Genome-wide interaction study with major depression identifies novel variants associated with cognitive function

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INTRODUCTION

Major Depressive Disorder (MDD) is an enormous health problem globally, with many years of life lived with disability [1]. In the 2017 Global Burden of Disease Study, MDD accounted for an estimated 32.8 million years lived with disability [2]. Cognitive dysfunction has been found to occur in over half of patients with MDD [3], including deficits in memory, executive function, attention, and slower reaction time [4, 5]. Deficits in memory involve immediate memory [6], verbal learning and memory [7], visual memory and working memory [8].

Cognitive dysfunction observed in MDD is associated with impairment in functioning, including social and occupational functioning [5, 9]. Specifically, unemployment has been associated with cognitive dysfunction in both current and remitted MDD [6].

MDD [3], including de
dysfunction has been found to occur in over half of patients with

MDD, as well as potential novel therapeutic agents that could be explored in patients with MDD associated cognitive dysfunction.

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Furthermore, increased severity of MDD has been correlated with reduced cognitive performance in measures of executive function, processing speed and episodic memory [10]. It has also been hypothesised that persistent cognitive dysfunction may be associated with a more disabling illness, including more frequent admissions to hospital [9] and non-response of depressive symptoms to pharmacotherapy [11].

Importantly, cognitive dysfunction observed in MDD often persists, even after other symptoms of depression have remitted [5]. In addition to the cognitive dysfunction persisting, the impairment in psychosocial function can persist [5, 9, 12]. These clinical observations suggest that cognitive dysfunction is not only a state marker of MDD, but can present as a trait marker of MDD. Hence, there is a need to explore the underlying biology of cognitive function in MDD, including its genetic architecture, in more detail. While a number of novel treatments are showing promise in improving cognitive dysfunction in MDD, the research is generally in the early stages [13]. Further exploration of the underlying biology of cognitive dysfunction may enhance better targeting of treatment, and lead to the identification of novel molecular targets for treatments in patients with MDD [5, 13].

Only few previous studies have specifically explored the genomic signature of cognitive performance in MDD patients and have produced heterogeneous results. A GWAS meta-analysis conducted in 24 independent cohorts as part of the Cognitive Genomics Consortium (COGENT) found genetic correlations between general cognitive performance and several psychiatric traits, but not for MDD [14]. In contrast, linkage disequilibrium score regression analyses using UK Biobank cognitive data found that MDD was genetically associated with slower reaction time [15]. In another study, healthy individuals with a higher MDD polygenic risk score (PRS) were found to show working memory activation patterns more like those seen in MDD [16]. Using data from over 7000 individuals participating in the Generation Scotland: the Scottish Family Health Study, Meijisen et al. [17] confirmed significant deficits in those with MDD across a number of cognitive domains but found no single nucleotide polymorphism (SNP) associations with cognitive performance in patients.

These previous findings highlight common difficulties in this research area. First, both MDD and cognitive function are complex psychological concepts characterised by high levels of phenotypic heterogeneity, requiring very large samples to detect meaningful genetic associations. Second, the psychometric tools used to measure cognitive domains vary widely, and ‘composite’ cognition scores inherently introduce more variation. To achieve progress, studies are required in cohorts that are large and well enough characterised to break down cognitive function into recognised subdomains. Third, clinical data suggest that cognitive performance and MDD status interact with each other in complex ways. Therefore, analytic approaches are warranted that allow for the identification of such interactions on a genetic level.

To address these challenges, we aimed to investigate the phenotypic and genetic relationship between cognitive function and MDD through a genome-wide interaction study, using several large European cohorts including MDD cases and healthy controls. Regular GWAS identifies the effect of a genetic variant on the phenotypes. The genome-wide interaction analysis aims to explore the modifying effect of an exposure variable on the genetic association. Due to the excellent clinical characterisation of these cohorts, we were able to conduct separate analyses for global cognition as well as individual cognitive domains including executive function, immediate and delayed memory, and processing speed. We hypothesised that genetic associations with cognitive performance differ by MDD status.

