

Supplementary Information for

Modeling islet enhancers using deep learning identifies candidate causal variants at loci associated with T2D and glycemic traits.

Sanjarbek Hudaiberdiev^{1,A}, D. Leland Taylor^{2,A}, Wei Song^{1,A}, Narisu Narisu^{2,A}, Redwan M. Bhuiyan^{3,4}, Henry J. Taylor^{2,5}, Xuming Tang^{6,7}, Tingfen Yan², Amy J. Swift², Lori L. Bonnycastle², DIAMANTE Consortium, Shuibing Chen^{6,7}, Michael L. Stitzel^{3,4,8}, Michael R. Erdos^{2,B}, Ivan Ovcharenko^{1,B}, Francis S. Collins^{2,B}

- 1. Computational Biology Branch, National Center for Biotechnology Information, National Library of Medicine, National Institutes of Health, Bethesda, MD 20892, USA
- 2. Center for Precision Health Research, National Human Genome Research Institute, National Institutes of Health, Bethesda, MD 20892, USA
- 3. The Jackson Laboratory for Genomic Medicine, Farmington, CT 06032, USA
- 4. Department of Genetics and Genome Sciences, University of Connecticut, Farmington, CT 06032, USA
- 5. British Heart Foundation Cardiovascular Epidemiology Unit, Department of Public Health and Primary Care, University of Cambridge, Cambridge CB1 8RN, UK
- 6. Department of Surgery, Weill Cornell Medicine, New York, NY 10065, USA
- 7. Center for Genomic Health, Weill Cornell Medicine, New York, NY 10065, USA
- 8. Institute of Systems Genomics, University of Connecticut, Farmington, CT 06032, USA

A. These authors contributed equally to this work.

B. To whom correspondence may be addressed. Email: mikee@mail.nih.gov, ovcharei@ncbi.nlm.nih.gov, and francis.collins@nih.gov.

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Supplementary Materials and Methods

Genome annotations

ENCODE and NIH Roadmap genomic and epigenomic profiles

We used previously published DNase I hypersensitive sites (DHSs), ChIP-seq peaks of histone marks (HM), and ChIP-seq peaks of transcription factor (TF) binding from the ENCODE (1) and NIH Roadmap (2) studies (1,924 features in total).

Islet genomic and epigenomic profiles

We used previously published ATAC-seq data from 33 islets, consisting of 64,129 peaks (3). As described in Viñuela et al. (3), since these islets originate from multiple studies, reads were downsampled to the minimum read depth across samples (27,994,993 reads) and merged across studies. Peaks were called across all samples (via the merged bed file) as well as within samples. The final 64,129 ATAC-seq peak calls were those peaks from the merged bed file that occurred in >17 of the individual samples ATAC-seq peak calls.

We reprocessed previously published H3K27ac ChIP-seq data from two islets (4). Briefly, in order to avoid bias from one specific sample, we downsampled the number of reads from each sample to the minimum read depth across samples (26,369,910 reads) and merged reads from both samples. We performed a similar process for the input controls for each sample, downsampling to 23,702,108 reads per sample before merging reads across samples. Next, we aligned reads and identified peaks using the ENCODE ChIP-seq processing pipeline (https://github.com/ENCODE-DCC/chip-seq-pipeline2, v1.2.0) with default parameters. We excluded the peaks overlapping Duke blacklisted regions (UCSC browser tables wgEncodeDacMapabilityConsensusExcludable and wgEncodeDacMapabilityConsensusExcludable), resulting in 87,007 H3K27ac peaks.

Enhancer definitions

We identified 9,918 islet enhancers by selecting ATAC-seq peaks that overlapped an islet H3K27ac ChIP-seq peak (≥1bp) and expanding 1kb up and down the genome from the middle position of the ATAC-seq peak. We considered the entire 2kb region, centered on the ATAC-seq peak, as an enhancer. We removed promoter regions, defined as 1.5kb upstream and 0.5kb downstream (2kb in total) of the transcription start site of known genes from the UCSC genome browser (ftp://hgdownload.soe.ucsc.edu/goldenPath/hg19/database/knownGene.txt.gz).

To define enhancers in HepG2 and K562, we used the ENCODE data and performed the same procedure, using ATAC-seq peaks for HepG2 (n=279,739; ENCSR042AWH) and K562 (n=269,800; ENCSR868FGK) from ENCODE. We identified 21,162 HepG2 and 25,357 K562 enhancers in total.

Two phase deep learning model to predict enhancers

We developed a two phase deep learning (DL) classifier, TREDNet, based on convolutional neural networks (CNNs; implemented in keras v2.1.2 and tensorflow-GPU v1.4.1) to predict enhancers from DNA sequence. In the first phase, we used a model with six convolutional layers (~143 million trainable parameters; Table S4) to predict 1,924 different genomic and epigenomic features simultaneously for a 2kb genomic region. These features included DHSs, TF ChIP-seq peaks, and histone mark ChIP-seq peaks from the ENCODE (1) and NIH Roadmap (2) studies. We tiled the entire human genome using a sliding window of length 2kb and the step length of 200bp. We selected those segments that overlapped at least one of the 1,924 epigenomic features and trained the DL model using these segments. For training, we fit the model on all autosomes, except for chromosomes 8 and 9. During training, we used signals on chromosome 7 as a validation set. We used signals on chromosomes 8 and 9 for testing the final model, evaluating both the area under the receiver operating characteristic curve (auROC) and area under the precision recall curve (auPRC; Fig. S1). Due to the cell/tissue type-specific nature of the features, the class distribution (positive/negative) in the training set was imbalanced across the features, with only 2% of the dataset being positive cases on average. To evaluate the optimal sequence window size, we randomly selected 10% of the training data and re-fit the model using different window sizes ranging from 800bp-4kb and the same training/testing strategy (i.e., chromosome 7 as a validation set during training and chromosomes 8 and 9 for testing the final model). We evaluated model performance using auROC and auPRC as metrics, testing for improved model performance (defined as *P*-value<0.05) across progressively larger window sizes using the Wilcoxon rank sum test (Fig. S2). We found that the models improved at each larger window size up to 2kb, after which there was no statistical improvement. Using the 2kb model, we compared the TREDNet phase one model to previously published, similar epigenomic feature prediction models—ExPecto (5), DeepSEA (6), and Basset (7)—on the data used for TREDNet with the same testing strategy (i.e., testing performance on chromosomes 8 and 9; Fig. S1).

For the second phase (enhancer prediction), we fit three smaller models to predict pancreatic islet, HepG2, and K562 enhancers (one for each cell/tissue type) from the output of the first model (a vector of the 1,924 epigenomic predictions for 2kb sequence segments). The second model consisted of two convolutional layers resulting in ~12 million trainable parameters (Table S5). For each biospecimen, we treated the enhancer regions as the positive set (encoded as 1); for the negative set (encoded as 0), we randomly sampled 10x of the number of enhancers from accessible chromatin regions (i.e., DHSs) across all biospecimens in NIH Roadmap, excluding the enhancer regions of the target biospecimen. For training, we adopted a similar strategy as phase one, using chromosome 7 to validate during training and withholding chromosomes 8 and 9 to evaluate the final model. We tested the model's performance (auROC and auPRC) using enhancers from chromosomes 8 and 9 withheld from training (Fig. 2A). To benchmark the TREDNet phase two model, we tested previously described enhancer prediction models—BiRen (8), Tan et al. (9), and SVM (10)—on the data used for TREDNet with the same testing strategy (i.e., testing performance on chromosomes 8 and 9). Since SVM did not distribute pre-trained models, we trained SVM using the same data (i.e., enhancer definitions) and training strategy as for TREDNet. For BiRen and Tan et al., we used the pre-trained models which were not cell type specific. For Tan et al., the method produces a binary output for each input region based on the scores generated by five different models. To generate auROC and auPRC values, we used the scores generated by each of the five Tan et al. models and picked the best performing one.

Finally, to evaluate the utility of the two phase TREDNet model structure as opposed to a single phase model, we (i) combined the phase two enhancer region training data with the phase one training data and (ii) fit a single model to predict both types of signals using the phase one model architecture (Fig. S3; training and testing strategy same as used previously with chromosomes 7, 8, and 9). We found that for epigenomic signals (i.e., transcription factors, histone modifications, DNase I hypersensitivity sites), the two phase TREDNet model performed better than the single phase model using auROC and auPRC as metrics (*P*-value<0.05, Wilcoxon rank sum test). We hypothesize that this difference may be due to the increased complexity of the single phase model that must predict both epigenomic signals and enhancer regions. For the task of enhancer prediction, the TREDNet model also outperformed the single phase model, although not at a statistically significant level (*P*-value>0.05, Wilcoxon rank sum test)—possibly due to the small sample size (n=3; i.e., enhancers from islets, HepG2, and K562). As a last comparison, we considered training speed and found that for the end goal of predicting enhancers, the two phase TREDNet model has an advantage over a single phase model in that it can be trained to predict enhancers much faster than the single phase model.

Analysis of in vitro enhancer mutagenesis experiments

We validated TREDNet enhancer probability scores using data from three massively parallel reporter assay (MPRA) studies (11–13), described below. For all datasets, we calculated computational scores based on the DNA sequence tested in the MPRA using TREDNet and the other enhancer modeling methods considered in this study: BiRen, Tan et al., and SVM (trained using the same enhancer dataset as used for TREDNet as described in "Two phase deep learning model to predict enhancers"). For TREDNet, SVM, and BiRen, we expanded each input genomic DNA segment to 2kb; for Tan et al., we extended the input DNA segments to 200bp, as required by the method. We compared each of the computational scores for each study to the MPRA signal by calculating Spearman's rank-order correlation and root mean squared error (RMSE; Fig. 2B,S4). To make RMSE comparable across models and datasets, we standardized all values prior to calculating RMSE. Since the Tan et al. method uses five models with varying architectures, we selected the best model for each dataset and comparison metric (i.e., largest value for Spearman's rank-order correlation and smallest value for RMSE.

Kheradpour et al. (11) performed MPRA experiments in HepG2 and K562 that quantified the capacity of DNA segments of predicted TF binding sites (TFBSs) in enhancers to induce gene expression. Using the normalized expression scores distributed by the authors, we filtered for sequences with a detectable impact on gene expression compared to null, scrambled sequences (FDR<5%, Benjamini-Hochberg procedure (14)). We applied the biologically relevant TREDNet model (i.e., the HepG2 model for HepG2, the K562 model for K562) to predict the enhancer probabilities of each DNA segment and compared these predictions to the MPRA signals. We repeated this process for BiRen, Tan et al., and SVM.

Kwasnieski et al. (13) conducted MPRA experiments in K562 that measured the capacity of DNA sequences in K562 enhancer regions ("enhancer" and "weak enhancer" chromatin states) to induce gene expression. We used the K562 TREDNet model to predict the enhancer probabilities of each DNA segment and compared these predictions to the MPRA signals, using the normalized expression scores provided by the authors. We repeated this process for BiRen, Tan et al., and SVM.

