB, Harris ES. The association between anxiety
and alcohol versus cannabis abuse disorders among adolescents in primary care settings. Fam
Pract. 2008;25(5):321-7. doi: 10.1093/fampra/cmn049. PubMed PMID: 18753288.
98. Rutledge PC, Sher KJ. Heavy drinking from the freshman year into early young
adulthood: the roles of stress, tension-reduction drinking motives, gender and personality. J
Stud Alcohol. 2001;62(4):457-66. PubMed PMID: 11523533.
99. Schmidt NB, Buckner JD, Keough ME. Anxiety sensitivity as a prospective predictor of
alcohol use disorders. Behav Modif. 2007;31(2):202-19. doi: 10.1177/0145445506297019.
PubMed PMID: 17307935.
100. Varlinskaya EI, Kim EU, Spear LP. Chronic intermittent ethanol exposure during
adolescence: Effects on stress-induced social alterations and social drinking in adulthood.
Brain Res. 2017;1654(Pt B):145-56. doi: 10.1016/j.brainres.2016.03.050. PubMed PMID:
27048754; PubMed Central PMCID: PMCPMC5047849.
101. Torigata K, Daisuke O, Mukai S, Hatanaka A, Ohka F, Motooka D, et al. LATS2 Positively
Regulates Polycomb Repressive Complex 2. PLoS One. 2016;11(7):e0158562. doi:

10.1371/journal.pone.0158562. PubMed PMID: 27434182; PubMed Central PMCID:
PMCPMC4951031.

102. Shen EY, Jiang Y, Javidfar B, Kassim B, Loh YE, Ma Q, et al. Neuronal Deletion of
Kmt2a/Mll1 Histone Methyltransferase in Ventral Striatum is Associated with Defective
Spike-Timing-Dependent Striatal Synaptic Plasticity, Altered Response to Dopaminergic
Drugs, and Increased Anxiety. Neuropsychopharmacology. 2016;41(13):3103-13. doi:
10.1038/npp.2016.144. PubMed PMID: 27485686; PubMed Central PMCID:
PMCPMC5101561.

103. Wong ML, Arcos-Burgos M, Liu S, Velez JI, Yu C, Baune BT, et al. The PHF21B gene is
associated with major depression and modulates the stress response. Mol Psychiatry.
2017;22(7):1015-25. doi: 10.1038/mp.2016.174. PubMed PMID: 27777418; PubMed Central
PMCID: PMCPMC5461220.

104. Walsh RM, Shen EY, Bagot RC, Anselmo A, Jiang Y, Javidfar B, et al. Phf8 loss confers
resistance to depression-like and anxiety-like behaviors in mice. Nat Commun. 2017;8:15142.
doi: 10.1038/ncomms15142. PubMed PMID: 28485378; PubMed Central PMCID:
PMCPMC5436068.

105. Gage SH, Jones HJ, Taylor AE, Burgess S, Zammit S, Munafo MR. Investigating causality
in associations between smoking initiation and schizophrenia using Mendelian
randomization. Sci Rep. 2017;7:40653. doi: 10.1038/srep40653. PubMed PMID: 28102331;
PubMed Central PMCID: PMCPMC5244403.

106. Hartz SM, Horton AC, Hancock DB, Baker TB, Caporaso NE, Chen LS, et al. Genetic
correlation between smoking behaviors and schizophrenia. Schizophr Res. 2017. doi:
10.1016/j.schres.2017.02.022. PubMed PMID: 28285025.

107. Dudbridge F. Power and predictive accuracy of polygenic risk scores. PLoS Genet.
2013;9(3):e1003348. doi: 10.1371/journal.pgen.1003348. PubMed PMID: 23555274;
PubMed Central PMCID: PMCPMC3605113.

Supporting information

S1 Supporting Information.

S1 Fig. Genetic stress-sensitivity effect representation. Genetic stress-sensitivity effect on MDD (β_{SS}) is defined as the difference between the regression coefficient in MDD cases (β_A) and the regression coefficient in controls (β_B) from linear models regressed on EPQN, adjusted by covariates. *A1*: allele 1. *A2* allele 2.

S2 Fig. QQ plot from stress-sensitivity meta-analysis. QQ plot of GWIS from sample size weighted meta-analysis (λ = 0.997; s.e. = 1.05×10^{-5}). All SNPs wit $p < 2 \times 10^{-5}$, p threshold (dot line) where some SNPs start to deviate from null distribution going outside 95% confidence intervals (grey shadow), were selected to perform DEPICT analyses to assess pathway and functional genomic analyses. 27 top variants from 12 independent loci were selected.

S3 Fig. QQ plots of GWIS p values. QQ plots of GWIS from (A) UKB (λ = 1.014; s.e.= 1.027×10^{-5}), (B) GS:SFHS (λ = 0.997; s.e. = 7.989×10^{-6}). The 95% confidence interval is shaded in grey.

S4 Fig. Miami plots on UK Biobank and Generation Scotland: Scottish Family Health Study. Miami plots showing comparison between association profile between SS and MDD main additive effects. Miami plots from (A) UKB filtering for SS p values (top) and MDD p values (bottom), (B) GS:SFHS filtering for SS p values (top) and MDD p values (bottom). Filter at $p = 1 \times 10^{-3}$. The x-axis is base-paired chromosomal position and y-axis is the significance (-log10 p) of association with (up; red

dots) SS effect and (down; blue dots) MDD. Dot line: genome-wide suggestive threshold ($p = 1 \times 10^{-}$

^{5}) at the filtered effect; dashes lines: p value = 0.01 and 0.05 at compared effect.

S5 Fig. Manhattan plot of the gene-based test for stress-sensitivity. Manhattan plot showing

gene-based association of stress-sensitivity. The x-axis is base-paired chromosomal position and y-

axis is the significance ($-\log_{10}$ p value) of association with SS effect. Genome-wide significance

threshold showed by red dashed line was defined at $p = 0.05/17{,}931 = 2.79 \times 10^{-6}$.

S6 Fig. PRS profiling predicting MDD in UK Biobank. MDD risk explained (R^2 coefficient (%); top

bar values) on the liability scale by each PRS in UKB; weighted by GWAS main additive and GWIS

stress-sensitivity effects independently and combined. (A) Using summary statistics from GS:SFHS

as discovery sample. (B) Replication fitting PRS_D and PRS_N using summary statistics from worldwide

consortiums (i.e. PGC & GPC). Significance codes: p values *** < 0.001 < ** < 0.01 < * < 0.05;

derived from likelihood ratio tests. *SS* stands for stress-sensitivity.

S1 Table. EPQN comparison between MDD cases and healthy controls.

S2 Table. Top 10 SNPs from GWIS on UK Biobank.

S3 Table. Top 10 SNPs from GWIS on Generation Scotland: Scottish Family Health Study.

S4 Table. Traits with significant evidence of association with closest gene to suggestive stress-

sensitive hits. The closest genes to SNPs associated with stress-sensitivity at suggestive

significance levels have prior evidence of association in dbGAP with a wide range of

neuropsychiatric traits such as schizophrenia, bipolar disorder, attention deficit disorder with

hyperactivity, mental competency, intuition, sleep or alcohol drinking.

S5 Table. Top 25 hits from gene-based analysis of GWIS meta-analysis.

S6 Table. : Summary results from polygenic risk score (PRS) analysis using PRSice-2.

S7 Table. MDD stratification.