Elucidating the genetic architecture of DNA methylation to identify promising molecular mechanisms of disease

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DNA methylation commonly occurs at cytosine-phosphate-guanine sites (CpGs) that can serve as biomarkers for many diseases. We analyzed whole genome sequencing data to identify DNA methylation quantitative trait loci (mQTLs) in 4126 Framingham Heart Study participants. Our mQTL mapping identified 94,362,817 cis-mQTL variant-CpG pairs (for 210,156 unique autosomal CpGs) at $P<1\text{e}^{-7}$ and 33,572,145 trans-mQTL variant-CpG pairs (for 213,606 unique autosomal CpGs) at $P<1\text{e}^{-14}$. Using cis-mQTL variants for 1258 CpGs associated with seven cardiovascular disease (CVD) risk factors, we found 104 unique CpGs that colocalized with at least one CVD trait. For example, cg11554650 (PPP1R18) colocalized with type 2 diabetes, and was driven by a single nucleotide polymorphism (rs2516396). We performed Mendelian randomization (MR) analysis and demonstrated 58 putatively causal relations of CVD risk factor-associated CpGs to one or more risk factors (e.g., cg05337441 [APOB] with LDL; MR $P=1.2\text{e}^{-99}$, and 17 causal associations with coronary artery disease (e.g. cg08129017 [SREBF1] with coronary artery disease; MR $P=5\text{e}^{-13}$). We also showed that three CpGs, e.g., cg14893161 (PM20D1), are putatively causally associated with COVID-19 severity. To assist in future analyses of the role of DNA methylation in disease pathogenesis, we have posted a comprehensive summary data set in the National Heart, Lung, and Blood Institute’s BioData Catalyst.

DNA methylation, the most frequently studied epigenetic modification, involves the transfer of a methyl group to the fifth carbon position of the cytosine DNA nucleotide to form 5-methylcytosine. DNA methylation is influenced both by genetic and environmental factors and may mediate gene-environment interactions; therefore, it may be used to determine the risk of many complex diseases through its critical role in gene expression regulation. Associations between DNA methylation and a wide range of phenotypes have been identified by epigenome-wide association studies (EWAS). DNA methylation therefore can serve both as a biomarker for disease and contribute to its pathogenesis. Identification of genetic loci associated with the methylation of cytosine-phosphate-guanine sites (CpGs)—i.e., DNA methylation quantitative trait loci (mQTLs)—can facilitate the interpretation of the biological underpinnings of disease relations and causal inference regarding the role of DNA methylation in disease. Genome-wide association studies (GWAS) have successfully identified many disease-associated genetic variants. Molecular

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mechanisms linking these variants to disease, however, are not fully understood. Exploring colocalization of disease-associated genetic variants from GWAS with mQTL variants may further reveal molecular mechanisms underlying the associations between genetic variants and diseases. We hypothesize that by studying the overlap of mQTL variants with known disease-associated genetic variants from GWAS, we can further explore the joint contributions of genetic and environmental influences to diseases. Furthermore, by colocalizing mQTLs with genetic variants associated with gene expression (expression quantitative trait loci, eQTLs), we can better interpret the biological functions of disease-associated CpGs. Utilizing effect sizes derived from GWAS for mQTL variants with different diseases, we can conduct causal inference testing to explore the putative causal roles of CpGs on a wide range of diseases.

In our earlier work, we performed GWAS of ~ 415,000 CpGs in whole blood derived DNA in Framingham Heart Study (FHS) participants with validation in the Atherosclerosis Risk in Communities (ARIC) study and the Grady Trauma Project (GTP). Genotyping was performed using commercial arrays with imputation across the genome. The present study greatly expands on our prior work by incorporating whole genome sequencing (WGS) data in FHS participants obtained as part of the National Heart, Lung, and Blood Institute's (NHLBI) Trans-Omics for Precision Medicine (TOPMed) Program. Use of WGS greatly reduces imputation uncertainty and vastly increases coverage of variation across the human genome. In this study, we utilized state-of-the-art WGS in conjunction with DNA methylation measured by commercial arrays to quantify single nucleotide polymorphism (SNP)-CpG associations in over 4000 FHS participants. Our primary goal was to create a robust mQTL resource to better understand the genetic architecture of DNA methylation and facilitate the discovery of molecular mechanisms underlying a variety of diseases. We also provide examples of how mQTLs can be used in colocalization and Mendelian randomization (MR) analyses to infer the causal roles of DNA methylation in relation to disease phenotypes, with a focus on cardiovascular disease (CVD) risk factors and severity of coronavirus disease 2019 (COVID-19).

Results

Participant characteristics. As shown in Table 1, our pooled analysis included 4126 participants (2320 with DNA methylation data from the 450K array and 1806 with data from the EPIC array). In the FHS Offspring cohort, blood samples used for the 450K array measurements were collected ~ 6 years earlier than those for the EPIC array measurements, while blood samples for both arrays in the Third Generation cohort were obtained at the same visit. Therefore, the mean age for participants with EPIC array data was older than that for the 450K array. There were no substantial differences in sex, BMI, or other CVD risk factors.