Finally, Kircher et al. (12) performed saturated mutagenesis experiments targeting several regulatory elements associated with disease. We used data from this study from enhancer regions that tested for effects of mutations in regions near *ZFAND3* and *TCF7L2* in MIN6 and *SORT1* in HepG2. Using the $log₂$ allelic MPRA expression effect estimates distributed by the authors, we filtered for alleles with >=10 unique barcode tags (as done by the authors) and for alleles that showed a statistical difference in the MPRA expression read out (FDR<5%, Benjamini-Hochberg procedure (14)). We applied the biologically relevant TREDNet model (i.e., the islet model for MIN6, the HepG2 model for HepG2) calculated the $log₂$ fold change of enhancer probability scores for the alternate allele compared to the reference allele, comparing these predictions to the MPRA signals. We repeated this process for Tan et al. and SVM. For BiRen, because the method takes as input coordinates of genomic regions, not DNA sequences, we used the enhancer probabilities of the overall regions.

Calculation of enhancer damage scores from in silico saturated mutagenesis

For each biospecimen, we performed in silico saturated mutagenesis of enhancer regions to evaluate the effects of mutations on the overall enhancer probability score. For each 2kb enhancer region (see "Enhancer definitions"), we calculated an enhancer damage (ED) score iteratively for each nucleotide position against the GRCh37 reference sequence (i.e., we mutate each nucleotide to all possible mutations but keep the remaining 1,999 nucleotide sequence the same as the reference):

$$
\Sigma(e_{reference} - e_{alternative})/3
$$

where the *e* term represents the probability that the 2kb sequence is an enhancer, *reference* indicates the GRCh37 reference nucleotide, and *alternate* indicates a non-reference nucleotide. This ED score, generated for each bp in the 2kb enhancer region, predicts the effects of mutations at a specific base on the overall enhancer probability of the region, such that a positive score indicates a negative change in the enhancer probability (enhancer damaging) and a negative score indicates a positive change in the enhancer probability (enhancer strengthening).

Identification and analysis of transcription factor binding sites (TFBSs)

For HepG2 and K562, we used TF ChIP-seq data spanning 77 TFs in HepG2 and 150 TFs in K562 (1). For each TF, in order to extract the TFBS position, we used HOMER v4.11 (15) to scan motifs found in the database packaged with HOMER (http://homer.ucsd.edu/homer/motif/motifDatabase.html), producing a list of predicted TFBSs for each motif in the database. We ranked the motifs in decreasing order of their enrichment *P*-value and kept the TF of the most enriched motif.

Because islets do not have as comprehensive TF ChIP-seq profiles as HepG2 and K562, we used predicted TFBSs derived from ATAC-seq footprints described previously (16). Briefly, for two islet ATAC-seq samples, Varshney et al. scanned for potential transcription factor binding sites

(TFBSs) in a haplotype-aware manner using the "find individual motif occurrences" (FIMO) tool (17) with position weight matrices (PWMs) from a previously described database (18) consisting of PWMs from ENCODE (19), JASPAR (20), and Jolma et al. (21). Next, Varshney et al. used CENTIPEDE (22) to call footprints in the islets ATAC-seq data, considering a given motif occurrence bound if both the CENTIPEDE posterior probability was ≥0.99 and the motif's coordinates were fully contained within an ATAC-seq peak.

For islets, because many of the predicted TFs share similar motif patterns and result in overlapping predicted TFBSs, we reduced redundancy by aggregating islet TF footprints with similar binding motifs. For each TF, we calculated the average ED score across all nucleotides within the predicted binding sites. For the TFs with a positive average ED score across all predicted TFBSs (690 TFs), we selected 156 TFs where the average lower boundary of 95% confidence interval (CI) the binding region was greater than the upper boundary of the CI of the flanking region (defined as 10bp on each side of the TFBS). For the TFs with a negative average ED score across all predicted TFBSs (49 TFs), we selected 10 TFs where the ED scores within the CI were all negative. Using these 166 TFs, we iteratively merged TFs if >40% of their predicted binding sites overlapped and the overlapping regions were greater than half of either binding site. In total, this procedure resulted in 100 non-redundant TFs groups for islets, which we used to analyze ED scores in islet enhancers.

We used TFBSs in islets, K562, and HepG2 to evaluate if ED scores mark TFBSs by comparing the absolute value of ED scores within TFBSs to 20bp regions immediately flanking each TFBS as well as randomly sampled enhancer regions. To generate random ED scores, we shuffled the TFBSs within enhancer regions for each biospecimen 10 times and recorded the absolute value of ED scores within these regions.

In addition, to compare ED scores to evolutionary conservation profiles at TFBSs, we calculated the information content (IC) at each position of PWMs for each TF. For evolutionary conservation profiles, we used phyloP scores generated from 46 vertebrate species (23, 24). Across all TF PWMs for each biospecimen, we calculated the correlation (Spearman's rho) between the IC of each PWM position and delta/phyloP scores.

Detection of enhancer damaging regions and enhancer strengthening regions

For each biospecimen, we trained two DL models, one to predict enhancer damaging regions (EDRs) and one to predict enhancer strengthening regions (ESRs) within enhancers from ED score enhancer profiles (six models total across all three cell lines).

To train the EDR/ESR classifiers for each biospecimen, we annotated nucleotides within enhancers with 1 (positive set) if the nucleotide overlapped a TFBS and otherwise 0 (control set). We subsequently excluded from the control set (i.e., enhancer nucleotides annotated as 0) genomic regions (i) between any two TFBSs in an enhancer (even if these TFBSs are on the opposite ends of the enhancer), (ii) within 10bp of a TFBS, (iii) within 20bp of an enhancer boundary, and (iv) in an enhancer of less than 50bp. For HepG2 and K562, we used all TFBSs, described in "Identification and analysis of transcription factor binding sites". For islets, we used the TFBSs from the 166 TFBSs derived from ATAC-seq footprints, described in "Identification and analysis of transcription factor binding sites".

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For each enhancer nucleotide, we derived a series of features from ED score predictions across various window sizes and used these features to predict the location of TFBSs within the enhancer sequence (i.e., the positive or control status of each nucleotide within the enhancer). For each nucleotide, we scanned a series of windows from 10bp in length to 1bp in length. For each window length >7bp, we defined a core region as the 6bp in the center of the window and calculated the following metrics: (i) the average ED score of nucleotides within the window, (ii) the maximum ED score of nucleotides within the window, (iii) the fraction of nucleotides within the window with a positive ED score, and (iv) the fraction of nucleotides within the core region with a positive ED score. For windows of length <6bp, we repeated the same procedure, but using a core region equal to the window size. For each window length, we iteratively scanned around the target nucleotide such that the target nucleotide occupied every position within the window (i.e., we incremented the window position by one base pair for each iteration resulting in 10 sliding windows for a window size of 10bp). For a single nucleotide, the result of this procedure was a series of four metrics defined across 55 windows (of size 10bp to 1bp). We concatenated these metrics together across all windows to generate a vector of 220 values for each nucleotide, representing a comprehensive description of a local mutational impact of each nucleotide on an enhancer. After iteratively performing this procedure across all nucleotides within enhancers, we then fit a two layer CNN (implemented in keras v2.0.8; architecture described in Table S6) to predict the TFBS annotation status (0 or 1) from the 220 values calculated for each nucleotide. During training, we randomly sampled 20% of the input data as a validation set and excluded chromosomes 8 and 9 entirely. We used signals on chromosomes 8 and 9 for testing the final model, evaluating both the auROC and auPRC (Fig. S7).

To train the EDR classifier, we selected for TFBSs where the average ED score was positive. To train the ESR classifier, we performed the same procedure, except we selected for TFBSs where the average ED score was negative.

Both the EDR and ESR models were highly accurate (Fig. S7) and resulted in a score for each nucleotide within an enhancer representing the likelihood that the nucleotide overlaps a TFBS. We used these scores to label regions as EDRs and ESRs. For the EDR models, we used the peak model for each biospecimen and labeled any span of nucleotides (one after the other) of length $>=$ 3 with a likelihood score >=0.312 as an EDR. We repeated the same procedure with the ESR models, calling regions with >=3 consecutive predicted negative EDR nucleotides and a likelihood score >=0.152 as ESRs.

We compared the TREDNet TFBS prediction model from enhancer damage scores to a model that predicted TFBSs directly from DNA sequence. For the DNA sequence TFBS prediction, we fit a single multi-task model to predict the TFBS annotation status (0 or 1) used in the EDR/ESR models from one-hot encoded DNA sequence of the 2kb region centered on the TFBSs (model architecture the same as TREDNet phase one). We fit a separate model for each biospecimen (i.e., islet, HepG2, K562), randomly sampling 20% of the TFBSs, and compared the resulting model to the TREDNet TFBS prediction model using the auROC and auPRC as metrics with the same training validation and test scheme as used in the ED score model (Fig. S8).

To validate the EDR and ESR predictions as regulatory sites within enhancer sequences, we compared the density of SNPs reported to have an allelic effect on transcription in K562 and HepG2 MPRA experiments (25) in DHSs, enhancer regions, and EDR/ESR regions ranked by their average ED score. For comparisons, we calculated the number of MPRA validated SNPs in each genomic region divided by the total length of the region.

Calculation and validation of islet enhancer perturbation scores

We generated a catalog of predicted effects of 67,226,155 SNPs on islet enhancers using the genome Aggregation Database (gnomAD) v3.0 (26), including SNPs with a minor allele frequency (MAF) >=0.0001. Since gnomAD v3.0 uses GRCh38 coordinates, we lifted these coordinates over to GRCh37 to match the data used to train the model. Across all SNPs, we calculated islet enhancer perturbation (IEP) scores using a two phase procedure. First for each SNP, we calculated the probability, *e*, of either allele falling in an enhancer, given 2kb of the flanking reference sequence (GRCh37) surrounding the SNP. Next, we generated IEP scores:

$$
max(e_{reference}^{}, e_{alternative}^{}) \cdot * abs(e_{reference}^{} - e_{alternative}^{})
$$

where the *e* term represents the probability of an allele residing in an islet enhancer. For enrichment calculations and subsequent binning, we calculated the percentile rank of IEP scores.

To validate IEP scores at the genome-wide level, we used previously published islet genetic studies spanning gene/exon expression (3), chromatin accessibility (27), and MPRA data generated from the MIN6 mouse pancreatic islet beta cell line (28). From these data, we generated genome annotations that were subsequently used for enrichment calculations. For the genetic association data (eQTLs, exonQTLs, and caQTLs), we selected all QTLs and marked the genomic location of all SNPs in LD (r²>0.8) with the lead SNP (minimum *P*-value at the locus). For the MIN6 MPRA data, we marked the genomic location of SNPs reported to induce activity in either the unstimulated (baseline) or stimulated (endoplasmic reticulum stress) conditions. We did not LD expand the MPRA SNPs because the MPRA data has SNP resolution since the alleles of single SNP were tested in a reporter construct, thereby breaking the LD structure that exists naturally in the human genome. Using these annotations, we calculated the enrichment of SNPs across progressive IEP percentile cutoffs using GARFIELD v2.0 (29), a logistic regression method that controls for the distance of each SNP to the nearest gene and the number of SNPs in LD. For these enrichments, we used the ~24 million SNPs from the UK10K project and their LD estimates included in the GARFIELD package. Rather than using binarized *P*-value thresholds from a genetic association study to define the dependent variable for the logistic regression, we used IEP percentile cutoffs. Across all enrichment tests, we used the Bonferroni procedure to control for the number of tests performed.

