Figure or Table # Please group Extended Data items by type, in sequential order. Total number of items (Figs. + Tables) must not exceed 10.	Figure/Table title One sentence only	Filename Whole original file name including extension. i.e.: Smith_ED_Fig1.jp g	Figure/Table Legend If you are citing a reference for the first time in these legends, please include all new references in the main text Methods References section, and carry on the numbering from the main References section of the paper. If your paper does not have a Methods section, include all new references at the end of the main Reference list.
Extended Data Fig. 1	Reduction in the number of genotypes stored per sample.	ext-data- fig1.eps	For 100 randomly chosen 100KGP participants belonging to each ancestry group (taken from amongst those with an inferred probability >0.9 of belonging): a , boxplots showing the distribution of the number of non-homozygous reference PASSing genotypes for variants on chromosomes 1–22 and X which meet the default Rareservoir MAF filtering criteria (i.e. a PMAF score >0 using gnomAD v3.0 and internal MAF <0.002); b , boxplots showing the distribution of the proportion of all PASSing non-homozygous reference genotypes that meet the default Rareservoir MAF filtering criteria. In both plots, the lower, centre and upper lines respectively indicate the lower quartile, median and upper quartile. Whiskers are drawn up to the most extreme points that are less than 1.5× the interquartile range away from the nearest quartile.
Extended Data Fig. 2	General schematic of the database build procedure and contents.	ext-data- fig2.eps	Variants are extracted from VCF files, filtered on internal cohort allele frequency, encoded as 64-bit RSVR IDs and loaded into a table containing the corresponding genotypes. The variants are annotated with scores reflecting their predicted deleteriousness (in this case, CADD scores) and probabilistic minor allele frequency scores (PMAF) from gnomAD. The consequences of each variant with respect to a reference set of transcripts are generated and loaded into a table. Sample information including pedigree membership

Extended Data Fig. 3 Extended Data Fig. 4	Detailed schematic of the database build procedure. Schematic showing the variant data in the 100KGP Main Programme Rareservoir.	ext-data- fig3.eps ext-data- fig4.eps	and membership of an MSUP is loaded into a table. The case groupings for case/control association analyses are stored in a table. Variants may be imported to a Rareservoir from either single gVCF files or a merged VCF file, following the procedures indicated by red and blue arrows respectively. The number of variant/transcript pairs, the distribution of CADD scores and a breakdown of gnomAD frequency classes is shown for each annotated SO term in the context of the structure of the ontology.
Extended Data Fig. 5	The 269 case sets, Disease Groups A–I.	ext-data- fig5.eps	The names and sizes of the case sets used for the genetic association analyses, grouped by Disease Group and coloured by type (Disease Sub Group or Specific Disease). Disease Sub Groups with only one Specific Disease were excluded to avoid repeating identical analyses. Case sets smaller than 5 are labelled '<5' and shown as having size 4 to comply with 100KGP policy on limiting participant identifiability. For legibility, only Disease Groups starting with the letters A–I are shown here.
Extended Data Fig. 6	The 269 case sets, Disease Groups M–Z.	ext-data- fig6.eps	An extension of Extended Data Fig. 5 showing the case sets in Disease Groups starting with the letters M–Z.
Extended Data Fig. 7	Breakdown of cases attributable to associations with 'Posterior segment abnormalities' by Specific Disease.	ext-data- fig7.eps	For each gene associated with the Disease Sub Group 'Posterior segment abnormalities', a bar plot showing the number of cases having each of the different Specific Diseases who have an inferred pathogenic configuration of alleles in the gene. This example illustrates that sets of cases with the same aetiological gene may be assigned different Specific Diseases. Consequently, pooling cases within Disease Sub Group can boost power.
Extended Data Fig. 8	Microscopy images of	ext-data- fig8.eps	Exemplar immunofluorescence microscopy images of HEK293 cells overexpressing wild

	HEK293 cells		type ERG (from 20 replicates) and each of				
	overexpressing		the p.S182Afs*22, p.T224Rfs*15 and				
	ERG.		p.A447Cfs*19 variants of ERG (each from 17 replicates). Cells were stained for ERG (green) and nuclear marker DAPI (blue).				
			Scale bar, 20µm.				
Extended Data Fig.	Illustrative	ext-data-	Air and bone conduction audiograms for the				
9	audiograms for	fig9.eps	two affected daughters of the family with				
	GPR156 cases.		compound heterozygous GPR156				
			truncating alleles.				