mQTL mapping. Our primary pooled analysis examined association of 20,696,115 SNPs with 452,567 whole blood derived CpGs. In the pooled analysis, we identified 94,362,817 cis-mQTL variant-CpG pairs (details in "Methods") for 210,156 unique autosomal CpGs and at P<1e−7 and 33,572,145 trans-mQTL-CpG pairs for 213,606 unique autosomal CpGs at P<1e−14. The numbers of cis- and trans-mQTL variant-CpG pairs for each chromosome are presented in Supplemental Table 1. The cis-mQTL variants accounted for 0.7% to 79.9% (median 1.6%) of heritability of DNA methylation, and trans-mQTLs accounted for 1.4% to 78.7% (median 2.1%) of heritability. There were 1,080,716 cis-mQTL variants, associated with 31,422 unique CpGs (2,345,086 or 2.5% of the 94,362,817 cis-mQTL variant-CpG pairs), that accounted for ≥20% of heritability of DNA methylation at the corresponding CpGs (Fig. 2). We also observed that 185,167 trans-mQTL variants accounted for ≥20% of heritability of DNA methylation for 2711 unique CpGs (314,660 or 0.9% of the 33,572,145 trans-mQTL variant-CpG pairs; Fig. 2). The array-specific results are presented in Supplemental Table 2.
We examined whether whole blood derived mQTL variant-CpG pairs identified by other studies\(^\text{16,17}\) were significant in our dataset. For the top independent cis-mQTL variant-CpG pairs (168,675 pairs for 104,619 CpGs; \(P < 1\mathrm{e}^{-7}\)) identified by the pooled analysis in five Dutch biobanks\(^\text{16}\), 66.1% of the pairs (111,557 pairs for 79,099 CpGs) overlapped with our cis-mQTL variant-CpG pairs (\(P < 1\mathrm{e}^{-7}\) with consistent effect direction). For the top independent trans-pairs (5865 pairs for 2066 CpGs with \(P < 1\mathrm{e}^{-14}\)) in the Dutch biobanks, 38.4% of the pairs (2250 pairs for 866 CpGs) overlapped with our trans-mQTL variant-CpG pairs (\(P < 1\mathrm{e}^{-14}\) with consistent effect direction). Using blood samples collected from 3799 Europeans and 3195 South Asians, Hawe et al. identified 10,346,172 cis- and 819,387 trans-mQTL variant-CpG pairs at \(P < 1\mathrm{e}^{-14}\) in a cross-ancestry analysis\(^\text{17}\). Compared to their study, at \(P < 1\mathrm{e}^{-14}\), we identified 41,224,533 more cis-mQTL variant-CpG pairs and 32,752,758 more trans-mQTL variant-CpG pairs. Among the 10,346,172 cis- and 819,387 trans-mQTL variant-CpG pairs reported by Hawe et al.\(^ \text{17}\), 78.3% (\(n = 8,105,456\)) of cis-mQTL variant-CpG pairs and 66% (\(n = 540,851\)) of trans-mQTL variant-CpG pairs were significant and had consistent effect direction in our mQTL database, respectively.

**GO analysis for cis- and trans-mQTLs.** To investigate the biological implications for diseases, we conducted Gene Ontology (GO) analysis to identify biological processes, cellular components, and molecular functions that are impacted by the detected mQTLs. Using the top 1000 unique cis-mQTL variants from the pooled analysis, we identified 19 significant GO pathways (16 for Biological Process and 3 for Cellular Component) at FDR < 0.05 (Supplemental Table 3); the top Biological Process term was dendrite development (GO:0016358; \(P = 8.8\mathrm{e}^{-7}\); FDR = 0.01) and the top Cellular Component term was cell periphery (GO:0071944; \(P = 3.4\mathrm{e}^{-6}\); FDR = 0.01). The top 1000 unique trans-mQTL variants from the pooled analysis were linked to nine significant GO pathways (six for Biological Process and three for Cellular Component) at FDR < 0.05 (Supplemental Table 4); the top Biological Process term was cellular component organization or biogenesis (GO:0071840; \(P = 7.8\mathrm{e}^{-7}\); FDR = 0.009) and the top Cellular Component term was cytoplasm (GO: 0005737; \(P = 3.4\mathrm{e}^{-6}\); FDR = 0.009).

**Enrichment analysis of mQTL GWAS signals.** To illustrate the potential health consequences associated with the mQTL variants, we examined the overlap between the detected mQTL variants with GWAS SNPs.

### Table 1. Characteristics of the study population. Values are mean ± SD.

|                      | Third generation cohort | Offspring cohort | Omni cohort |
|----------------------|-------------------------|-----------------|-------------|
| N                    | 1945                    | 2129            | 52          |
| Women (%)            | 52.7                    | 54.7            | 46.2        |
| Age (years)          | 46 ± 8                  | 67 ± 9          | 70 ± 9      |
| BMI: kg/m\(^2\)      | 27.9 ± 5.7              | 28.2 ± 5.3      | 27.8 ± 4.9  |
| Systolic blood pressure (mm Hg) | 116 ± 14 | 129 ± 17 | 126 ± 16 |
| Diastolic blood pressure (mm Hg) | 74 ± 9 | 73 ± 10 | 68 ± 10 |
| Hypertension (%)     | 33.9                    | 53.5            | 42.3        |
| Fasting glucose (mg/dL) | 96.7 ± 20.8             | 106.3 ± 22.1    | 100.5 ± 12.6|
| Diabetes (%)         | 6.0                     | 14.7            | 9.6         |
| Triglyceride (mg/dL) | 112 ± 79.3              | 119.8 ± 71.9    | 94.9 ± 43.9 |
| High density lipoprotein (mg/dL) | 59.3 ± 17.2     | 57.3 ± 18.1     | 65.5 ± 19.3 |
| Low density lipoprotein (mg/dL) | 104.5 ± 29.4  | 104.8 ± 31.1   | 87.9 ± 28.9 |