For islet specificity comparisons, we calculated the enrichment of previously published MPRA data from the K562 and HepG2 cell lines (25). We compared the enrichment coefficients of the MIN6 MPRA data to K562 and HepG2 using a z-test as described in Paternoster et al. (30).

Finally, in addition to the genome-wide enrichments, we also compared the enrichment of credible set SNPs to SNPs in LD across IEP scores. We used credible set SNPs for T2D, fasting blood glucose levels, blood glucose levels, and glycated hemoglobin (HbA1c) levels as described in

the "Refinement of credible sets for T2D and glycemic traits" section. For each credible set SNP, we selected the SNPs in LD (r^2 >0.8) based on the 1000 genomes phase 3 ($v5$) European reference panel (31). We calculated the enrichment of both credible set SNPs and LD SNPs across increasing IEP percentile cutoffs by performing a hypergeometric test (phyper function in R), controlling for the number of tests using the Bonferroni procedure. We also calculated the enrichment of credible set SNPs and LD SNPs across SNPs ranked by IEP scores using fGSEA v1.25.1 (32).

Refinement of credible sets for T2D and glycemic traits

To empirically define a threshold for prioritizing candidate causal SNPs using IEP scores, we used 99% credible sets from two T2D fine-mapping genetic studies (uniform priors): a European ancestry study (33) and a trans-ancestry study (34). To focus on likely distal regulatory signals, we excluded signals where >=1 SNP fell in a coding region from both datasets. For each T2D-associated signal in each study, we calculated the ratio of the IEP score of the largest IEP score to the second largest IEP score (IEP ratio_{1:2}). Next, we treated the trans-ancestry study as a "truth set", since trans-ancestry studies have greater power to fine-map due to different LD patterns across ancestries, and asked how often we could nominate the trans-ancestry candidate causal SNP using progressive IEP ratio_{1:2} cutoffs in the European ancestry study. To make the trans-ancestry "truth set", we selected the 11 signals with one SNP in the 99% credible set that were not fine-mapped to a single candidate causal SNP in the European ancestry study. We selected the 179 from the European ancestry study with >1 SNP in the 99% credible set and performed a hypergeometric test (phyper function in R) across progressive IEP ratio_{1:2} thresholds. We selected the minimum IEP ratio_{1:2} cutoff with $P<0.05$, corresponding to an IEP ratio_{1:2} of 24, and applied the cutoff to the trans-ancestry credible sets to identify additional signals with a signal candidate causal SNP.

We applied the IEP ratio_{1:2} of 24, to 99% credible sets for T2D (34), 99% credible sets for blood glucose levels after fasting (35), 95% credible sets for blood glucose levels (36), and 95% credible sets for glycated hemoglobin (HbA1c) levels (36). We note that the credible sets for blood glucose levels after fasting were obtained from the Open Targets genetics platform (https://genetics.opentargets.org).

Allelic imbalance analysis

For allelic imbalance analysis, we collected 24 islet ATAC-seq samples from non-diabetic donors for which SNP genotypes were also available: 1 sample from Varshney et al. (16), 10 samples from Rai et al. (37), and 13 samples from Khetan et al. (27). We note that in instances where the same sample was sequenced more than once across studies, we chose one sample randomly. We tested for allelic imbalance at all SNPs in the 95/99% credible sets for T2D and glycemic traits where our model predicts a single candidate causal SNP that previously had >1 candidate causal SNP at each association signal (Table S2). We followed the computational procedure outlined in Greenwald et al. (38). Briefly, we mapped reads using bwa v0.7.17-r1194-dirty (39) and filtered reads with low mapping quality ("-q 30 -M"). We then used WASP v0.3.4 (40) to remove duplicate reads and correct for reference mapping bias. Using a binomial test to assess imbalance on a per sample basis, we

tested for allelic imbalance at SNPs that had at least two heterozygotes with two or more reads covering each allele. Finally, we calculated z-scores and used Stouffer's method (41) to calculate a combined z-score and *P*-value across samples, weighting the z-scores by the sequencing depth of each sample (42). We controlled for the number of tests using the Benjamini-Hochberg procedure (14) .

TFBSs enrichment of candidate causal SNPs

To calculate the enrichment of the candidate causal SNPs in TFBSs, we calculated the fraction of SNPs that overlap TFBSs predicted from ATAC-seq footprints (see "Identification and analysis of transcription factor binding sites") using both the candidate causal set and a 10-fold control set, derived from islet DHS regions. We computed the fold-enrichment, calculated *P*-values using Fisher's exact test, and controlled for the number of tests using the Benjamini-Hochberg procedure (14).

Calculation of the effects of candidate causal SNPs on TFBS motifs

To calculate the allelic effects of candidate causal SNPs on binding motifs, we used TFBS motifs from ENCODE (19), JASPAR (20), and HOMER (http://homer.ucsd.edu/homer/motif/motifDatabase.html). We ran FIMO (packaged with MEME v4.9.0) with a *P*-value threshold of 0.01, keeping motifs that had hits for the sequences of both alleles. The remaining motifs were sorted in the decreasing order of the value $|log(P\text{-value}_\text{ref}) - log(P\text{-value}_\text{alt}|).$

Electrophoresis mobility shift assay (EMSA) experiments

For EMSA experiments, we designed 21bp biotin end-labeled complementary oligonucleotides with each SNP allele tested centered at the 11th position of the oligo (Integrated DNA Technologies; Table S7). Each forward and reverse oligo for the biotinylated probes were biotinylated at their 5' ends. We annealed complementary oligos to create double-stranded probes for each tested sequence. Using the NE-PER Extraction Kit (Thermo Scientific), we prepared nuclear extract from human EndoC-βH3 cells in the non-proliferating, excised state (43) and completed EMSAs using the LightShift Chemiluminescent EMSA kit (Thermo Scientific) according to the manufacturer's instructions. Each binding reaction contained 1X binding buffer, 1 µg poly dI-dC, 4 µg EndoC-βH3 nuclear extract, and 200 fmol of biotinylated double-stranded probe. For competition reactions, 20- or 40-fold excess of unlabeled probe for each allele was added to the reaction mix and pre-incubated at 25°C for 15 minutes prior to addition of the labeled probe. We incubated reactions at 25°C for 25 minutes, after which we resolved DNA-protein complexes on a 6% DNA retardation gel (Invitrogen) and detected them by chemiluminescence after transfer and UV crosslinking to a nitrocellulose membrane.

Luciferase experiments

We synthesized 701bp DNA fragments around the identified SNPs (GenScript Biotech Corporation) and cloned the fragments into a pGL3-Promoter vector with XhoI and BglII restriction

sites. We co-transfected the reporter construct and a pRL-TK Renilla luciferase reporter (Promega) into EndoC-bH1 cells using lipofectamine 2000 (Thermo Fisher). 48 hours after transfection, we lysed cells and loaded the cell lysates into a 96-well plate to detect luciferase activity using a Synergy H1 Microplate reader. We calculated relative luciferase activity, normalizing firefly luciferase activity to that of Renilla luciferase. We performed 12 replicates for each DNA fragment and compared the relative luciferase activity between each allele using the Wilcoxon rank sum test.

Data availability

The models from this study (architecture and weights), enhancer locations, EDR/ESR locations, and IEP scores for gnomAD SNPs are available through zenodo (https://zenodo.org/record/8161621). The models are also available at kipoi (http://kipoi.org/models/TREDNet).

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DIAMANTE Consortium Authors

The following authors were part of the Diabetes Meta-Analysis of Trans-Ethnic association studies (DIAMANTE) Consortium:

