Generating synthetic data

The synthetic datasets include the paired synthetic SNPs data \mathcal{T} and synthetic QTs data \mathcal{H} for subjects. The details of generating synthetic data are described as follows.

1) Generating the synthetic SNPs data \mathcal{T}

The synthetic SNPs data is defined as $\mathcal{T} = [\mathcal{T}_{normal}, \mathcal{T}_{disease}]$, where \mathcal{T}_{normal} is the synthetic SNPs data from the normal control (NC) subjects and $\mathcal{T}_{disease}$ is the synthetic SNPs data from the Alzheimer's disease (AD) subjects.

For the NC subjects, we first extract the n_{ts} risk SNPs from the ADNI dataset, then calculate the mutation rate $\varphi_n(g_n)$ of each $(g_n)^{\text{th}}$ subject by adopting the following formula, $\varphi_n(g_n) = \{\frac{1}{n_{ts}}\sum_{t=1}^{n_n}\sum_{t=1}^2 t_{g_n}^{(ts)_i} \mid t_{g_n}^{(ts)_i} = 1,\ t_{g_n}^{(ts)_2} = 2,\ g_n = 1,2,...,G_n\}$, where $t_{g_n}^{ts}$ is the value of $(ts)^{\text{th}}$ SNP in $(g_n)^{\text{th}}$ subject, G_n is the number of NC subjects. We assume the mutation rate φ_n following a normal distribution, i.e. $\varphi_n \sim \mathcal{N}(\mu_n,\sigma_n^2)$ (p-value = 2.2E-16) as shown in Fig. S1 (a), where $\mu_n = \frac{1}{G_n}\sum_{g_n=1}^{G_n}\varphi_n(g_n)$ and $\sigma_n^2 = \frac{1}{G_n}[\varphi_n(g_n) - \mu_n]^2$. Using φ_n , we synthetic SNPs data $t_{m_i,v}$ of m_i SNP in subject v following a Bernoulli distribution, i.e. $t_{m_i,v} \sim Bernoulli(\varphi_n)$. In this work, we generate 500 NC subjects, each with 1000 SNPs.

For the AD subjects, we first extract n_{ts} risk SNPs from ADNI dataset, and then calculate the mutation rate $\varphi_d(g_d)$ of each $(g_d)^{\text{th}}$ subject by adopting the following formula, $\varphi_d(g_d) = \{\frac{1}{n_{ts}}\sum_{t=1}^{n_{ts}}\sum_{i=1}^{2}t_{g_d}^{(ts)_i}\,|\,t_{g_d}^{(ts)_1}=1,\,t_{g_d}^{(ts)_2}=2,\,g_d=1,2,...,G_d\}$, where $t_{g_d}^{ts}$ is the value of $(ts)^{\text{th}}$ SNP in $(g_d)^{\text{th}}$ subject, G_d is the number of AD subjects. We assume the mutation rate φ_n following a normal distribution, *i.e.* $\varphi_d \sim \mathcal{N}(\mu_d, \sigma_d^2)$ (p-value = 2.7E-18) as shown in Fig. S1 (b). Using φ_d , we synthetic SNPs data $t_{m_2,d}$ of m_2 SNP in subject d following a Bernoulli distribution, i.e. $t_{m_2,d} \sim Bernoulli(\varphi_d)$. In this work, we generate 500 AD subjects, each with 1000 SNPs.

In this work, $n_{ts}=2000$, $G_n=223$, $\mu_n=0.146$, $\sigma_n^2=0.0292$, $G_d=277$, $\mu_d=0.481$, $\sigma_d^2=0.0444$.

2) Calculating the related mean μ_1 and nonrelated mean μ_2

First, based on the empirical distribution as shown in Fig. S1 (c), we obtain the related SNPs-QTs distribution $\beta_1 \sim \mathcal{N}(-0.3, 0.1)$ from AD subjects, the unrelated SNPs-QTs distribution $\beta_2 \sim \mathcal{N}(0, 0.02)$ from NC subjects, respectively.

Second, we assume the random effect variable $b_{qt,v}$ of $(qt)^{\text{th}}$ QT in subject v following a Gaussian distribution, i.e. $b_{qt,v} \sim \mathcal{N}(\mu_b^-, \sigma_b^2^-)$, and then use the generalized linear mixed model (glmmTMB) to estimate the parameters μ_b^- and $\sigma_b^2^-$ for each subject based on the matrix composed of QT n_r^- (r=1,2,...,119) and the top selected n_{ts} risk SNPs (Fig. S1 d-e). In this work, $\mu_b^-=3.07$ and $\sigma_b^2=1.48$.