**Figure 2.** Heritability of DNA methylation explained by the cis- and trans-mQTLs identified in the pooled analysis. The total number of cis-mQTLs is 94,362,817 and the total number of trans-mQTLs is 32,434,987.
Table 2. Top colocalization analysis results for CVD risk factor-associated CpGs. The top two colocalization results are presented for each outcome trait of interest (BMI, SBP, DBP, HDL, LDL, TG, T2D, & CAD), BMI, body mass index; SBP, systolic blood pressure; DBP, diastolic blood pressure; HDL, high density lipoprotein cholesterol; LDL, low density lipoprotein cholesterol; TG, triglyceride; T2D, type 2 diabetes; CAD, coronary artery disease; PPFC, posterior probability of colocalization; PPE, proportion of PPFC explained by the listed SNP. *Shore is region from 1 to 2 Kb away from a CpG island and shelf is located at 2–4 Kb from a CpG island. Prefixes N_ and S_ represent north (i.e., upstream) and south (i.e., downstream) regions relative to a CpG island. TSS, transcription start site.

| CpG | Chr | Position | Annotated Gene of CpGs | Relation to CpG island* | Distance to TSS | CVD risk factors associated with CpGs in EWAS catalog | Colocalized traits | Colocalized cis-mQTL variants | PPFC | PPE % |
|------|-----|----------|------------------------|------------------------|---------------|-------------------------------------------------|---------------------|--------------------------------|------|------|
| cg14509967 | 17 | 48601772 | H0X16 | S_shelf | 6021 | BMI | BMI | rs9299 | 1 | 100 |
| cg01856529 | 12 | 54259306 | CEBX5 | BMI | 28,364 | HDL | BMI | rs4759073 | 0.9869 | 74.42 |
| cg27087650 | 19 | 44752538 | BCL3 | N_shore | 4833 | BMI | CAD | rs62117206 | 0.889 | 46.72 |
| cg05337441 | 2 | 21043695 | APOB | N_shore | 42,266 | LDL | CAD | rs668948 | 0.7996 | 41.29 |
| cg03676485 | 7 | 2524181 | LFNG | Island | 11,652 | HDL | DBP | rs4632959 | 0.9999 | 100 |
| cg14099685 | 11 | 47524515 | CUGBP1 | Island | 58,578 | SBP | DBP | rs43412154 | 0.993 | 57.7 |
| cg21506299 | 6 | 136784086 | MAP3K5 | Island | 227,040 | BMI | HDL | rs6924387 | 0.9978 | 99.74 |
| cg27087650 | 19 | 44752538 | BCL3 | N_shore | 4833 | BMI | HDL | rs1531517 | 0.9961 | 59.67 |
| cg27087650 | 19 | 44752538 | BCL3 | N_shore | 4833 | BMI | LDL | rs4803750 | 0.9989 | 100 |
| cg03725309 | 1 | 109214962 | SARS1 | S_shelf | 1069 | BMI | SBP | TG | LDL | rs4970829 | 0.9962 | 100 |
| cg03676485 | 7 | 2524181 | LFNG | Island | 11,652 | HDL | SBP | rs4632959 | 0.9999 | 99.99 |
| cg02672879 | 20 | 59008418 | CTSZ | S_shore | 13,233 | WC | SBP | rs151343 | 0.9979 | 100 |
| cg11554650 | 6 | 30685413 | PPP1R18 | N_shore | 9024 | BMI | T2D | rs2516396 | 0.9835 | 100 |
| cg08973118 | 16 | 324569 | AXIN1 | N_shore | 37,129 | BMI | T2D | rs8049265 | 0.9505 | 99.33 |
| cg27087650 | 19 | 44752538 | BCL3 | N_shore | 4833 | BMI | TG | rs4803750 | 0.9988 | 98.56 |
| cg14099685 | 11 | 47524515 | CELF1 | Island | 58,578 | SBP | TG | rs34312154 | 0.9997 | 54.52 |

Colocalization analysis. We tested 1258 CVD risk factor-associated CpGs for colocalization with five CVD-related traits to further explore the clinical implication of the detected mQTLs. We found that 104 unique CpGs colocalized with at least one CVD-related traits at PPFC threshold ≥ 0.7 (overall 155 colocalized pairs; Supplemental Tables 7 and 8). In Table 2, we present the top two CpGs that colocalized with each CVD-related trait. For example, cg11554650 (PPP1R18), a BMI-associated CpG on chromosome 6, colocalized with type 2 diabetes at SNP rs2516396 (PPFC = 0.98), which explained 100% of the observed PPFC; cg05337441 (APOB), an LDL-associated CpG at chromosome 2, colocalized with coronary artery disease at rs668948 (PPFC = 0.8), which explained 41% of the observed PPFC; and cg03676485 (LFNG), a HDL-associated CpG at chromosome 7, colocalized with systolic and diastolic BP at rs4632959 (PPFC = 0.99), which explained 100% of the observed PPFC.