Anubha Mahajan^{1,2,278}, Cassandra N. Spracklen^{3,4}, Weihua Zhang^{5,6}, Maggie C. Y. Ng^{7,8,9}, Lauren E Petty⁷, Hidetoshi Kitajima^{2,10,11,12}, Grace Z. Yu^{1,2}, Sina Rüeger¹³, Leo Speidel^{14,15}, Young Jin Kim¹⁶, Momoko Horikoshi¹⁷, Josep M. Mercader^{18,19,20}, Daniel Taliun²¹, Sanghoon Moon¹⁶, Soo-Heon Kwak²², Neil R. Robertson^{1,2}, Nigel W. Rayner^{1,2,23,24}, Marie Loh^{5,25,26}, Bong-Jo Kim¹⁶, Joshua Chiou^{27,279}, Irene Miguel-Escalada^{28,29}, Pietro della Briotta Parolo¹³, Kuang Lin³⁰, Fiona Bragg^{30,31}, Michael H. Preuss³², Fumihiko Takeuchi³³, Jana Nano³⁴, Xiuqing Guo³⁵, Amel Lamri^{36,37}, Masahiro Nakatochi³⁸, Robert A. Scott³⁹, Jung-Jin Lee⁴⁰, Alicia Huerta-Chagoya^{41,280}, Mariaelisa Graff⁴², Jin-Fang Chai⁴³, Esteban J Parra⁴⁴, Jie Yao³⁵, Lawrence F. Bielak⁴⁵, Yasuharu Tabara⁴⁶, Yang Hai³⁵, Valgerdur Steinthorsdottir⁴⁷, James P. Cook⁴⁸, Mart Kals⁴⁹, Niels Grarup⁵⁰, Ellen M. Schmidt²¹, Ian Pan⁵¹, Tamar Sofer^{52,53,54}, Matthias Wuttke⁵⁵, Chloe Sarnowski^{56,281}, Christian Gieger^{57,58,59}, Darryl Nousome⁶⁰, Stella Trompet^{61,62}, Jirong Long⁶³, Meng Sun², Lin Tong⁶⁴, Wei-Min Chen⁶⁵, Meraj Ahmad⁶⁶, Raymond Noordam⁶², Victor J. Y. Lim⁴³, Claudia H. T. Tam^{67,68}, Yoonjung Yoonie Joo^{69,70,282}, Chien-Hsiun Chen⁷¹, Laura M. Raffield³, Cécile Lecoeur^{72,73}, Bram Peter Prins²³, Aude Nicolas⁷⁴, Lisa R. Yanek⁷⁵, Guanjie Chen⁷⁶, Richard A. Jensen⁷⁷, Salman Tajuddin⁷⁸, Edmond K. Kabagambe^{63,283}, Ping An⁷⁹, Anny H. Xiang⁸⁰, Hyeok Sun Choi⁸¹, Brian E. Cade^{20,53}, Jingyi Tan³⁵, Jack Flanagan^{17,48}, Fernando Abaitua^{2,284}, Linda S. Adair⁸², Adebowale Adeyemo⁷⁶, Carlos A. Aguilar-Salinas⁸³, Masato Akiyama^{84,85}, Sonia S. Anand^{36,37,86}, Alain Bertoni⁸⁷, Zheng Bian⁸⁸, Jette Bork-Jensen⁵⁰, Ivan Brandslund^{89,90}, Jennifer A. Brody⁷⁷, Chad M. Brummett⁹¹, Thomas A. Buchanan⁹², Mickaël Canouil^{72,73}, Juliana C. N. Chan^{67,68,93,94}, Li-Ching Chang⁷¹, Miao-Li Chee⁹⁵, Ji Chen^{96,285}, Shyh-Huei Chen⁹⁷, Yuan-Tsong Chen⁷¹, Zhengming Chen^{30,31}, Lee-Ming Chuang^{98,99}, Mary Cushman¹⁰⁰, Swapan K. Das¹⁰¹, H. Janaka de Silva¹⁰², George Dedoussis¹⁰³, Latchezar Dimitrov⁸, Ayo P. Doumatey⁷⁶, Shufa Du^{82,104}, Qing Duan³, Kai-Uwe Eckardt^{105,106}, Leslie S. Emery¹⁰⁷, Daniel S. Evans¹⁰⁸, Michele K. Evans⁷⁸, Krista Fischer⁴⁹, James S. Floyd⁷⁷, Ian Ford¹⁰⁹, Myriam Fornage¹¹⁰, Oscar H. Franco³⁴, Timothy M. Frayling¹¹¹, Barry I. Freedman¹¹², Christian Fuchsberger^{21,113}, Pauline Genter¹¹⁴, Hertzel C. Gerstein^{36,37,86}, Vilmantas Giedraitis¹¹⁵, Clicerio González-Villalpando¹¹⁶, Maria Elena González-Villalpando¹¹⁶, Mark O. Goodarzi¹¹⁷, Penny Gordon-Larsen^{82,104}, David Gorkin¹¹⁸, Myron Gross¹¹⁹, Yu Guo⁸⁸, Sophie Hackinger²³, Sohee Han¹⁶, Andrew T. Hattersley¹²⁰, Christian Herder^{57,121,122}, Annie-Green Howard^{104,123}, Willa Hsueh¹²⁴, Mengna Huang^{51,125}, Wei Huang¹²⁶, Yi-Jen Hung127,128, Mi Yeong Hwang16, Chii-Min Hwu129,130, Sahoko Ichihara131, Mohammad Arfan Ikram34, Martin Ingelsson¹¹⁵, Md Tariqul Islam¹³², Masato Isono³³, Hye-Mi Jang¹⁶, Farzana Jasmine⁶⁴, Guozhi Jiang^{67,68}, Jost B. Jonas¹³³, Marit E. Jørgensen^{134,135}, Torben Jørgensen^{136,137,138}, Yoichiro Kamatani^{84,139}, Fouad R. Kandeel¹⁴⁰, Anuradhani Kasturiratne¹⁴¹, Tomohiro Katsuya^{142,143}, Varinderpal Kaur¹⁹, Takahisa Kawaguchi⁴⁶, Jacob M. Keaton^{8,63,286}, Abel N. Kho^{144,145}, Chiea-Chuen Khor¹⁴⁶, Muhammad G. Kibriya⁶⁴, Duk-Hwan Kim¹⁴⁷, Katsuhiko Kohara^{148,287}, Jennifer Kriebel^{57,58,59}, Florian Kronenberg¹⁴⁹, Johanna Kuusisto¹⁵⁰, Kristi Läll^{49,151}, Leslie A. Lange¹⁵², Myung-Shik Lee^{153,154}, Nanette R. Lee¹⁵⁵, Aaron Leong^{19,156,157}, Liming Li¹⁵⁸, Yun Li³, Ruifang Li-Gao¹⁵⁹, Symen Ligthart³⁴, Cecilia M. Lindgren^{2,160,161}, Allan Linneberg^{136,162}, Ching-Ti Liu⁵⁶, Jianjun Liu^{146,163}, Adam E. Locke^{164,165,288}, Tin Louie¹⁰⁷, Jian'an Luan³⁹, Andrea O. Luk^{67,68}, Xi Luo¹⁶⁶, Jun Lv¹⁵⁸, Valeriya Lyssenko^{167,168}, Vasiliki Mamakou¹⁶⁹, K. Radha Mani^{66,277}, Thomas Meitinger^{170,171,172}, Andres Metspalu⁴⁹, Andrew D. Morris¹⁷³, Girish N. Nadkarni^{32,174,175}, Jerry L. Nadler¹⁷⁶, Michael A. Nalls^{74,177,178}, Uma Nayak⁶⁵, Suraj S. Nongmaithem⁶⁶, Ioanna Ntalla¹⁷⁹, Yukinori Okada^{180,181,182}, Lorena Orozco¹⁸³, Sanjay R. Patel¹⁸⁴, Mark A. Pereira¹⁸⁵, Annette Peters^{57,58,172}, Fraser J. Pirie¹⁸⁶, Bianca Porneala¹⁵⁷, Gauri Prasad^{187,188}, Sebastian Preissl¹¹⁸, Laura J. Rasmussen-Torvik¹⁸⁹, Alexander P. Reiner¹⁹⁰, Michael Roden^{57,121,122}, Rebecca Rohde⁴², Kathryn Roll³⁵, Charumathi Sabanayagam^{95,191,192}, Maike Sander^{193,194,195}, Kevin Sandow³⁵, Naveed Sattar¹⁹⁶, Sebastian Schönherr¹⁴⁹, Claudia Schurmann^{32,174,197}, Mohammad Shahriar^{64,289}, Jinxiu Shi¹²⁶, Dong Mun Shin¹⁶, Daniel Shriner⁷⁶, Jennifer A. Smith^{45,198}, Wing Yee So^{67,93}, Alena Stančáková¹⁵⁰, Adrienne M. Stilp¹⁰⁷, Konstantin Strauch^{199,200,201}, Ken Suzuki^{17,84,180,202}, Atsushi Takahashi^{84,203}, Kent D. Taylor³⁵, Barbara Thorand^{57,58}, Gudmar Thorleifsson⁴⁷, Unnur Thorsteinsdottir^{47,204}, Brian Tomlinson^{67,205}, Jason M. Torres^{2,290}, Fuu-Jen Tsai²⁰⁶, Jaakko Tuomilehto^{207,208,209,210}, Teresa Tusie-Luna^{211,212}, Miriam S. Udler^{18,19,156}, Adan Valladares-Salgado²¹³, Rob M. van Dam^{43,163}, Jan B. van Klinken^{214,215,216}, Rohit Varma²¹⁷, Marijana Vujkovic²¹⁸, Niels Wacher-Rodarte²¹⁹, Eleanor Wheeler³⁹, Eric A. Whitsel^{42,220}, Ananda R. Wickremasinghe¹⁴¹, Ko Willems van Dijk^{214,215,221}, Daniel R. Witte^{222,223}, Chittaranjan S. Yajnik²²⁴, Ken Yamamoto²²⁵, Toshimasa Yamauchi²⁰², Loïc Yengo²²⁶, Kyungheon Yoon¹⁶, Canqing Yu¹⁵⁸, Jian-Min Yuan^{227,228}, Salim Yusuf^{36,37,86}, Liang Zhang⁹⁵, Wei Zheng⁶³, FinnGen, eMERGE Consortium, Leslie J. Raffel²²⁹, Michiya Igase²³⁰, Eli Ipp¹¹⁴, Susan Redline^{20,53,231}, Yoon Shin Cho⁸¹, Lars Lind²³²,

Michael A. Province⁷⁹, Craig L. Hanis²³³, Patricia A. Peyser⁴⁵, Erik Ingelsson^{234,235}, Alan B. Zonderman⁷⁸, Bruce M. Psaty^{77,236,237}, Ya-Xing Wang²³⁸, Charles N. Rotimi⁷⁶, Diane M. Becker⁷⁵, Fumihiko Matsuda⁴⁶, Yongmei Liu^{87,239}, Eleftheria Zeggini^{23,24,240}, Mitsuhiro Yokota²⁴¹, Stephen S. Rich²⁴², Charles Kooperberg¹⁹⁰, James S. Pankow¹⁸⁵, James C. Engert^{243,244}, Yii-Der Ida Chen³⁵, Philippe Froguel^{72,73,245}, James G. Wilson²⁴⁶, Wayne H. H. Sheu^{128,130,247}, Sharon L. R. Kardia⁴⁵, Jer-Yuarn Wu⁷¹, M. Geoffrey Hayes^{69,248,249}, Ronald C. W. Ma^{67,68,93,94}, Tien-Yin Wong^{95,191,192}, Leif Groop^{13,167}, Dennis O. Mook-Kanamori¹⁵⁹, Giriraj R. Chandak⁶⁶, Francis S. Collins²⁵⁰, Dwaipayan Bharadwaj^{187,251}, Guillaume Paré^{37,252}, Michèle M. Sale^{65,277}, Habibul Ahsan⁶⁴, Ayesha A. Motala¹⁸⁶, Xiao-Ou Shu⁶³, Kyong-Soo Park^{22,253,254}, J. Wouter Jukema^{61,255}, Miguel Cruz²¹³, Roberta McKean-Cowdin⁶⁰, Harald Grallert^{57,58,59}, Ching-Yu Cheng^{95,191,192}, Erwin P. Bottinger^{32,174,197}, Abbas Dehghan^{5,34,256}, E-Shyong Tai^{43,163,257}, Josée Dupuis⁵⁶, Norihiro Kato³³, Markku Laakso¹⁵⁰, Anna Köttgen⁵⁵, Woon-Puay Koh^{258,259}, Colin N. A. Palmer²⁶⁰, Simin Liu^{51,125,261}, Goncalo Abecasis²¹, Jaspal S. Kooner^{6,256,262,263}, Ruth J. F. Loos^{32,50,264}, Kari E. North⁴², Christopher A. Haiman⁶⁰, Jose C. Florez^{18,19,156}, Danish Saleheen^{40,265,266}, Torben Hansen⁵⁰, Oluf Pedersen⁵⁰, Reedik Mägi⁴⁹, Claudia Langenberg^{39,267}, Nicholas J. Wareham³⁹, Shiro Maeda^{17,268,269}, Takashi Kadowaki^{202,291}, Juyoung Lee¹⁶, Iona Y. Millwood^{30,31}, Robin G. Walters^{30,31}, Kari Stefansson^{47,204}, Simon R. Myers^{2,270}, Jorge Ferrer^{28,29,271}, Kyle J. Gaulton^{193,194}, James B. Meigs^{18,156,157}, Karen L. Mohlke³, Anna L. Gloyn^{1,2,272,273}, Donald W. Bowden^{8,9,274}, Jennifer E. Below⁷, John C. Chambers^{5,6,25,256,262}, Xueling Sim⁴³, Michael Boehnke²¹, Jerome I. Rotter³⁵, Mark I. McCarthy1,2,272,278, and Andrew P. Morris2,48,49,275,276