Third, after generating the synthetic NC SNPs data $t_{m_1,v}$, the synthetic AD SNPs data $t_{m_2,d}$, and obtaining the related regression coefficients β_1 , the unrelated regression coefficients β_2 , and the random effect variable $b_{qt,v}$, we calculate the normalized expected related mean $\mu_{1,d} = e^{\beta_1 t_{m_2,d} + b_{qt,v}}$, and the unrelated mean $\mu_{2,v} = e^{\beta_2 t_{m_1,v} + b_{qt,v}}$, $\mu_{2,d} = e^{\beta_2 t_{m_2,d} + b_{qt,v}}$.

3) Calculating random variance σ^2

After getting the QT matrix $M_R \in \mathbb{R}^{G_n \times 119}$ for NC subjects, where G_n is the number of NC subjects, we generate the scatter plot of the mean μ and the variance σ^2 based on the M_R as shown in Fig. S1 (f). From Fig. S1 (f), we can see that the variance σ^2 follows a binomial distribution, i.e. $\sigma^2 \sim binomial\ distribution(\mu, 2),\ i = 1, 2$. Therefore, the random variance corresponding to μ_1 is $\sigma_1^2 \sim binomial\ distribution(\mu_1, 2)$ and the random variance corresponding to μ_2 is $\sigma_2^2 \sim binomial\ distribution(\mu_2, 2)$.

4) Generating the synthetic QTs data

The synthetic QTs data is defined as $\mathcal{H} = [\mathcal{H}_{hormal}, \mathcal{H}_{disease}]$. \mathcal{H}_{hormal} is generated by $h_{normal} \sim \mathcal{N}(\mu_1, \sigma_1^2)$ and $\mathcal{H}_{disease}$ is generated by $h_{disease} \sim \mathcal{N}(\mu_2, \sigma_2^2)$.

For the AD subjects, let two sparse vectors: $\mathbf{Q} \in \mathbb{R}^{s_a \times 1}$ and $\mathbf{T} \in \mathbb{R}^{s_b \times 1}$ represent AD-related QTs and SNPs, respectively, s_a denotes the dimension number for QTs randomly selected from 30% of the 119 QTs, and s_b denotes the number of SNPs related to QTs of AD subjects. In this work, we set $s_a = 36$, and s_b to 10, 20, 25. For example, we set $s_a = 36$, $s_b = 10$, and $QT_{18}, QT_{19}, ..., QT_{53}$ are the QTs related with AD, i.e., $QT_1, QT_2, ..., QT_{17}, QT_{18}, QT_{19}, ..., QT_{53}, QT_{54}, QT_{55}, ..., QT_{119}$

AD, i.e.,
$$QT_1, QT_2, ..., QT_{17}$$
, $QT_{18}, QT_{19}, ..., QT_{53}$, $QT_{54}, QT_{55}, ..., QT_{119}$
unrelated QTs unrelated QTs

where,

$$QT_{18}: \underbrace{eta_1^{18},eta_2^{18},...,eta_{10}^{18}}_{10 ext{ related SNPs}}, \underbrace{...,eta_{1000}^{18}}_{unrelated ext{ SNPs}}$$

$$QT_{19}: \underbrace{\beta_{1}^{19}, \beta_{2}^{19}, ..., \beta_{10}^{19}}_{\text{unrelated SNPs}}, \underbrace{\beta_{11}^{19}, \beta_{12}^{19}, ..., \beta_{20}^{19}}_{\text{10 related SNPs}}, \underbrace{..., \beta_{1000}^{19}}_{\text{unrelated SNPs}}, \text{ and so on.}$$

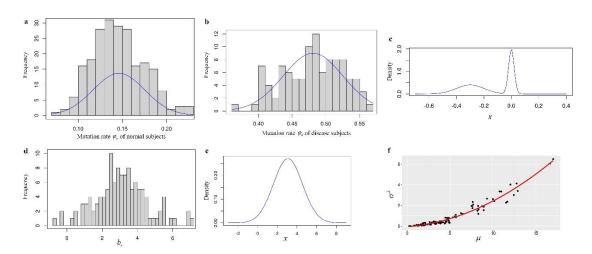


Fig. S1. a. The mutation rate φ_n of NC subjects from ADNI dataset and its gaussian distribution map (blue line). b. The mutation rate φ_d of AD subjects from ADNI dataset and its gaussian distribution map (blue line). c. The gaussian distribution map of SNPs related to QT ($\beta_1 \sim \mathcal{N}(-0.3,0.1)$) and SNP unrelated to QT ($\beta_2 \sim \mathcal{N}(0,0.02)$). d. The histogram of the random effect variable b_r . e. The gaussian distribution map based on b_r . f. The binomial distribution map of random variance σ^2 based on the μ .