Mendelian randomization analysis. To further demonstrate the clinical implications of the detected mQTLs in the development of complex diseases, we performed MR analysis to test the putative causal relationships between mQTL and CVD risk factors and COVID-19 severity. Using the cis-mQTL variants for the 1258 CVD risk factor-associated CpGs (P < 1e−6) reported in the EWAS catalog, we conducted MR analysis to test for putative causal relations of CVD risk factor-associated CpGs with the corresponding CVD risk factors (e.g., LDL-associated-CpGs with HDL and fasting glucose associated-CpGs with type 2 diabetes). After Bonferroni correction for the number of tests in analysis for each trait (e.g., 0.05/566 or 8.8e−5 in analysis for BMI), we identified 58 significant MR associations (Supplemental Tables 9). Information for the cis-mQTL variants and their corresponding CpGs is presented in Supplemental Table 8. The top three Cpg-trait pairs reflected increased methylation levels at cg05337441 (APOB) with lower LDL (MR effect size: -2.94 ± 0.14, P = 1.2e−9), increased methylation levels at cg26663590 (closest gene is NFATC2IP in UCSC genome browser) with lower BMI (MR effect size: -1.39 ± 0.13, P = 6.3e−26), and increased methylation levels at cg14099685 (CELF1) with higher systolic BP (MR effect size: 138.64 ± 14.85, P = 9.9e−21). We also demonstrated that 17 CVD risk factor-CpGs
were associated with coronary artery disease (Table 3; corresponding \( P < 3.9 \times 10^{-5} \)), e.g., at cg08129017 (SREBF1; reported as associated with BMI and triglyceride in the EWAS catalog) and cg02050917 (SKI; BMI-associated CpG), higher methylation levels were associated with increased CVD risk, MR effect size: 1.81 ± 0.25, \( P = 5 \times 10^{-13} \) and 2.65 ± 0.39, \( P = 1.4 \times 10^{-11} \), respectively.

A recent study conducted in 407 patients with COVID-19 showed that whole blood derived DNA methylation levels at 23 CpGs (annotated to 20 genes) were associated with COVID-19 severity\(^{18}\). We found that ten of the 23 COVID-19 severity-associated CpGs had at least one \( \text{cis} \)-mQTL variant in our database. We used independent \( \text{cis} \)-mQTL variants (linkage disequilibrium \( R^2 < 0.1 \), which overlapped with the SNPs tested by the two COVID-19 severity GWAS\(^{19,20}\), to conduct MR analyses. As shown in Table 4, we observed that higher methylation levels at cg14893161 (PM20D1; \( P = 6 \times 10^{-5} \) and 0.002 for the two COVID GWAS, respectively), lower methylation levels at cg17178900 (PM20D1; \( P = 7 \times 10^{-4} \) and 0.008), and higher methylation levels at cg14859874 (UBAP2L; \( P = 0.002 \) and 2\( \times 10^{-4} \)), were causally associated with COVID-19 severity after Bonferroni correction in analyses using both COVID GWAS databases.

### Table 3. Mendelian randomization analysis for CVD risk factor-associated CpGs (exposure) with coronary artery disease (outcome). IV: instrument variables, i.e., independent \( \text{cis} \)-mQTL variants with linkage disequilibrium \( R^2 < 0.1 \). Beta, SE, and \( P \) are derived from Mendelian randomization analysis using the inverse variance weighted (IVW) method.

| CpG        | Chr | Position | Gene     | Relation to CpG island | Distance to TSS | N of IVs | Beta | SE  | \( P \) |
|------------|-----|----------|----------|------------------------|-----------------|---------|------|-----|-------|
| cg08129017 | 17  | 17825345 | SREBF1   | S_Shore                | 14,011          | 20      | 1.81 | 0.25 | 5.0e−13 |
| cg00184953 | 6   | 31178444 | PSORS1C3 | N_Shelf                | 4709            | 7       | −4.86| 0.70 | 4.7e−12 |
| cg02050917 | 1   | 2242131  | SKI      | S_Shore                | 13,812          | 13      | 2.65 | 0.39 | 1.4e−11 |
| cg05337441 | 2   | 21043695 | APOB     | N_Shore                | 42,266          | 17      | 1.26 | 0.19 | 3.5e−11 |
| cg15878377 | 12  | 48351459 | SREBF1   | N_Shore                | 16,782          | 29      | −0.89| 0.16 | 2.6e−8  |
| cg31357416 | 1   | 15423826 | UBA2L    | S_Shore                | 4833            | 1       | 7.36 | 1.63 | 6.1e−6  |
| cg04545296 | 12  | 48351459 | SREBF1   | N_Shore                | 31,174          | 4       | 3.71 | 0.75 | 7.1e−7  |
| cg20544516 | 17  | 17813868 | MIR33B   | S_Shore                | 31,232          | 36      | 0.64 | 0.21 | 0.002   |

### Table 4. Mendelian randomization analysis of putatively causal relations of COVID-19 severity-associated CpGs to COVID-19 severity. IVs are independent \( \text{cis} \)-mQTL variants with linkage disequilibrium \( R^2 < 0.1 \). Inverse variance weighted (IVW) method was used to conduct Mendelian randomization analysis, using data from two COVID-19 GWAS (COVID-19 Host Genetics Initiative\(^{20}\) and GenOMICC study\(^{19}\)).