Finally, to explore the biological functions of the loci identified in the genome-wide interaction study, we conducted analyses including psychiatric PRS, gene expression data, and Ingenuity Pathway Analysis (IPA).

METHODS

The overall sample consists of 9567 participants (3510 MDD cases and 6057 controls) with both genetic and other phenotypic data from four cohorts (Table 1). A detailed description of the cognitive tests in each cohort, including how each test is administered, appears in the supplementary material—including Table S1 (refer also to Supplementary Fig. 1). A description of the method used to calculate z-scores for each cognitive test within each cohort, for each cognitive domain, and then for each cohort (i.e. a global cognitive score) is also provided in the supplementary material.

BiDirect study

BiDirect includes three different cohorts. The first cohort is comprised of individuals with a current episode of MDD at the time of recruitment; the second cohort consists of individuals with cardiovascular disease, and the third cohort is a reference cohort that was randomly sampled from the population [18]. Cognitive tests in the study assess executive function, processing speed, immediate memory, and delayed memory – with complete data available for close to 1600 participants.

FOR2107 cohort

The FOR2107 consortium investigates MDD, as well as Bipolar Disorder (BD), Schizoaffective Disorder, and Schizophrenia (SCZ) [19]. In addition to study participants meeting criteria for these disorders, the cohort includes participants at risk, as well as healthy controls, with a total of 2500 individuals [19]. Healthy controls are those without genetic risk (no relatives with MDD or BD) or environmental risk (no Childhood Trauma Questionnaire subscales meeting the maltreatment threshold) [19]. Executive function, processing speed, immediate and delayed memory are all measured in this cohort.

Generation Scotland cohort

Generation Scotland: Scottish Family Health Study (GS-SFH) is a large community based study, with close to 24,000 participants [20]. The wide range of clinical information includes medical history, family history, as well as phenomenology of personality traits and mental health [20]. Cognitive tests measure processing speed, executive function, immediate and delayed memory.

SHIP Trend cohort

The Study of Health in Pomerania consists of two population-based independent cohorts (SHIP and SHIP-TREND) [21]. The SHIP-TREND study is the first large European cohort, with data collected from 2008 to 2011 [21]. Complete data were available for 602 participants from SHIP Trend. Executive function and verbal episodic memory are assessed in the cohort.

Genome-wide association analysis. We performed the GWAS using SNP by MDD status interaction analysis based on three statistical tests, but summarised the main finding using the joint test of SNP and SNP by MDD interaction effect (2 degrees of freedom (2 df) test). This has been shown to be more powerful in detecting SNPs than either the marginal SNP or the pure SNP by MDD interaction test alone [22]. For each cohort and for each cognitive domain score, three genome-wide association tests, the marginal SNP effect, pure interaction effect of SNP with MDD status (SNP × MDD) and a joint test of both SNP and SNP by MDD status were performed using the GoScan [23] software. To account for confounding and population stratification issues, an additional set of covariates such as age, sex, total years of education and the first ten principal components were used in the regression models. Meta-analysis methods were used to combine each of the three GWAS results across the cohorts. Quality controlled GWAS results were meta-analysed for the marginal SNP effects and the interaction effect (SNP × MDD) using the METAL package [24]. Meta p values for the joint effect were obtained using the sample size weighted linear combination of the joint effect 2df chi-square statistics [25]. The results were summarised based on the meta-analysis p values of the joint test of SNP and SNP × MDD status (2 df) tests. The list of SNPs reported by the 2 df tests are either associated with cognitive function and/or differentially associated between the MDD subgroups. In other words, identified SNPs are associated with cognitive function domains, while also being moderated by MDD status. The GWAS p value threshold was set at $p < 5 \times 10^{-8}$, unadjusted for the number of traits as these traits are correlated.
The gene-based GWAS of the joint SNP and SNP × MDD (2df tests) were performed using MAGMA [26] and the polygenic risk scores were generated using PRS-CS [27] software. Regression analyses of the combined PRS score with relevant covariates were performed using R package v4.0.0 [28]. Additional details of the statistical analyses are provided in the supplementary material.