1 Oxford Centre for Diabetes, Endocrinology and Metabolism, Radcliffe Department of Medicine, University of Oxford, Oxford, UK. ²Wellcome Centre for Human Genetics, Nuffield Department of Medicine, University of Oxford, Oxford, UK. ³Department of Genetics, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA. ⁴Department of Epidemiology and Biostatistics, University of Massachusetts-Amherst, Amherst, MA, USA. ⁵Department of Epidemiology and Biostatistics, Imperial College London, London, UK. ⁶Department of Cardiology, Ealing Hospital, London North West Healthcare NHS Trust, London, UK. ⁷Vanderbilt Genetics Institute, Division of Genetic Medicine, Vanderbilt University Medical Center, Nashville, TN, USA. ⁸Center for Genomics and Personalized Medicine Research, Wake Forest School of Medicine, Winston-Salem, NC, USA. ⁹Department of Biochemistry, Wake Forest School of Medicine, Winston-Salem, NC, USA. ¹⁰The Advanced Research Center for Innovations in Next-Generation Medicine (INGEM), Tohoku University, Sendai, Japan. ¹¹ Department of Integrative Genomics, Tohoku Medical Megabank Organization, Tohoku University, Sendai, Japan. ¹²Cancer Center, Tohoku University Hospital, Tohoku University, Sendai, Japan. ¹³Institute for Molecular Medicine Finland (FIMM), University of Helsinki, Helsinki, Finland. 14Genetics Institute, University College London, London, UK. 15Francis Crick Institute, London, UK. ¹⁶Division of Genome Science, Department of Precision Medicine, National Institute of Health, Cheongju-si, Republic of Korea. 17Laboratory for Genomics of Diabetes and Metabolism, RIKEN Center for Integrative Medical Sciences, Yokohama, Japan. ¹⁸Programs in Metabolism and Medical & Population Genetics, Broad Institute of Harvard and MIT, Cambridge, MA, USA. ¹⁹Diabetes Unit and Center for Genomic Medicine, Massachusetts General Hospital, Boston, MA, USA. ²⁰Harvard Medical School, Boston, MA, USA. ²¹Department of Biostatistics and Center for Statistical Genetics, University of Michigan, Ann Arbor, MI, USA. ²²Department of Internal Medicine, Seoul National University Hospital, Seoul, South Korea. ²³Department of Human Genetics, Wellcome Sanger Institute, Hinxton, UK. ²⁴Institute of Translational Genomics, Helmholtz Zentrum München, German Research Center for Environmental Health, Neuherberg, Germany. ²⁵Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore, Singapore. ²⁶Translational Laboratory in Genetic Medicine (TLGM), Agency for Science, Technology and Research (A*STAR) and National University of Singapore (NUS), Singapore, Singapore. ²⁷Biomedical Sciences Graduate Studies Program, University of California San Diego, La Jolla, CA, USA. ²⁸Regulatory Genomics and Diabetes, Centre for Genomic Regulation, The Barcelona Institute of Science and Technology, Barcelona, Spain. ²⁹Centro de Investigación Biomédica en Red Diabetes y Enfermedades Metabólicas asociadas (CIBERDEM), Madrid, Spain. ³⁰Nuffield Department of Population Health, University of Oxford, Oxford, UK. ³¹Medical Research Council Population Health Research Unit, University of Oxford, Oxford, UK. 32The Charles Bronfman Institute for Personalized Medicine, Icahn School of Medicine at Mount Sinai, New York, NY, USA. 33Department of Gene Diagnostics and Therapeutics, Research Institute, National Center for Global Health and Medicine, Tokyo, Japan. ³⁴Department of Epidemiology, Erasmus University Medical Center, Rotterdam, The Netherlands. ³⁵The Institute for Translational Genomics and Population Sciences, Department of Pediatrics, The Lundquist Institute for Biomedical Innovation (formerly Los Angeles Biomedical Research Institute) at Harbor-UCLA Medical Center, Torrance, CA, USA. ³⁶Department of Medicine, McMaster University, Hamilton, ON, Canada. 37Population Health Research Institute, Hamilton Health Sciences and McMaster University, Hamilton, ON, Canada. 38Public Health Informatics Unit, Department of Integrated Health Sciences, Nagoya University Graduate School of Medicine, Nagoya, Japan. 39MRC Epidemiology Unit, Institute of Metabolic Science, University of Cambridge, Cambridge, UK. 40Division of Translational Medicine and Human Genetics, University of Pennsylvania, Philadelphia, PA, USA. 41Consejo Nacional de Ciencia y Tecnología (CONACYT), Instituto Nacional de Ciencias Médicas y Nutrición Salvador Zubirán, Mexico City, Mexico. ⁴²Department of Epidemiology, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA. ⁴³Saw Swee Hock School of Public Health, National University of

Singapore and National University Health System, Singapore, Singapore. ⁴⁴Department of Anthropology, University of Toronto at Mississauga, Mississauga, ON, Canada. 45Department of Epidemiology, School of Public Health, University of Michigan, Ann Arbor, MI, USA. ⁴⁶Center for Genomic Medicine, Kyoto University Graduate School of Medicine, Kyoto, Japan. ⁴⁷deCODE Genetics, Amgen inc., Reykjavik, Iceland. ⁴⁸Department of Health Data Science, University of Liverpool, Liverpool, UK. ⁴⁹Estonian Genome Centre, Institute of Genomics, University of Tartu, Tartu, Estonia. ⁵⁰Novo Nordisk Foundation Center for Basic Metabolic Research, Faculty of Health and Medical Sciences, University of Copenhagen, Copenhagen, Denmark. 51Department of Epidemiology, Brown University School of Public Health, Providence, RI, USA. 52Department of Biostatistics, Harvard University, Boston, MA, USA. 53Division of Sleep and Circadian Disorders, Brigham and Women's Hospital, Boston, MA, USA. ⁵⁴Department of Medicine, Harvard University, Boston, MA, USA. ⁵⁵Institute of Genetic Epidemiology, Department of Data Driven Medicine, Faculty of Medicine and Medical Center, University of Freiburg, Freiburg, Germany. 56Department of Biostatistics, Boston University School of Public Health, Boston, MA, USA. 57 German Center for Diabetes Research (DZD), Neuherberg, Germany. ⁵⁸Institute of Epidemiology, Helmholtz Zentrum München, German Research Center for Environmental Health, Neuherberg, Germany. ⁵⁹Research Unit of Molecular Epidemiology, Helmholtz Zentrum München, German Research Center for Environmental Health, Neuherberg, Germany. ⁶⁰Department of Population and Public Health Sciences, Keck School of Medicine of USC, Los Angeles, CA, USA, ⁶¹Department of Cardiology, Leiden University Medical Center, Leiden, The Netherlands. ⁶²Section of Gerontology and Geriatrics, Department of Internal Medicine, Leiden University Medical Center, Leiden, The Netherlands, ⁶³Division of Epidemiology, Department of Medicine, Institute for Medicine and Public Health, Vanderbilt Genetics Institute, Vanderbilt University Medical Center, Nashville, TN, USA. ⁶⁴Institute for Population and Precision Health, The University of Chicago, Chicago, IL, USA. 65Department of Public Health Sciences and Center for Public Health Genomics, University of Virginia School of Medicine, Charlottesville, VA, USA. ⁶⁶Genomic Research on Complex Diseases (GRC-Group), CSIR-Centre for Cellular and Molecular Biology (CSIR-CCMB), Hyderabad, India. 67Department of Medicine and Therapeutics, The Chinese University of Hong Kong, Hong Kong, China. 68Chinese University of Hong Kong-Shanghai Jiao Tong University Joint Research Centre in Diabetes Genomics and Precision Medicine, The Chinese University of Hong Kong, Hong Kong, China. 69Division of Endocrinology, Metabolism, and Molecular Medicine, Department of Medicine, Northwestern University Feinberg School of Medicine, Chicago, IL, USA. ⁷⁰Department of Health and Biomedical Informatics, Northwestern University Feinberg School of Medicine, Chicago, IL, USA. ⁷¹Institute of Biomedical Sciences, Academia Sinica, Taipei, Taiwan. ⁷²Inserm U1283, CNRS UMR 8199, European Genomic Institute for Diabetes, Institut Pasteur de Lille, Lille, France. ⁷³University of Lille, Lille University Hospital, Lille, France. ⁷⁴Laboratory of Neurogenetics, National Institute on Aging, National Institutes of Health, Bethesda, MD, USA. ⁷⁵Department of Medicine, Johns Hopkins University School of Medicine, Baltimore, MD, USA. ⁷⁶Center for Research on Genomics and Global Health, National Human Genome Research Institute, National Institutes of Health, Bethesda, MD, USA, ⁷⁷Cardiovascular Health Research Unit, Department of Medicine, University of Washington, Seattle, WA, USA. ⁷⁸Laboratory of Epidemiology and Population Sciences, National Institute on Aging, National Institutes of Health, Baltimore, MD, USA. ⁷⁹Division of Statistical Genomics, Washington University School of Medicine, St. Louis, MO, USA. ⁸⁰Department of Research and Evaluation, Division of Biostatistics Research, Kaiser Permanente of Southern California, Pasadena, CA, USA. ⁸¹Department of Biomedical Science, Hallym University, Chuncheon, South Korea. ⁸²Department of Nutrition, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA. 83Unidad de Investigación en Enfermedades Metabólicas and Departamento de Endocrinología y Metabolismo, Instituto Nacional de Ciencias Médicas y Nutrición Salvador Zubirán, Mexico City, Mexico. ⁸⁴Laboratory for Statistical and Translational Genetics, RIKEN Center for Integrative Medical Sciences, Yokohama, Japan. 85Department of Ocular Pathology and Imaging Science, Graduate School of Medical Sciences, Kyushu University, Fukuoka, Japan. ⁸⁶Department of Health Research Methods, Evidence, and Impact, McMaster University, Hamilton, ON, Canada. ⁸⁷Department of Epidemiology and Prevention, Division of Public Health Sciences, Wake Forest School of Medicine, Winston-Salem, NC, USA. 88Chinese Academy of Medical Sciences, Beijing, China. ⁸⁹Institute of Regional Health Research, University of Southern Denmark, Odense, Denmark. 90Department of Clinical Biochemistry, Vejle Hospital, Vejle, Denmark. 91Department of Anesthesiology, University of Michigan Medical School, Ann Arbor, MI, USA. ⁹²Department of Medicine, Division of Endocrinology and Diabetes, Keck School of Medicine of USC, Los Angeles, CA, USA. ⁹³Hong Kong Institute of Diabetes and Obesity, The Chinese University of Hong Kong, Hong Kong, China. ⁹⁴Li Ka Shing Institute of Health Sciences, The Chinese University of Hong Kong, Hong Kong, China. ⁹⁵Singapore Eye Research Institute, Singapore National Eye Centre, Singapore, Singapore. 96Wellcome Sanger Institute, Hinxton, UK. ⁹⁷Department of Biostatistics and Data Science, Wake Forest School of Medicine, Winston-Salem, NC, USA. ⁹⁸Division of Endocrinology and Metabolism, Department of Internal Medicine, National Taiwan University Hospital, Taipei, Taiwan. ⁹⁹Institute of Epidemiology and Preventive Medicine, National Taiwan University, Taipei, Taiwan, ¹⁰⁰Department of Medicine, University of Vermont, Colchester, VT, USA, ¹⁰¹Section on Endocrinology and Metabolism, Department of Internal Medicine, Wake Forest School of Medicine, Winston-Salem, NC, USA. ¹⁰²Department of Medicine, Faculty of Medicine, University of Kelaniya, Ragama, Sri Lanka. ¹⁰³Department of Nutrition and Dietetics, Harokopio University of Athens, Athens, Greece. ¹⁰⁴Carolina Population Center, University of North