| CpG        | Chr | Position | Gene     | Relation to CpG island | Distance to TSS | COVID-19 Host Genetics Initiative GWAS (release 6) | GenOMICC study |
|------------|-----|----------|----------|------------------------|-----------------|--------------------------------------------------|---------------|
| cg07796016 | 1   | 15277958 | LCE1C    | Island                 | 2275            | 19       | 0.08  | 0.26  | 0.76   | 22       | −0.35  | 0.28  | 0.20   |
| cg14859874 | 1   | 15423826 | URA2P2L  | Island                 | 45,616          | 36       | 0.64  | 0.21  | 0.002  | 37       | 0.65   | 0.18  | 0.0002 |
| cg17178900 | 1   | 205818956| PM20D1   | Island                | 21,802          | 34       | −0.54 | 0.16  | 0.0007 | 31       | −0.46  | 0.17  | 0.008  |
| cg14893161 | 1   | 205819251| PM20D1   | S_Shore               | 22,097          | 34       | −0.69 | 0.17  | 6.1e−05 | 38       | −0.54  | 0.17  | 0.002  |
| cg08309069 | 6   | 31240651 | HLA-C    | S_Shore               | 4124            | 46       | −0.40 | 0.19  | 0.04   | 45       | 0.31   | 0.28  | 0.28   |
| cg05030953 | 6   | 31241000 | HLA-C    | S_Shore               | 4473            | 50       | −0.24 | 0.15  | 0.10   | 43       | 0.47   | 0.18  | 0.01   |
| cg02872426 | 6   | 110736772| DDO      | Island               | 27,247          | 28       | 0.77  | 0.27  | 0.004  | 27       | 0.39   | 0.28  | 0.16   |
| cg12682382 | 8   | 74787918 | UBE2W    | N_Shelf               | 95,586          | 28       | 0.18  | 0.17  | 0.29   | 27       | 0.03   | 0.19  | 0.88   |
| cg13571460 | 9   | 124989337| LHX6     | Island               | 24,475          | 17       | 0.10  | 0.35  | 0.78   | 18       | −0.21  | 0.33  | 0.53   |

were associated with coronary artery disease (Table 3; corresponding \( P < 3.9 \times 10^{-5} \), e.g., at cg08129017 (SREBF1; reported as associated with BMI and triglyceride in the EWAS catalog) and cg02050917 (SKI; BMI-associated CpG), higher methylation levels were associated increased CVD risk, MR effect size: 1.81 ± 0.25; \( P = 5 \times 10^{-13} \) and 2.65 ± 0.39, \( P = 1.4 \times 10^{-11} \), respectively.

A recent study conducted in 407 patients with COVID-19 showed that whole blood derived DNA methylation levels at 23 CpGs (annotated to 20 genes) were associated with COVID-19 severity\(^{18}\). We found that ten of the 23 COVID-19 severity-associated CpGs had at least one \( \text{cis} \)-mQTL variant in our database. We used independent \( \text{cis} \)-mQTL variants (linkage disequilibrium \( R^2 < 0.1 \), which overlapped with the SNPs tested by the two COVID-19 severity GWAS\(^{19,20}\), to conduct MR analyses. As shown in Table 4, we observed that higher methylation levels at cg14893161 (PM20D1; \( P = 6 \times 10^{-5} \) and 0.002 for the two COVID GWAS, respectively), lower methylation levels at cg17178900 (PM20D1; \( P = 7 \times 10^{-4} \) and 0.008), and higher methylation levels at cg14859874 (UBAP2L; \( P = 0.002 \) and 2\( \times 10^{-4} \)), were causally associated with COVID-19 severity after Bonferroni correction in analyses using both COVID GWAS databases.
Discussion
To create a cutting-edge genome wide resource of cis- and trans-mQTLs, we analyzed whole genome sequences in conjunction with array-based DNA methylation data from 4126 FHS participants. Our pooled analysis identified 94,362,817 cis-mQTL variant-CpG pairs (9,395,367 cis-mQTL variants; 210,156 unique autosomal CpGs; $P < 1e^{-7}$ and 33,572,145 trans-mQTL variant-CpG pairs (6,039,960 trans-mQTL variants; 213,606 unique autosomal CpGs; $P < 1e^{-14}$). This comprehensive database can bridge a GWAS knowledge gap regarding mechanisms of effects of disease-associated SNPs. For example, we demonstrated enrichment of mQTL variants for disease-associated SNPs from GWAS. Using cis-mQTL variants, our colocalization analyses support connections between CpGs with CVD traits. MR analyses further demonstrated that cis-mQTLs can be used to test causal relations of CpGs to multiple phenotypes. In particular, we showed that DNA methylation at several CpGs, e.g., cg14893161 (annotated to PM20D1), may play an important role in relation to COVID-19 severity. Taken together, our study created a robust mQTL repository to better understand the epigenetic mechanisms underlying a wide range of diseases. A comprehensive summary data set will be posted to the National Heart, Lung, and Blood Institute’s BioData Catalyst site and will be freely accessible to the scientific community.

Consistent with our previous mQTL study and others, a majority of SNP-CpG pairs are cis. For example, the number of cis-mQTL-CpG pairs was 2.8 times of that of trans-mQTL-CpG pairs in our pooled analysis (1.5 times using $P < 1e^{-14}$). To the best of our knowledge, our study is the largest mQTL mapping project using WGS, including ~20 million SNPs and INDELs and ~850 thousand CpGs. Our database expands the existing literature by adding ~40 million novel cis- and ~30 million trans-mQTL-CpG pairs based on WGS rather than imputed genotypes from array-based genotyping. In addition, our database included cis- and trans-mQTLs for 180,692 unique CpGs present on the EPIC array that are not on the 450K array. Compared to the older 450K array, the EPIC array increases CpG coverage of specific genomic regions such as enhancers and non-coding regions. Therefore, our data will facilitate future studies that examine the potential biological function and clinical impact of DNA methylation at these genomic regions.