Functional analyses of GWAS findings. We conducted functional analyses of our GWAS findings using Qiagen’s Ingenuity Pathways Analysis software (IPA®, QIAGEN Redwood City, CA, USA, www.qiagen.com/ingenuity). Lists of genes for IPA® input were prepared using results from the genome-wide 2df tests and SNP × MDD interaction tests for all cognitive domains. For intergenic SNPs, the closest gene was added to the list. The input to IPA was an unranked list of these genes. IPA compares the proportion of input genes mapping to a biological pathway to the reference genes list in the ingenuity databases. The significance of the overrepresented canonical pathways and functional networks is determined using the right-tailed Fisher’s exact test and later adjusted for multiple testing using the Benjamini-Hochberg (BH) method. Significant results are determined at BH adjusted \( p \) value < 0.01.

RESULTS

Study cohorts
A description of the study cohorts is provided in Table 1. Across all cohorts, there were a total of 9567 study participants.

|                            | BiDirect | FOR2107 | Generation Scotland | SHIP-Trend | Total |
|---------------------------|----------|---------|---------------------|------------|-------|
| Total Sample (MDD and No MDD) |          |         |                     |            |       |
| Number                    | 1554     | 1254    | 6157                | 602        | 9567  |
| Sex:                      |          |         |                     |            |       |
| Male                      | 728 (46.8%) | 478 (38.1%) | 2399 (39.0%)        | 282 (46.8%) | 3887(40.6%) |
| Female                    | 826 (53.2%) | 776 (61.9%) | 3758 (61.0%)        | 320 (53.2%) | 5680(59.4%) |
| Age (years)               |          |         |                     |            |       |
| Average                   | 51.1     | 34.8    | 47.9                | 48.8       | 46.75 |
| SD                        | 7.8      | 13.2    | 13.2                | 13.2       | 13.34 |
| Range                     | 35.1–66.1 | 18.0–69.0 | 18.0–93.0           | 22.0–80.0  | 18.0–93.0 |
| Education (years)         |          |         |                     |            |       |
| Average                   | 14.3     | 13.5    | 13.8                | 10.4       | 13.66 |
| SD                        | 2.7      | 2.6     | 3.4                 | 1.2        | 3.23  |
| Range                     | 0.0–18.0 | 9.0–18.0 | 0.0–24+             | 8.0–12.0   | 0.0–24.5 |
| MDD Sample                |          |         |                     |            |       |
| Number                    | 912 (58.7%) | 573 (45.7%) | 1877 (30.5%)        | 148 (24.6%) | 3510 (36.7%) |
| Sex:                      |          |         |                     |            |       |
| Male                      | 391      | 223     | 538                 | 40         | 1192  |
| Female                    | 521      | 350     | 1339                | 108        | 2318  |
| Age (years)               |          |         |                     |            |       |
| Average                   | 49.98    | 37.55   | 46.23               | 48.95      | 45.91 |
| SD                        | 7.28     | 13.53   | 12.63               | 12.08      | 12.29 |
| Range                     | 35.08–66 | 18–69   | 18–84               | 22.0–80.0  | 18–84 |
| Education (years)         |          |         |                     |            |       |
| Average                   | 13.95    | 13.02   | 13.85               | 10.43      | 13.60 |
| SD                        | 2.70     | 2.72    | 3.41                | 1.18       | 3.15  |
| Range                     | 0–18     | 9–18    | 0–24.5              | 8.0–12.0   | 0–24.5 |
| Current MDD              | 817 (89.6%) | 423 (73.8%) | 349 (18.6%)        | 84 (56.8%) | 1673 (47.7%) |
| No MDD Sample             |          |         |                     |            |       |
| Number                    | 642 (41.3%) | 681 (54.3%) | 4280 (69.5%)       | 454 (75.4%) | 6057(63.3%) |
| Sex:                      |          |         |                     |            |       |
| Male                      | 305      | 255     | 1861                | 242        | 2695  |
| Female                    | 337 (P = 0.0002) | 426 (P = 0.634) | 2419 (P < 2.2e–16) | 212 (P = 4.54e–08) | 3362 (P < 2.2e–16) |
| Age (years)               |          |         |                     |            |       |
| Average                   | 52.56    | 32.56   | 48.63               | 48.74      | 47.25 |
| SD                        | 8.14     | 12.49   | 13.37               | 13.51      | 13.9  |
| Range                     | 35.19–66.09 (P = 2.03e–10) | 18–65 (P = 2.38e–11) | 18–93 (P = 2.02e–11) | 22.0–80.0 (P = 0.858) | 18–93 (P = 9.92e–07) |
| Education (years)         |          |         |                     |            |       |
| Average                   | 14.84    | 13.92   | 13.82               | 10.44      | 13.68 |
| SD                        | 2.69     | 2.48    | 3.35                | 1.25       | 3.23  |
| Range                     | 0–18 (P = 2.0e–10) | 9–18 (P = 1.97e–09) | 2.5–24.5 (P = 0.780) | 8.0–12.0 (P = 0.943) | 0–24.5 (P = 0.174) |