Carolina at Chapel Hill, Chapel Hill, NC, USA. ¹⁰⁵Department of Nephrology and Medical Intensive Care Medicine, Charité
Universitätsmedizin Berlin, Berlin, Germany. ¹⁰⁶Department of Nephrology and Hypertension, Universitätsmedizin Berlin, Berlin, Germany. ¹⁰⁶Department of Nephrology and Hypertension, Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, Germany. ¹⁰⁷Department of Biostatistics, University of Washington, Seattle, WA, USA. ¹⁰⁸California Pacific Medical Center Research Institute, San Francisco, CA, USA. ¹⁰⁹Robertson Centre for Biostatistics, University of Glasgow, Glasgow, UK. ¹¹⁰Institute of Molecular Medicine, University of Texas Health Science Center at Houston, Houston, TX, USA. ¹¹¹Genetics of Complex Traits, University of Exeter Medical School, University of Exeter, Exeter, UK. ¹¹²Department of Internal Medicine, Wake Forest School of Medicine, Winston-Salem, NC, USA. ¹¹³Institute for Biomedicine, Eurac Research, Affiliated Institute of the University of Lübeck, Bolzano, Italy. 114Department of Medicine, Division of Endocrinology and Metabolism, Lundquist Research Institute at Harbor-UCLA Medical Center, Torrance, CA, USA. ¹¹⁵Department of Public Health and Caring Sciences, Uppsala University, Uppsala, Sweden. ¹¹⁶Centro de Estudios en Diabetes, Unidad de Investigacion en Diabetes y Riesgo Cardiovascular, Centro de Investigacion en Salud Poblacional, Instituto Nacional de Salud Publica, Mexico City, Mexico. ¹¹⁷Department of Medicine, Division of Endocrinology, Diabetes and Metabolism, Cedars-Sinai Medical Center, Los Angeles, CA, USA. ¹¹⁸Center for Epigenomics, University of California San Diego, La Jolla, CA, USA. ¹¹⁹Department of Laboratory Medicine and Pathology, University of Minnesota, Minneapolis, MN, USA. ¹²⁰University of Exeter Medical School, University of Exeter, Exeter, UK. ¹²¹Institute for Clinical Diabetology, German Diabetes Center, Leibniz Center for Diabetes Research at Heinrich Heine University Düsseldorf, Düsseldorf, Germany. ¹²²Department of Endocrinology and Diabetology, Medical Faculty and University Hospital Düsseldorf, Heinrich Heine University Düsseldorf, Düsseldorf, Germany. 123Department of Biostatistics, Gillings School of Global Public Health, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA. 124Department of Internal Medicine, Diabetes and Metabolism Research Center, The Ohio State University Wexner Medical Center, Columbus, OH, USA. ¹²⁵Center for Global Cardiometabolic Health, Brown University, Providence, RI, USA. ¹²⁶Shanghai-MOST Key Laboratory of Health and Disease Genomics, Chinese National Human Genome Center at Shanghai (CHGC) and Shanghai Institute for Biomedical and Pharmaceutical Technologies (SIBPT), Shanghai, China. 127Division of Endocrine and Metabolism, Tri-Service General Hospital Songshan Branch, Taipei, Taiwan. ¹²⁸School of Medicine, National Defense Medical Center, Taipei, Taiwan. ¹²⁹Section of Endocrinology and Metabolism, Department of Medicine, Taipei Veterans General Hospital, Taipei, Taiwan. ¹³⁰School of Medicine, National Yang Ming Chiao Tung University, Taipei, Taiwan. ¹³¹Department of Environmental and Preventive Medicine, Jichi Medical University School of Medicine, Shimotsuke, Japan. 132University of Chicago Research Bangladesh, Dhaka, Bangladesh. 133Institute of Molecular and Clinical Ophthalmology Basel, Basel, Switzerland. ¹³⁴Steno Diabetes Center Copenhagen, Gentofte, Denmark. ¹³⁵National Institute of Public Health, Southern Denmark University, Copenhagen, Denmark. ¹³⁶Center for Clinical Research and Prevention, Bispebjerg and Frederiksberg Hospital, Frederiksberg, Denmark. ¹³⁷Faculty of Health and Medical Sciences, University of Copenhagen, Copenhagen, Denmark, ¹³⁸Faculty of Medicine, Aalborg University, Aalborg, Denmark. ¹³⁹Laboratory of Complex Trait Genomics, Department of Computational Biology and Medical Sciences, Graduate School of Frontier Sciences, The University of Tokyo, Tokyo, Japan. ¹⁴⁰Department of Clinical Diabetes, Endocrinology & Metabolism, Department of Translational Research and Cellular Therapeutics, City of Hope, Duarte, CA, USA. ¹⁴¹Department of Public Health, Faculty of Medicine, University of Kelaniya, Ragama, Sri Lanka. ¹⁴²Department of Clinical Gene Therapy, Osaka University Graduate School of Medicine, Osaka, Japan. ¹⁴³Department of Geriatric and General Medicine, Graduate School of Medicine, Osaka University, Osaka, Japan. 144Division of General Internal Medicine and Geriatrics, Department of Medicine, Northwestern University Feinberg School of Medicine, Chicago, IL, USA. 145Center for Health Information Partnerships, Institute for Public Health and Medicine, Northwestern University Feinberg School of Medicine, Chicago, IL, USA. ¹⁴⁶Genome Institute of Singapore, Agency for Science, Technology and Research, Singapore, Singapore. 147Department of Molecular Cell Biology, Sungkyunkwan University School of Medicine, Suwon, South Korea. 148Department of Regional Resource Management, Ehime University Faculty of Collaborative Regional Innovation, Ehime, Japan. ¹⁴⁹Institute of Genetic Epidemiology, Department of Genetics and Pharmacology, Medical University of Innsbruck, Innsbruck, Austria. ¹⁵⁰Institute of Clinical Medicine, Internal Medicine, University of Eastern Finland and Kuopio University Hospital, Kuopio, Finland. 151Institute of Mathematics and Statistics, University of Tartu, Tartu, Estonia. 152Department of Medicine, University of Colorado Denver, Anschutz Medical Campus, Aurora, CO, USA. 153Severance Biomedical Science Institute and Department of Internal Medicine, Yonsei University College of Medicine, Seoul, South Korea. 154Department of Medicine, Samsung Medical Center, Sungkyunkwan University School of Medicine, Seoul, South Korea. ¹⁵⁵USC-Office of Population Studies Foundation, Inc., University of San Carlos, Cebu City, Philippines. 156Department of Medicine, Harvard Medical School, Boston, MA, USA. 157Division of General Internal Medicine, Massachusetts General Hospital, Boston, MA, USA. ¹⁵⁸Department of Epidemiology and Biostatistics, Peking University Health Science Centre, Peking University, Beijing, China. ¹⁵⁹Department of Clinical Epidemiology, Leiden University Medical Center, Leiden, The Netherlands. ¹⁶⁰Program in Medical & Population Genetics, Broad Institute, Cambridge, MA, USA. 161Big Data Institute, Li Ka Shing Centre for Health Information and Discovery, University of Oxford, Oxford, UK. ¹⁶²Department of Clinical Medicine, Faculty of Health and Medical Sciences, University of Copenhagen, Copenhagen, Denmark. 163Department of Medicine, Yong Loo Lin School of Medicine, National University of Singapore

and National University Health System, Singapore, Singapore. 164McDonnell Genome Institute, Washington University School of Medicine, St. Louis, MO, USA. ¹⁶⁵Department of Medicine, Division of Genomics and Bioinformatics, Washington University School of Medicine, St. Louis, MO, USA. ¹⁶⁶Department of Biostatistics and Data Science, University of Texas Health Science Center at Houston, Houston, TX, USA. 167Department of Clinical Sciences, Diabetes and Endocrinology, Lund University Diabetes Centre, Malmö, Sweden. ¹⁶⁸Department of Clinical Science, Center for Diabetes Research, University of Bergen, Bergen, Norway. ¹⁶⁹Dromokaiteio Psychiatric Hospital, National and Kapodistrian University of Athens, Athens, Greece. ¹⁷⁰Institute of Human Genetics, Helmholtz Zentrum München, German Research Center for Environmental Health, Neuherberg, Germany. ¹⁷¹Institute of Human Genetics, Technical University of Munich, Munich, Germany. 172German Centre for Cardiovascular Research (DZHK), Partner Site Munich Heart Alliance, Munich, Germany. ¹⁷³The Usher Institute to the Population Health Sciences and Informatics, University of Edinburgh, Edinburgh, UK. ¹⁷⁴Digital Health Center, Digital Engineering Faculty of Hasso Plattner Institue and University Potsdam, Potsdam, Germany. 175The Division of Data Driven and Digital Medicine (D3M), Department of Medicine, Icahn School of Medicine at Mount Sinai, New York, NY, USA. ¹⁷⁶Department of Medicine and Pharmacology, New York Medical College, Valhalla, NY, USA. ¹⁷⁷Data Tecnica International LLC, Glen Echo, MD, USA. ¹⁷⁸Center for Alzheimer's and Related Dementias, National Institutes of Health, Baltimore, MD, USA. ¹⁷⁹William Harvey Research Institute, Barts and The London School of Medicine and Dentistry, Queen Mary University of London, London, UK. ¹⁸⁰Department of Statistical Genetics, Osaka University Graduate School of Medicine, Osaka, Japan. ¹⁸¹Laboratory of Statistical Immunology, Immunology Frontier Research Center (WPI-IFReC), Osaka University, Osaka, Japan. ¹⁸²Laboratory for Systems Genetics, RIKEN Center for Integrative Medical Sciences, Yokohama, Japan. ¹⁸³Instituto Nacional de Medicina Genómica, Mexico City, Mexico. 184Division of Pulmonary, Allergy, and Critical Care Medicine, Department of Medicine, University of Pittsburgh, Pittsburgh, PA, USA. ¹⁸⁵Division of Epidemiology and Community Health, School of Public Health, University of Minnesota, Minneapolis, MN, USA. 186 Department of Diabetes and Endocrinology, Nelson R Mandela School of Medicine, College of Health Sciences, University of KwaZulu-Natal, Durban, South Africa. ¹⁸⁷Academy of Scientific and Innovative Research, CSIR-Human Resource Development Centre Campus, Ghaziabad, Uttar Pradesh, India. ¹⁸⁸Genomics and Molecular Medicine Unit, CSIR-Institute of Genomics and Integrative Biology, New Delhi, India. ¹⁸⁹Department of Preventive Medicine, Northwestern University Feinberg School of Medicine, Chicago, IL, USA. ¹⁹⁰Fred Hutchinson Cancer Research Center, Seattle, WA, USA. 191Ophthalmology and Visual Sciences Academic Clinical Program (Eye ACP), Duke-NUS Medical School, Singapore, Singapore. ¹⁹²Department of Ophthalmology, Yong Loo Lin School of Medicine, National University of Singapore and National University Health System, Singapore, Singapore. ¹⁹³Department of Pediatrics, Pediatric Diabetes Research Center, University of California San Diego, La Jolla, CA, USA. ¹⁹⁴Institute for Genomic Medicine, University of California San Diego, La Jolla, CA, USA. ¹⁹⁵Department of Cellular and Molecular Medicine, University of California San Diego, La Jolla, CA, USA. ¹⁹⁶Institute of Cardiovascular and Medical Sciences, University of Glasgow, Glasgow, UK. ¹⁹⁷Hasso Plattner Institute for Digital Health at Mount Sinai, Icahn School of Medicine at Mount Sinai, New York, NY, USA. ¹⁹⁸Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI, USA. ¹⁹⁹Institute of Genetic Epidemiology, Helmholtz Zentrum München, German Research Center for Environmental Health, Neuherberg, Germany. ²⁰⁰Chair of Genetic Epidemiology, IBE, Faculty of Medicine, LMU Munich, Munich, Germany. ²⁰¹Institute of Medical Biostatistics, Epidemiology and Informatics (IMBEI), University Medical Center, Johannes Gutenberg University, Mainz, Germany. ²⁰²Department of Diabetes and Metabolic Diseases, Graduate School of Medicine, The University of Tokyo, Tokyo, Japan. ²⁰³Department of Genomic Medicine, National Cerebral and Cardiovascular Center, Osaka, Japan. ²⁰⁴Faculty of Medicine, University of Reykjavik, Reykjavik, Iceland. ²⁰⁵Faculty of Medicine, Macau University of Science and Technology, Macau, China. ²⁰⁶Department of Medical Genetics and Medical Research, China Medical University Hospital, Taichung, Taiwan. ²⁰⁷Department of Health, Finnish Institute for Health and Welfare, Helsinki, Finland. ²⁰⁸National School of Public Health, Madrid, Spain. ²⁰⁹Department of Neuroscience and Preventive Medicine, Danube-University Krems, Krems, Austria. ²¹⁰Diabetes Research Group, King Abdulaziz University, Jeddah, Saudi Arabia. ²¹¹Unidad de Biología Molecular y Medicina Genómica, Instituto Nacional de Ciencias Médicas y Nutrición Salvador Zubirán, Mexico City, Mexico. ²¹²Departamento de Medicina Genómica y Toxiología Ambiental, Instituto de Investigaciones Biomédicas, UNAM, Mexico City, Mexico. ²¹³Unidad de Investigacion Medica en Bioquimica, Hospital de Especialidades, Centro Medico Nacional Siglo XXI, IMSS, Mexico City, Mexico. 214Einthoven Laboratory for Experimental Vascular Medicine, Leiden University Medical Center, Leiden, The Netherlands. 215Department of Human Genetics, Leiden University Medical Center, Leiden, The Netherlands. ²¹⁶Department of Clinical Chemistry, Laboratory of Genetic Metabolic Disease, Amsterdam University Medical Center, Amsterdam, The Netherlands. 217Southern California Eye Institute, CHA Hollywood Presbyterian Medical Center, Los Angeles, CA, USA. ²¹⁸Department of Medicine, University of Pennsylvania Perelman School of Medicine, Philadelphia, PA, USA. 219Unidad de Investigación Médica en Epidemiologia Clinica, Hospital de Especialidades, Centro Medico Nacional Siglo XXI, IMSS, Mexico City, Mexico. ²²⁰Department of Medicine, School of Medicine, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA. ²²¹Department of Internal Medicine, Division of Endocrinology, Leiden University Medical Center, Leiden, The Netherlands. ²²²Department of Public Health, Aarhus University, Aarhus, Denmark. ²²³Danish Diabetes Academy, Odense, Denmark.