To showcase the application of our mQTL database, we demonstrated the enrichment of mQTL variants for disease-associated SNPs from GWAS using the GWAS Catalog. For example, analysis utilizing cis-mQTL variants showed enrichment for SNPs associated with CVD and multiple CVD risk factors including BMI, systolic BP, triglyceride, type 2 diabetes, and coronary artery disease. Our colocalization analysis using cis-mQTL variants for CpGs and GWAS summary statistics of these variants for CAD identified colocalization of an LDL-associated CpG, cg05337441 (APOB), with coronary artery disease. A intergenic SNP rs668948, mapped to APOB and TDRD15, explained 41% of the observed colocalization. The product encoded by APOB is the main apolipoprotein of LDL that serves as the ligand for the LDL receptor. The atherogenic potential of apolipoprotein B-100 has been demonstrated by many studies including MR analysis. Our data are consistent with the notion that DNA methylation contributes to the atherogenicity of LDL and suggest that future studies are needed to examine the exact molecular underpinnings of these observations. Also, in line with these observations, our MR analysis showed that many CVD risk factor-associated CpGs are putatively causal for CVD and CVD risk factors (Supplemental Table 8). These findings provide epigenetic insights into associations reported in GWAS. For example, we observed that cg12816198 (IRF5) was associated with systolic BP (MR $P = 6.3e^{-8}$). SNP rs4728142, an intergenic variant mapped to genes IRF5 and KCP, has been reported to be associated with hypertension in previous GWAS. This SNP (rs4728142) is a strong cis-mQTL variant for cg12816198 (IRF5; $P = 7e^{-215}$) and the leading instrumental variable in the MR analysis for systolic BP (single SNP MR analysis $P = 2.7e^{-9}$), suggesting a causal pathway whereby rs4728142 modifies DNA methylation levels at cg12816198 with downstream effects on systemic BP. Interestingly, both colocalization analysis and MR analysis showed a connection between cg27087650 (BCL3) and coronary artery disease through cis-mQTL variant rs62117206 (intronic to BCL3; $P = 3.6e^{-15}$; linkage disequilibrium $R^2 = 1$ with rs4803750, another cis-mQTL variant of cg27087650; $P = 1.8e^{-14}$). CpG cg27087650 is located in the gene body of BCL3, which encodes a protein functioning as a transcriptional co-activator through its association with NF-kappa B homodimers. Expression of BCL3 has been linked to CVD and cancer. These examples provide proof of principle that integrating cis-mQTLs with CpGs and traits can reveal biological pathways by linking DNA methylation to a variety of diseases.

Our mQTL database can also be used to screen candidate DNA methylation sites for further consideration in experimental and interventional studies. This is exemplified by our MR analysis that revealed a putatively causal effect of COVID-19 associated CpGs on disease severity. Our COVID analysis focused on ten CpGs that were identified in a case–control study of COVID-19 severity. Because of the retrospective design of the study, it could not infer causal relations between DNA methylation at these CpGs and the severity of COVID-19. Our analysis highlighted three COVID-related CpGs annotated to genes PM20D1 and UBAP2I that were putatively causal for COVID-19 severity; more research is needed to understand if and how these CpGs might influence outcome in patients with the COVID-19.

In parallel with our mQTL project, our research team is examining eQTLs and expression quantitative trait methylation sites (eQTM) using WGS, RNA sequencing, and DNA methylation resources obtained in FHS participants. The eQTL and eQTM resources are also freely available online via the BioData Catalyst site. These molecular resources enable users to explore how DNA methylation affects transcriptional activities and pathways leading to a wide range of disease phenotypes. These molecular resources can be used in concert to reduce bias due to reverse causality and unmeasured confounding, particularly environmental confounders. Nonetheless, this study has several limitations that warrant discussion. Our analysis was conducted in a group of middle-aged and older, primarily white adults; therefore, the findings in this study may not be generalizable to other populations. Nonetheless, we demonstrated that mQTLs identified in other studies, including those identified in a cross-ancestry analysis, were well replicated in our database. We captured whole blood-based DNA methylation profiles, which can serve as candidate biomarkers for diseases; however, they may not reflect tissue-specific
DNA methylation levels, which may be relevant to specific diseases. Utilizing a publicly available database, Lowe et al. compared DNA methylation profiles measured by the same commercial 450K array in multiple tissues and showed a higher number of tissue-specific differentially methylated positions in blood compared to other tissues. Their study provided evidence supporting a critical role of blood in crosstalk with other tissues. A recent study by Ng et al. further advanced this notion by showing that T cells are directly involved in the pathogenesis of cardiovascular comorbidities through increased interactions with endothelial cells in individuals with non-alcoholic fatty liver disease. MR analysis was used to showcase the potential application of our mQTL database; however, MR analysis is based on assumptions that may not be testable. Also, DNA methylation can be affected by both genetic and environmental factors. We did not attempt to test effect modification by environmental factors in this study. Future studies with larger sample sizes in diverse population are needed to replicate and expand our mQTL resource.

In conclusion, we have identified millions of cis- and trans-mQTL variant CpG pairs using state-of-the-art WGS data in conjunction with high-throughput DNA methylation data. We demonstrated the utility of this vast mQTL resource by conducting GWAS signal enrichment analyses, colocalization, and MR analyses. Our mQTL repository is freely available via the BioData Catalyst site for the scientific community to study the role of DNA methylation in health and disease.