\( p \) value in parenthesis is for comparison between MDD vs No MDD. \( t \)-test was used for comparison of age and education and chi-square test was done to test the association between sex and MDD status.

MDD Major Depressive Disorder (lifetime), SD standard deviation.
In all cohorts, there is a higher percentage of females (Table 1). Average age of participants is highest in the BiDirect cohort, with a similar average age in the BiDirect, Generation Scotland, and SHIP-Trend cohorts (51.1, 47.9 and 48.8 years, respectively). The average age of the FOR2107 study was considerably lower at 34.8 years. The average age of participants is highest in the BiDirect cohort, with a lower lifetime MDD case to control ratio, with 30.5% and 24.6% of study participants respectively meeting MDD criteria. There is a significant difference between lifetime MDD cases and controls in age across the cohorts except in SHIP-Trend; in sex ratio except in FOR2107; and in education in BiDirect and FOR2107 (Table 1).

The marginal SNP, SNP × MDD and gene-modified by MDD status. The QQ plots are provided in Supplementary Fig. 2. The marginal SNP X MDD and gene-based association results are provided in the supplementary text.

The domain of executive function showed significant association with 48 SNPs. This included the SNP rs188552424 in TNFRSF21, a gene which has a role in the negative regulation of oligodendrocyte maturation [31], and rs112979588 in DCAF6, a gene thought to be involved in stability of the neuromuscular junction [32]. Individual SNPs in TSLP (a gene involved in immune function [33]), REEP3 (involved in microtubule binding [34, 35]), and 2 SNPs in PDE3A (a gene implicated in cerebral endothelial dysfunction [36]) were also associated with executive function (Supplementary Table 2a).

In the domain of delayed memory, the SNPs rs117823280 (near ZNF839) and rs117688348 (near MYH10) were found to be significantly associated (Supplementary Table 2b). A point mutation of the MYH10 gene in mice is involved in developmental cardiac and brain defects [37].

With processing speed 116 SNPs were found to be GWAS significant (Supplementary Table 2c). These included the SNPs in DCAF6, REEP3, and PDE3A associated with executive function, plus rs72635025 in ADAMT55 (involved in regulation of reelin—an important protein for cortical development [38]), and rs114216628 in ROBO1 (a gene involved in axon guidance [39]).

Thirty-two SNPs were significantly associated with global cognition (Supplementary Table 2d). Several of these SNPs were also associated in the domains of executive function and processing speed (SNP rs139747326 in PTAR1, rs14858269 in REEP3, rs112979588 in DCAF6, rs117658905 in CPX1l, and rs72635025 in ADAMT55). No SNPs reached genome-wide significance for the domain of immediate memory (Supplementary Fig. 3).

### ii. Polygenic risk scores analyses

Association of PRSes of BD, MDD, SCZ and mood instability (MIN) with cognitive domains were examined. PRS of SCZ and MIN were significantly associated with all the cognitive domains in our sample. BD PRS was associated with four cognitive domains (delayed memory, immediate memory, processing speed, global cognition), but not with executive function. MDD PRS had significant association with the cognitive domains of processing speed, immediate memory, and global cognition, but the effect was not in a consistent direction (Supplementary Table 2g, marginal).