²²⁴Diabetology Research Centre, King Edward Memorial Hospital and Research Centre, Pune, India. ²²⁵Department of Medical Biochemistry, Kurume University School of Medicine, Kurume, Japan. ²²⁶Institute for Molecular Bioscience, University of Queensland, Brisbane, Australia. 227Division of Cancer Control and Population Sciences, UPMC Hillman Cancer Center, University of Pittsburgh, Pittsburgh, PA, USA. ²²⁸Department of Epidemiology, Graduate School of Public Health, University of Pittsburgh, Pittsburgh, PA, USA. ²²⁹Department of Pediatrics, Division of Genetic and Genomic Medicine, UCI Irvine School of Medicine, Irvine, CA, USA. ²³⁰Department of Anti-aging Medicine, Ehime University Graduate School of Medicine, Ehime, Japan. 231Division of Pulmonary, Critical Care, and Sleep Medicine, Beth Israel Deaconess Medical Center, Boston, MA, USA. ²³²Department of Medical Sciences, Uppsala University, Uppsala, Sweden. ²³³Human Genetics Center, University of Texas Health Science Center at Houston, Houston, TX, USA. ²³⁴Department of Medicine, Division of Cardiovascular Medicine, Stanford University School of Medicine, Stanford, CA, USA, 235Department of Medical Sciences, Molecular Epidemiology and Science for Life Laboratory, Uppsala University, Uppsala, Sweden. ²³⁶Department of Epidemiology, University of Washington, Seattle, WA, USA. ²³⁷Department of Health Services, University of Washington, Seattle, WA, USA. ²³⁸Beijing Institute of Ophthalmology, Ophthalmology and Visual Sciences Key Laboratory, Beijing Tongren Hospital, Capital Medical University, Beijing, China. ²³⁹Department of Medicine, Division of Cardiology, Duke University School of Medicine, Durham, NC, USA. ²⁴⁰Technical University of Munich (TUM) and Klinikum Rechts der Isar, TUM School of Medicine, Munich, Germany. ²⁴¹Kurume University School of Medicine, Kurume, Japan. ²⁴²Center for Public Health Genomics, University of Virginia School of Medicine, Charlottesville, VA, USA. ²⁴³Department of Medicine, McGill University, Montreal, QC, Canada. ²⁴⁴Department of Human Genetics, McGill University, Montreal, QC, Canada. 245Department of Genomics of Common Disease, School of Public Health, Imperial College London, London, UK. 246 Department of Physiology and Biophysics, University of Mississippi Medical Center, Jackson, MS, USA. 247 Division of Endocrinology and Metabolism, Department of Medicine, Taichung Veterans General Hospital, Taichung, Taiwan. ²⁴⁸Center for Genetic Medicine, Northwestern University Feinberg School of Medicine, Chicago, IL, USA. ²⁴⁹Department of Anthropology, Northwestern University, Evanston, IL, USA. ²⁵⁰Center for Precision Health Research, National Human Genome Research Institute, National Institutes of Health, Bethesda, MD, USA. ²⁵¹Systems Genomics Laboratory, School of Biotechnology, Jawaharlal Nehru University, New Delhi, India. ²⁵²Department of Pathology and Molecular Medicine, McMaster University, Hamilton, ON, Canada. 253Department of Internal Medicine, Seoul National University College of Medicine, Seoul, South Korea. 254Department of Molecular Medicine and Biopharmaceutical Sciences, Graduate School of Convergence Science and Technology, Seoul National University, Seoul, South Korea. ²⁵⁵Netherlands Heart Institute. Utrecht, The Netherlands. 256MRC-PHE Centre for Environment and Health, Imperial College London, London, UK. ²⁵⁷Duke-NUS Medical School, Singapore, Singapore. ²⁵⁸Singapore Institute for Clinical Sciences, Agency for Science Technology and Research (A*STAR), Singapore, Singapore. ²⁵⁹Healthy Longevity Translational Research Programme, Yong Loo Lin School of Medicine, National University of Singapore, Singapore, Singapore. ²⁶⁰Pat Macpherson Centre for Pharmacogenetics and Pharmacogenomics, University of Dundee, Dundee, UK. ²⁶¹Department of Medicine, Brown University Alpert School of Medicine, Providence, RI, USA. ²⁶²Imperial College Healthcare NHS Trust, Imperial College London, London, UK. ²⁶³National Heart and Lung Institute, Imperial College London, London, UK. ²⁶⁴The Mindich Child Health and Development Institute, Ichan School of Medicine at Mount Sinai, New York, NY, USA. 265Department of Biostatistics and Epidemiology, University of Pennsylvania, Philadelphia, PA, USA. ²⁶⁶Center for Non-Communicable Diseases, Karachi, Pakistan. 267Computational Medicine, Berlin Institute of Health at Charité Universitätsmedizin, Berlin, Germany. 268Department of Advanced Genomic and Laboratory Medicine, Graduate School of Medicine, University of the Ryukyus, Okinawa, Japan. ²⁶⁹Division of Clinical Laboratory and Blood Transfusion, University of the Ryukyus Hospital, Okinawa, Japan. ²⁷⁰Department of Statistics, University of Oxford, Oxford, UK. ²⁷¹Section of Genetics and Genomics, Department of Metabolism, Digestion and Reproduction, Imperial College London, London, UK. ²⁷²Oxford NIHR Biomedical Research Centre, Churchill Hospital, Oxford University Hospitals NHS Foundation Trust, Oxford, UK. ²⁷³Division of Endocrinology, Department of Pediatrics, Stanford School of Medicine, Stanford University, Stanford, CA, USA. 274Center for Diabetes Research, Wake Forest School of Medicine, Winston-Salem, NC, USA. 275Centre for Genetics and Genomics Versus Arthritis, Centre for Musculoskeletal Research, Division of Musculoskeletal and Dermatological Sciences, University of Manchester, Manchester, UK. ²⁷⁶NIHR Manchester Biomedical Research Centre, Manchester University NHS Foundation Trust, Manchester, UK. ²⁷⁷Deceased. ²⁷⁸Present address: Genentech, South San Francisco, CA, USA. 279Present address: Internal Medicine Research Unit, Pfizer Worldwide Research, Cambridge, MA, USA. ²⁸⁰Present address: Departamento de Medicina Genómica y Toxicología Ambiental, Instituto de Investigaciones Biomédicas, UNAM, Ciudad de Mexico, Mexico. ²⁸¹Present address: The University of Texas Health Science Center at Houston, School of Public Health, Department of Epidemiology, Human Genetics, and Environmental Sciences, Houston, TX, USA. ²⁸²Present address: Institute of Data Science, Korea University, Seoul, South Korea. ²⁸³Present address: Division of Academics, Ochsner Health, New Orleans, LA, USA. 284Present address: Vertex Pharmaceuticals Ltd, Oxford, UK. 285Present address: Exeter Centre of Excellence in Diabetes (ExCEeD), Exeter Medical School, University of Exeter, Exeter, UK. 286Present address: Center for Precision Health Research, National Human Genome Research Institute, National Institutes of Health, Bethesda, MD, USA. ²⁸⁷Present address: Ibusuki Kozenkai Hospital, Ibusuki, Japan.

²⁸⁸Present address: Regeneron Genetics Center, Tarrytown, NY, USA ²⁸⁹Present address: Institute for Population and Precision Health (IPPH), Biological Sciences Division, The University of Chicago, Chicago, IL, USA. ²⁹⁰Present address: Clinical Trial Service Unit and Epidemiological Studies Unit, Nuffield Department of Population Health, University of Oxford, Oxford, UK. ²⁹¹ Present address: Toranomon Hospital, Tokyo, Japan.

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Supplementary Figures and Tables

Fig. S1. Characterization of TREDNet phase one. Phase one TREDNet peak prediction accuracy for transcription factors (TFs), histone modifications (HMs), and DNase I hypersensitivity sites (DHSs; x-axis) compared to other models (colors) using area under the receiver operating characteristic (auROC; left) and area under the precision recall curve (auPRC; right) metrics (y-axis).