Methods

Study population. The study sample included consenting participants from the FHS Offspring, Third Generation, and Omni cohorts. In 1971, the FHS recruited the offspring of participants in the Original FHS cohort as well as the spouses of offspring to form the FHS Offspring cohort. The children of the Offspring cohort participants were recruited to the Third Generation cohort beginning in 2002. Omni cohorts were established in parallel with the Offspring and the Third Generation cohorts. In the current investigation, the study sample included 4126 FHS participants with whole blood derived DNA methylation and WGS data; 2129 participants in the Offspring cohort (exam 8, N = 869; exam 9, N = 1260), 1945 participants in the Third Generation cohort (exam 2), and 52 participants in the Omni cohort. The FHS protocols and procedures were approved by the Institutional Review Board for Human Research at Boston University Medical Center, and all participants provided written informed consent. All research was performed in accordance with relevant guidelines/regulations.

Study design. A flow chart of the study design is presented in Fig. 1. The FHS had two sets of DNA methylation data, one set included 3460 participants assayed with the Illumina BeadChip 450K (450K array; 2009 Offspring exam 8 participants and 1451 Third Generation exam 2 participants) and the second set included 1806 participants assayed with the Illumina EPIC array (EPIC array; 1260 Offspring exam 9 participants, 493 Third Generation exam 2 participants, and 52 Omni cohort participants). To maximize the sample size, as our primary analysis we conducted a pooled analysis of the two data sets. Of note, 1140 Offspring participants were included in both sets, i.e., these participants had 450K array-based methylation data from exam 8 and EPIC array-based methylation data from exam 9. In the pooled analysis, we selected the EPIC array-based data for these 1140 participants to avoid any duplication. We also conducted array-specific analysis to explore if mQTLs were replicable and to examine mQTLs that are unique to the EPIC array. We then examined the top cis- and trans-mQTLs by conducting GO pathway analysis and enrichment analysis. We tested cis-mQTLs for colocalization and causal association using two-sample MR analysis with CVD traits and COVID-19 severity.

DNA methylation profiling. Preparation of whole blood samples for DNA methylation profiling was conducted as detailed previously. Briefly, DNA was obtained from whole blood buffy coat samples and prepared using bisulfite conversion before whole-genome amplification, fragmentation, array hybridization, and single-base pair extension. DNA methylation was then measured in 4170 FHS participants using the Illumina Infinium Human Methylation-450 Beadchip (450K array) in three batches (Batch 1, N = 499; Batch 2, N = 2149; and Batch 3, N = 1522). Of these, 3460 participants also had WGS data. Additionally, the Illumina MethylationEPIC 850 K BeadChip (EPIC array) was used in 1806 FHS participants with WGS. All participants were with missing methylation levels of no more than 5% of CpGs (detection \( P < 0.01 \)) and none of them were outliers in a multidimensional scaling plot. The CpGs have been prefiltered so that all CpGs had > 5% missing values (detection \( P < 0.01 \)). We calculated DNA methylation beta values (range 0 to 1) as the ratio of mean methylated and unmethylated probe signal intensities. We used the DASEN method to normalize the methylation beta values.

Whole genome sequencing. WGS of FHS participants was performed by the Broad Institute as part of the NHLBI’s TOPMed program. Genomic DNA from whole blood samples from 2194 FHS Offspring cohort and 1582 Third Generation cohort participants was sequenced at \( > 30 \) depth of coverage. Genetic variations were identified in a joint calling of all samples by the TOPMed Informatics Resource Center at University of Michigan. Centralized read mapping, genotype calling, and quality control were also performed at the TOPMed Informatics Research Center. This analysis used genetic variants generated from TOPMed Freeze 10a. We analyzed 20,696,115 SNPs and insertion/deletion polymorphisms (INDELs) with minor allele count (MAC) \( \geq 10 \). WGS data acquisition is described on the Database of Genotype and Phenotype (dbGaP) website (https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study_id=phs000974.v4.p3).

mQTL mapping. The mQTL mapping was conducted separately for DNA methylation data generated using the 450K array and the EPIC array. In the analysis for the 450K array data, we calculated residuals for methylation beta values obtained within each of the three methylation batches after adjusting for relevant technical
covariates. Whereas, in the analysis for the EPIC array data, we derived residuals using all available samples, also adjusting for technical covariates. The residuals from separate datasets were then combined. We then used linear regression models to perform the association analyses between the SNPs and the CpGs, adjusting for sex, age, differential leukocyte counts (estimated using the Houseman method), along with the top 15 residual methylation principal components (PCs) and five genetic PCs. We chose to adjust for 15 methylation PC's and five genetic PCs because this strategy resulted in the highest replication rate between the 450K array data and the EPIC array data. Because of relatedness among FHS study participants, linear mixed models were used in mQTL mapping to account for family structure. The primary pooled analysis examined 452,567 CpGs that are common to both arrays. The 450K array-specific analysis analyzed the same 452,567 CpGs and the EPIC array-specific analysis examined 413,524 additional CpGs (i.e., CpGs not included in the pooled analysis). We defined SNPs residing within 1 million base pairs from a CpG site as cis-variants and those located ≥ 1 million base pairs away from the CpG site or on a different chromosome as trans-variants. We considered cis-variants as cis-mQTL variants if they were associated with DNA methylation levels at the corresponding CpG site with a two-sided \( P < 1e^{-7} \), whereas we considered variants as trans-mQTL variants when the variant-CpG associations had a two-sided \( P < 1e^{-14} \). The \( P \) value thresholds were selected for cis-mQTLs based on the Bonferroni correction for the number of CpGs tested (i.e., \( n = 452,567 \)) and for trans-mQTLs based on an internal discovery-validation experiment that gave the highest trans replication rate. We counted the number of pairs of mQTL variants (cis or trans) with their corresponding CpGs at all autosomal chromosomes. R-squared values derived from a linear regression model were used to represent heritability \((hSNP^2)\) of each cis- or trans-mQTL variant.