### Functional analyses

#### i. Gene expression analysis of significant genes

Expression pattern and tissue specific enrichment of the significantly associated genes (corresponding to the associated SNPs) across all cognitive domains were examined using the gene2func module of the FUMA software [40] using the GTEx (https://gtexportal.org/home/) gene expression data. Tissue specific gene expression is displayed in Fig. 2. A number of genes are expressed in brain, in particular the amygdala (TNFRSF21, DCAF6), anterior cingulate cortex (TNFRSF21), basal ganglia (MYH10, DCAF6), frontal cortex (TNFRSF21, DCAF6, VMP1), hippocampus (REEP3), hypothalamus (TNFRSF21, REEP3) and cerebellum (REEP3, TNFRSF21, DCAF6, VMP1, PTAR1)—but also in other body tissues. No tissue specific enrichment tests were found to be significant (Supplementary Fig. 4; Supplementary Table 2h).

#### ii. IPA®—Functional analyses of genes associated with cognitive phenotypes

We used IPA® to map genes implicated in the GWAS analysis to the service’s proprietary knowledge databases, which include canonical pathways, functional gene networks, upstream regulators, causal networks, diseases and bio-functions, toxicology functions, and toxicity lists. Detailed IPA® results for a summary gene list for all cognitive domains are provided in (Supplementary Table 3). Overall, there is a relatively small number of genes that drive the IPA® associations with various functional categories (canonical pathways, diseases and biofunctions etc.), including MPO, FOXO1, PDE3A, TSLP, NLRP9, ADAMT55, ROBO1 and REST.

MPO was the dataset gene in the IPA® top canonical pathway, melatonin degradation, for the combined domains analysis and for processing speed, while FOXO1 and PDE3A drove the top canonical pathway for executive function (leptin signalling in obesity) [Supplementary Table 3].

When all dataset genes were analysed, the two top IPA®-defined functional interaction networks implicated TSLP (network 1) and ADAMT55, the latter together with beta-estradiol (network 2), as central functional nodes (Fig. 3a, b). For executive function, the top interaction network centrally implicated the dataset gene NPNT, as well as the oestrogen receptor 2 (ESR2), androgen receptor (AR), tumour protein 53 (TP 53), and amyloid precursor protein (APP). For processing speed, central connectivity was shown for the dataset gene VMP1 together with TP53, TGFβ1, HNF4A, and the NFκB complex [Supplementary Table 3].

Further, IPA® identified upstream regulators and causal networks with associations to dataset genes. Amongst the top-listed molecules, the vitamin D receptor (VDR), beta-estradiol, the phosphodiesterase inhibitor tadalafl and the protein kinase C inhibitor Go 6976 impact on several dataset genes and could therefore be of particular translational interest [Supplementary Table 3].
DISCUSSION

We conducted a genome-wide interaction analysis of MDD with cognitive function in the BiDirect, FOR2107, Generation Scotland, and SHIP Trend cohorts. We observed a set of SNPs to be specifically associated with cognitive function, in the context of MDD. In other words, these SNPs became GWAS significant in the joint test of SNP and SNP × MDD, but were not marginally significant when the MDD status was not included in the analysis. The joint tests of SNP and SNP×MDD have improved power to find SNPs/genes which would have been missing by the routine GWAS (our marginal test) because it looks for average effect among MDD vs non-MDD samples. Hence, MDD status has demonstrated a moderating effect on the association of these SNPs with cognitive domains.

Fig. 1 Manhattan plot for GWAS of SNP and SNP×MDD with cognitive domains. Joint test of SNP and SNP×MDD interaction with cognitive domains. GWAS significant ($p \leq 5 \times 10^{-8}$) loci are highlighted with the gene name closest to the top SNP. Identified SNPs are associated with cognitive function domains and/or moderated by MDD status.
Fig. 2  Tissue specific expression of top genes \((p < 5.0 \times 10^{-8})\) associated with cognitive function across all cognitive domains. Tissue types are on the x-axis and gene symbols are on the y-axis. Scale bar on the right gives colour coding and level of gene expression.