Fig. S2. Optimization of TREDNet phase one DNA sequence window size. TREDNet prediction accuracies for genomic and epigenomic features (e.g., transcription factor binding signals, histone modification signals, DNase I hypersensitivity signals) across different DNA sequence window sizes (x-axis) using area under the receiver operating characteristic (auROC; left) and area under the precision recall curve (auPRC; right) as metrics (y-axis). Stars indicate Wilcoxon rank sum test *P*-values less than various cutoffs: * indicates $P < 0.05$, ** indicates $P < 0.01$, and *** indicates $P < 0.001$.

Fig. S3. Comparison of single phase model to TREDNet two phase model. (A) Schematic of a single phase model compared to the two phase TREDNet model. (B) Prediction accuracy (y-axis) of the single phase model (blue), TREDNet phase one model (gold), and TREDNet phase two model (green) across various epigenomic features (xaxis) using area under the receiver operating characteristic (auROC; left) and area under the precision recall curve (auPRC; right) metrics. *** indicates Wilcoxon rank sum test *P<* 0*.*001. (C) Training speed (y-axis) of each model (x-axis).

Fig. S4. Extended characterization of TREDNet in MPRA data. Root mean square error (RMSE; y-axis) between predictions of computational methods (colors) and MPRA signals from different experiments (x-axis; coded using PubMed Central identifiers) across biospecimens (facets).

(A) Average enhancer damage and phyloP scores across FOXA binding sites in islet enhancers

(B) Correlation between ED/phyloP scores and information content

Fig. S5. Comparison of delta scores and motif information content. (A) FOXA position weight matrix (PWM; top panel). The average enhancer damage (ED) score of each position at FOXA transcription factor binding sites (TFBSs), including a 20bp flanking region around the central motif, using the islet TREDNet model (middle panel). The average evolutionary conservation phyloP scores of each position at FOXA TFBSs, including a 20bp flanking region around the central motif (bottom panel). (B) Distribution of correlation coefficients (Spearman's rho; y-axis) between ED/phyloP scores and information content (IC) of each position in PWMs for TFBSs in enhancer regions across biospecimens (x-axis).

ED score profile

Fig. S6. Detection framework for enhancer damaging and strengthening regions. (A) For each 2kb enhancer region, we calculate the TREDNet enhancer probability score (*e*) using the "wildtype" GRCh37 reference sequence (*ewt*). To predict the mutational effect of each nucleotide, we calculate enhancer probability scores for all three non-reference nucleotides at each enhancer position while the remaining enhancer DNA sequence remains unchanged. We generate enhancer damage (ED) score mutational profiles at each sequence position (ED score*i*) by computing the average difference between the wildtype and allele-specific enhancer scores. (B) We find that known TFBSs correspond to enhancer damaging regions (EDRs; red bars) and enhancer strengthening regions (ESRs; blue bars). To identify known and unknown TFBSs (EDRs/ESRs in gray bars) directly from ED scores, we train a second model to annotate each nucleotide position as an enhancer damaging, enhancer strengthening, or neutral. TF-1 depicts a novel predicted EDR. TF-2 depicts a novel predicted ESR. The ED scores in this plot are for illustrative purposes only.

Fig. S7. Performance of EDR and ESR detection models. TFBSs detection performance (y-axis) for EDR and ESR models (colors) for each biospecimen (x-axis) using area under the receiver operating characteristic (auROC; left) and area under the precision recall curve (auPRC; right) metrics.

Fig. S8. Prediction of TFBSs based on DNA sequence compared to TREDNet enhancer damage scores. (A) Schematic of the two TFBS prediction models. (B) Accuracy (y-axis) of TFBS prediction models based on DNA sequence (blue) and TREDNet enhancer damage scores (orange) across enhancer damaging and enhancer strengthening TFBSs (x-axis) using area under the receiver operating characteristic (auROC; left) and area under the precision recall curve (auPRC; right) metrics. * indicates Wilcoxon rank sum test $P < 0.05$. (C) Training speed (y-axis) of each model (x-axis).

(A) Example of EDRs and ESRs at a locus

(B) Intersection of EDRs and ESRs

Fig. S9. Enhancer damaging region and enhancer strengthening region results. (A) Example islet enhancer damaging regions (EDRs; blue) and enhancer strengthening regions (ESRs; red) overlaid on the corresponding enhancer damage (ED) scores (y-axis) in an islet enhancer region (x-axis). (B) Comparison of the overlap (*>*= 1 shared bp) of EDRs (orange) and ESRs (blue) across biospecimens, where set groups are shown in bubble plots (bottom).

Fig. S10. TREDNet IEP scores at credible set SNPs and SNPs in LD. (A) Comparison of IEP scores (y-axis) of credible set SNPs (green) and SNPs in LD with credible set SNPs (orange; x-axis). Error bars depict 95% confidence intervals of the median. **** indicates Wilcoxon rank sum test $P < 0.0001$. (B) Fold enrichment (y-axis) of credible set SNPs (green) and SNPs in LD with credible set SNPs (orange) at progressive IEP score percentile cutoffs. (C) Enrichment *P*-value (y-axis) from fGSEA analysis of all SNPs ordered by IEP scores. Error bars depict 95% confidence interval of the *P*-value estimate from fGSEA.

Fig. S11. IEP ratio_{1:2} prioritization cutoff. (A) *P*-values from hypergeometric test (y-axis) evaluating the enrichment of SNPs prioritized by increasing IEP ratio_{1:2} cutoffs (x-axis) from 99% European T2D credible sets in 99% trans-ancestry T2D credible sets at signals where *>* 1 SNPs are in the 99% European credible set and exactly 1 SNP occurs in the corresponding 99% trans-ancestry credible set. Dashed line at $P = 0.05$. (B) Distribution of IEP ratio_{1:2} values (x-axis) for each signal in the 99% credible set for all disease/traits considered. Dashed line indicates cutoff derived from panel A.

(A) Calculation of IEP ratio_{1:2} cutoff

(B) Distribution of IEP ratio_{1:2} values

Fig. S13. *GLIS3* **locus.** Locus zoom around the 9:4290085 T2D association (T2D $-log₁₀(P)$ facet) in a *GLIS3* intron. Top facet shows islet enhancers, called from islet H3K27ac ChIP-seq and ATAC-seq data. rs4237150 (blue) is one of two SNPs in the 99% T2D credible set (PPA facet), has a large IEP score (IEP facet), and occurs in an enhancer strengthening region (green; ED score facet). Dashed box indicates the enhancer strengthening region containing the candidate SNP (blue line).

Fig. S14. *DLK1* **locus.** Locus zoom around the 14:101255172 HbA1C association (HbA1C $-log_{10}(P)$ facet), near *DLK1* which is outside of the genomic coordinates shown. Top facet shows islet enhancers, called from islet H3K27ac ChIP-seq and ATAC-seq data. rs73347525 (blue) is one of the 95% HbA1C credible set SNPs (PPA facet), has a large IEP score (IEP facet), and occurs in an enhancer damaging region (orange; ED score facet). Dashed box indicates the enhancer damaging region containing the candidate SNP (blue line).

Fig. S15. *ZBED3* **locus.** Locus zoom around the 5:76435004 T2D association (T2D *log*10(*P*) facet), at *ZBED3*. Top facet shows islet enhancers, called from islet H3K27ac ChIP-seq and ATAC-seq data. rs7732130 (blue) is one of the 99% T2D credible set SNPs (PPA facet), has a large IEP score (IEP facet), and occurs in an enhnacer damaging region (orange; ED score facet). Dashed box indicates the enhnacer damaging region containing the candidate SNP (blue line).

Table S1. Prioritization of islet relevant transcription factors using enhancer

damage scores. Islet TF footprints ranked by the ratio of the average ED score within the TF footprint motif to the flanking region. TFBS refers to the predicted TF binding site from islet TF footprints. TFs with similar PWMs are merged (Methods) and separated by ":" in the TFBS column.

Table S2. Signals where IEP ratio_{1:2} refined 95/99% credible set SNPs to one SNP. Signals with a single SNP identified by IEP ratio_{1:2} that previously had > 1 SNPs in the 95% or 99% credible set, depending on the study (see Methods). Gene column refers to the nearest gene except in the case of the T2D data, for which we used the gene reported by the original study. N SNP column refers to the number of SNPs in the original 95/99% credible set (uniform prior). Note: IEP percentiles are rounded.

Table S3. Disruption of transcription factor motifs by prioritized SNPs. Difference in the binding predictions of transcription factors with motifs that overlap prioritized SNPs. Difference measured by the absolute value of the difference in the log of *P*-values for binding at each allele (log difference column). The "high score allele" column refers to the allele with the greatest enhancer probability score from TREDNet.

Table S4. TREDNet phase one network architecture. All kernels were subject to $maximum$ normalization value of 0.9. Total trained parameters: \sim 143 million. Model was trained with *Adadelta* optimizer using *binary cross entropy* as a cost function.

Table S5. TREDNet phase two network architecture. All kernels were subject to $maximum$ *normalization* value of 0.9. Total trained parameters: \sim 12 million. Model was trained with *RMSProp* optimizer using *binary cross entropy* as a cost function.

Table S6. EDR/ESR detection network architecture. All kernels were subject to *maximum normalization* value of 1.0. Model was trained with *ADAM* optimizer using *binary cross entropy* as a cost function.

Table S7. Probes used for EMSA experiments. Each forward and reverse oligo for the biotinylated probes were 5' biotinylated.

rs117720468 C/C CTTATGAGGGTTCCTGTTAGACTATTGGATATTTTTTGTTGTTTTCAGTTATATATGAAAATAATGGTGATAAAAATACTTTTTTTCCTGCTTAACTTTGGTGTCCTTGCTTTTT GGATATATGTTCTTAATTGTATTATTCCTATTCATGGTTTCACAGATATCTTTAATCTCACCCTATCCAAAGGAATTCTAAAGGTAAAATAACACCCTACATTGATAGCTTGGTC CATTAAGTCATTTGTCTTGGGGAAAAGTTGTAGCATAAAGTCATAGTCAGTTTTTGGTTAGGAGGACCTTATAGAAGAGATGAATGAGCATACATACACCCTGGAGTTAGTCCAA GTTTT**C**GATTCTCTGAAGCTTACCTCTGTAACTTAATCTTTCTGAACTTTAGTTTCCTCATCTAGAGAATGGTTTGTGATATTACTGCTCTGTTAATGTTATTGTGCTCCTTCAA TGAGATAGTGTATATAAAGGTCTAGTGTGGGCTCTGGCAGAGATGTGGTGCTGAATAGATGATTTATTTTTTTGATTGATTGTGATTGCCATTATTTTTGGTTTCCTAGGACATC CTCTTCCACCCAGTCCCTCTTCTTATGGAAATATATCTTGTCCAACCATCCCCTCCCACCAACCACGAGAGAGGTGGGCACATTATTCATCCTGGCCAATTTAGATTAATCCTCT AAATATAATGG

Table S8. Luciferase reporter assay oligonucleotides. 701bp DNA fragments used for luciferase assay.