**mQTL replication.** To explore consistency between our mQTLs with published databases, we examined whole blood derived mQTLs identified in two large studies, one conducted by Bonder et al. in 3841 individuals from five Dutch biobanks and the other conducted by Hawe et al. in 3799 European individuals and 3195 individuals from South Asia. Both studies analyzed SNPs based on commercial arrays with imputation. Because the number of SNPs analyzed in the two studies (~ 5 and ~ 9 million, respectively) was smaller than that tested in the present study (~ 20 million), we examined whether mQTLs identified in the two studies were also significant in our database.

**Gene Ontology analysis.** We tested the over-representation of GO terms based on genes annotated to the top 1000 cis-mQTL variants (for 1000 CpGs) with Entrez IDs identified by the pooled analysis. The default setting in the `goana` function from the `limma` (Linear Models for Microarray and RNA-seq Data) package was used to conduct the GO analysis. GO terms (Biological Process, Cellular Component, and Molecular Function) with false positive rate (FDR) < 0.05 were reported. We repeated the same analysis for the top 1000 trans-mQTL variants.

**GWAS enrichment analysis.** We analyzed all SNPs with association \( P < 5e^{-8} \) included in the NHGRI-EBI GWAS Catalog (https://www.ebi.ac.uk/gwas/). We identified 243,587 entries for 2960 GWAS traits. In this analysis, we examined all mQTL variants with unique RSIDs in cis or trans at \( P < 1e^{-7} \) or \( P < 1e^{-14} \), respectively. Fisher's exact test was used to perform the enrichment analysis for each trait, and traits with FDR < 0.05 were reported.

**Colocalization analysis.** We conducted colocalization analysis using the R `HyPrColoc` package, a highly efficient deterministic Bayesian algorithm based on GWAS summary statistics. We reported the posterior probability of full colocalization (PPFC). Default prior configuration parameters (\( prior.c = 0.02 \)) and threshold of 0.7 for PPFC were used. We extracted cis-mQTL variants (\( P < 1e^{-7} \)) derived from the present pooled analysis for 1258 CpGs associated with CVD risk factors in the EWAS catalog (\( P < 1e^{-6} \)) including BMI, waist circumference, fasting glucose, systolic blood pressure (systolic BP), diastolic blood pressure (diastolic BP), high-density lipoprotein cholesterol (HDL), low-density lipoprotein cholesterol (LDL), and triglyceride. We examined the colocalization of these CVD risk factor-associated CpGs with CVD-related traits including BMI, BP, lipid concentrations, type 2 diabetes, and coronary artery disease. Summary statistics for associations between cis-mQTL variants and GWAS for CVD-related traits were obtained from published GWAS databases.

**Mendelian randomization analysis.** To showcase the potential use of the mQTL resource in causal inference analyses, we conducted MR analyses to infer causal associations of the CpGs with the abovementioned CVD-related traits and COVID-19 severity. In the MR analysis for CVD-related traits, we used the same cis-mQTL variants for the 1258 CVD risk factors. COVID-19-associated CpGs were obtained from a recently published EWAS of COVID-19 severity. We performed MR analyses using a two-sample MR approach. We used independent cis-mQTL variants with pair-wise linkage disequilibrium (LD) \( r^2 < 0.1 \) as instrumental variables (IVs). Using the `TwoSampleMR` R package, we performed the primary analysis using the inverse variance weighted (IVW) method and sensitivity analysis using the MR-Egger method. We tested for potential horizontal pleiotropy by examining the MR-Egger intercept \( P \) value. The effect sizes and standard errors for IV-CpG associations were obtained from the pooled mQTL analysis. The effect sizes and standard errors for associations between IVs and CVD-related traits were obtained from the published large GWAS described above. We obtained effect sizes and standard errors from two GWAS for COVID-19 severity conducted by the COVID-19 Host Genetics Initiative and the Genetics of Mortality in Critical Care (GenOMICC) study. The COVID-19 Host Genetics Initiative included 8779 cases (death or hospitalization requiring respiratory support due to COVID-19) and 1,001,875 population controls and the GenOMICC study included 7491 cases (confirmed
COVID-19 requiring continuous cardiorespiratory monitoring in intensive care units) and 48,400 population controls.

**Data availability**

The datasets analyzed in the present study are available at the dbGAP repository phs000007.v32.p13 (https://www.ncbi.nlm.nih.gov/projects/gap/cgi-bin/study.cgi?study_id=phs000007.v30.p11).

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Author contributions
D.L. and J.M. designed research, interpreted results, and had primary responsibility for final content; R.J. and J.M. conducted the analyses; J.M. and R.J. wrote the manuscript; H.B. contributed to the literature review used in the paper; C.L. A.K., H.S., B.T., M.S., P.J.M., C.Y.D., P.C., N.L.H., A.N.P., M.E., N.S., R.S.V., and T.H. critically reviewed the manuscript; and all authors read and approved the final manuscript.

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Competing interests
The authors declare no competing interests.

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