Fig. 3  Functional pathway analyses of cognition relevant genes using ingenuity pathway analyses. a and b: IPA\textsuperscript{®}—functional networks 1 & 2 for all cognition-associated genes.
Significant SNPs from our GWAS were from various genes including LINCO0520 (observed to promote tumour processes in glioma cells [41]), CPXM1 (also known as CPX-1 [42]), involved in adipogenesis [43], VMP1 (thought to be important in releasing lipoproteins from the endoplasmic reticulum membrane [44]) and REEP3 (involved in microtubule binding [34, 35] and possibly synaptic plasticity [34]). REEP3 is also involved in neural pathways linked to obsessive-compulsive disorder [45] and has been proposed as a positional candidate gene for autism spectrum disorder [46].

A number of significant SNPs were located in genes involved in negative regulation of oligodendrocyte maturation (TNFRSF21) [31], axon guidance (ROBO1) [39] and myelination (ARFGEF1) [47]. It is also notable that genes such as REEP3, TNFRSF21 and ARFGEF1 are all expressed in brain (Fig. 2). Furthermore, SNPs from REEP3 and DCAF6 (also expressed in brain areas including the amygdala, basal ganglia, and frontal cortex) were specifically associated with multiple cognitive domains.

Several significant SNPs for global cognition are located in the REST gene (Supplementary Table 2d), which as a transcription repressor has an important role in the development of neurons [48, 49], and in regulating secretion of insulin from pancreatic β-cells [49].

The functional analysis using IPA® software highlighted genes mapping to a high number of canonical pathways as well as to various disease- and biofunctions (MPO, FOXO1, PDE3A, TSLP, NLRP9, ADAMTS5, ROBO1 and REST). Several of these have previously been implicated in the neurobiology of cognitive function. For example, myeloperoxidase (MPO) is an enzyme highly expressed by neutrophils and is a primary mediator of neutrophils’ oxidative stress response. Elevated MPO levels have been implicated in the pathogenesis of Alzheimer’s disease, and mice with MPO deficiency were shown to exhibit superior cognitive performance [50]. Forkhead Box O (FOXO) transcription factor 1 is one of four isoforms which have previously been described as ‘guardians of neuronal integrity’ by inhibiting age-progressive axonal degeneration in mammals through regulation of neuroprotective mechanisms under pro-inflammatory conditions [51]. In mice, depletion of neuronal FOXO 1, 3 and 4 initiates neurodegeneration and advances brain ageing [51]. ADAMT55, at the centre of functional network 2, is a metalloprotease recently shown to play a role in cortical development through interactions with reelin and DISC1 [38]. Interestingly, a variant of TP53, which is implicated in the top functional networks for executive function and processing speed, has been described as a disease modifier in fronto-temporal dementia [52].

The IPA®-defined upstream regulator molecules and causal networks may provide a genetic rationale for further clinical evaluation and therapeutic strategies, in the context of MDD. These include beta-estradiol and the oestrogen receptor, whose potential for cognitive enhancement has been demonstrated in a wide range of preclinical and clinical studies (for overview see Hamson et al. [53]). Signalling through the VDR, another IPA® upstream regulator, has been proposed as a strategy for cognitive enhancement [54] but has not been tested in depressed populations. Tauine supplementation has been observed to reduce MPO levels and boost the effects of exercise on cognition in women >60 years [55], but also does not appear to have been investigated as a therapeutic adjunct in MDD. Further, previous clinical and pre-clinical studies have suggested potential benefit of the upstream regulator tadalafil (a 5-phosphodiesterase inhibitor) on cognitive function [56–58].

While only the PRS of MDD had significant interaction with MDD status (PRS associated with processing speed and executive function, although the effect was in an inconsistent direction), the PRS of SCZ and MIN were associated with all cognitive domains. The relationship between mood instability and psychiatric disorders has been previously investigated, with mood instability found to have a strong genetic correlation with MDD, and small but significant correlation with SCZ [59]. More specifically, mood instability and cognitive dysfunction are common in MDD, BD and SCZ [60, 61]. These changes in affect regulation and cognitive function seen across diagnoses may relate to areas of the brain such as the prefrontal cortex. Specifically, reduced functional connectivity between the prefrontal cortex and amygdala, brain regions important in emotion regulation [62], has been observed in BD [63] and SCZ [64]. The prefrontal cortex is important not only in emotion regulation, but also in planning and other components of executive function [65]. With regard to MDD, altered functional connectivity has also been observed, with decreased resting state connectivity between prefrontal cortex and amygdala in adolescents, and increased connectivity between the amygdala and hippocampus in adults [66].

No tissue specific enrichment tests of genes were significant. We also did not identify identical genome-wide significant SNPs found in previous GWA studies of cognitive function from the Cohorts for Heart and Aging Research in Genomic Epidemiology (CHARGE) consortium [67], the UK Biobank [68], in meta-analyses of GWA studies from CHARGE [69], or in a meta-analysis combining the UK Biobank, CHARGE, and COGENT samples [70]. It is possible that biological pathways which may be involved in MDD, including inflammation, are associated with different genetic variants of cognitive traits.

Similarly, in our analyses, none of the genome-wide significant SNPs found in the recent Psychiatric Genomics Consortium GWA meta-analysis in MDD, which identified 44 significant loci [71] or from the 23andMe MDD discovery data set [72] were identified in the context of MDD and cognitive function. Reasons for this could extend beyond the smaller sample size of our cohorts, to include age, as well as MDD severity - with different genetic variants contributing to cognitive dysfunction during (compared with in between) depressive episodes.

There are strengths and limitations of our study. Strengths of this study include the number of cognitive tests performed and the coverage of a broad range of cognitive domains, covering multiple domains (for example the BiDirect and FOR2107 cohorts are rich in phenotypes, and assess MDD in a clinical sample). In addition, we conducted functional analyses of the genes associated with cognitive function, which we believe adds to the understanding of the neurobiology of cognitive dysfunction in MDD. Several limitations need to be considered when interpreting the results. First, the total sample size is relatively modest (particularly in comparison to the CHARGE Consortium, COGENT, and UK Biobank—which are all population studies). Hence, replications in other independent cohorts are important especially for those SNPs with low minor allele frequency (MAF). Second, although our GWAS covered a broad range of cognitive domains relevant to MDD, not all cohorts from our study contributed to the cognitive domains in the same way; hence, depending on the availability of individual tests in each cohort, different individual measures were used for a particular cognitive domain within the cohorts. Therefore, to address the heterogeneity of cognitive tests and best represent the relevant cognitive domain, we calculated z scores for each domain that was assessed by more than a single cognitive test. Any impact of this heterogeneity will therefore be more in a cohort where more than one cognitive measure was used within an individual domain. Third, cohorts included a mix of patients, with some tested during a major depressive episode, and some tested during remission. Hence, there may be SNPs associated with an acute episode of severe MDD and cognitive dysfunction that are different to those associated with persistent cognitive dysfunction following a major depressive episode. Fourth, the clinical and cognitive measures were obtained at a single time point only, hence the presented results are related to a trait of cognitive dysfunction rather than to changes in cognitive function over time. Fifth, some age-related impact on cognition in
cohorts with participants over 75 years is possible, however, only a small number of participants were of this age. Sixth, databases for functional analysis such as IPA are not biologically complete, and CNS processes are typically not as well covered as processes that can be studied in peripheral tissues such as blood. Therefore, it is possible that our functional analysis was unable to detect additional important pathways directly relevant to brain function.

CONCLUSIONS

We find a set of SNPs to be specifically associated with cognitive function, in the context of MDD. Many of these SNPs are expressed in brain, and functional analysis of the results point to central physiological processes involved in neuronal development, neuroprotection, and maintenance of optimal cognition, thereby offering putative therapeutic targets. Potentially this cognitive phenotype—if confirmed in future analyses—represents a subgroup in MDD, with unique biological characteristics.

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AUTHOR CONTRIBUTIONS

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COMPETING INTERESTS

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