2. Supplementary Information:

A. PDF Files

Item	Present?	Filename Whole original file name including extension. i.e.: Smith_SI.pdf. The extension must be .pdf	A brief, numerical description of file contents. i.e.: Supplementary Figures 1-4, Supplementary Discussion, and Supplementary Tables 1-4.
Supplementary	No		
Information			
Reporting Summary	Yes.	nr-reporting-	
		summary-	
		comments-	
		addressed.pdf	
Peer Review	No	OFFICE USE	
Information		ONLY	

3. Source Data

Parent Figure or	Filename	Data description
Table	Whole original file name including	i.e.: Unprocessed western Blots and/or gels, Statistical
	extension. i.e.:	Source Data, etc.
	Smith_SourceData_Fig1.xls, or	
	Smith_	
	Unmodified_Gels_Fig1.pdf	
Source Data Fig. 1	source-data-fig1b.xlsx	Sheet 1, Table of associations shown in Fig.
		1b annotated with BeviMed PPAs (PPA), the
		level of the case set in the disease label
		hierarchy (Level), the inferred variant class
		and MOI for the association, the matched

		PanelApp panel for the association, the					
		method that was used to find the match					
		(Match method, either 'Automatic' or 'Manual'),					
		the associated evidence level for the match,					
		and the notes on the consistency between the					
		MOI listed by PanelApp for the association					
		and the inferred MOI (MOI match comment).					
		Sheet 2 , Table of variants having a probability					
		of pathogenicity >0.8 conditional on the modal					
		model and forming a pathogenic configuration					
		of alleles in at least one case. While these					
		variants contributed to the reported statistical					
		associations, they have not been individually					
		scrutinised according to ACMG guidelines.					
Source Data Fig. 2	source-data-fig2e.jpg	Uncropped western blot images corresponding					
		to Fig. 2e.					
Source Data Fig. 3	source-data-fig4e.jpg	Uncropped western blot images corresponding					
		to Fig. 4e.					

Genetic association analysis of 77,539 genomes reveals rare disease etiologies

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Abstract

The genetic aetiologies of more than half of rare diseases remain unknown. Standardised genome sequencing (GS) and phenotyping of large patient cohorts provides an opportunity for discovering the unknown aetiologies, but this depends on efficient and powerful analytical methods. We built a compact database, the 'Rareservoir,' containing the rare variant genotypes and phenotypes of 77,539 participants sequenced by the 100,000 Genomes Project (100KGP). We then used the Bayesian genetic association method BeviMed to infer associations between genes and each of 269 rare disease classes assigned by clinicians to the participants. We identified 241 known and 19 previously unidentified associations. We validated associations with *ERG*, *PMEPA1* and *GPR156* by searching for pedigrees in other cohorts and using bioinformatic and experimental approaches. We provide evidence that (1) loss-of-function variants in the ETS-family transcription factor encoding gene *ERG* lead to primary lymphoedema, (2) truncating variants in the last exon of TGFβ regulator *PMEPA1* result in Loeys-Dietz syndrome, and (3) loss-of-function variants in *GPR156* give rise to recessive congenital hearing impairment. The Rareservoir provides a lightweight, flexible and portable system for synthesising the genetic and phenotypic data required to study rare disease cohorts with tens of thousands of participants.

Introduction

Collectively, rare diseases affect 1 in 20 people¹, but fewer than half of the approximately 10,000 catalogued rare diseases have a resolved genetic aetiology². Standardised GS of large, phenotypically diverse collections of rare disease patients enables aetiological discovery across a wide range of pathologies^{3,4,5} while boosting genetic diagnostic rates for patients. The 100KGP, the largest GS study of rare disease patients to date, sequenced 34,523 United Kingdom National Health Service patients with rare diseases and 43,016 of their unaffected relatives. The linked genetic and phenotypic data of 100KGP participants were then made available to researchers through a web portal called the Genomics England Research Environment. The scale and complexity of such large GS datasets and the hierarchical nature of patient phenotype coding⁶ induce numerous bioinformatic and statistical challenges. Most importantly, the full genotype data from GS studies of tens of thousands of individuals are typically stored in unmodifiable files many terabytes in size, leading to high storage and processing costs. Recently developed frameworks such as Hail⁷ and OpenCGA⁸ afford greater flexibility. However, they are designed to capture genotypes for variants across the full minor allele frequency (MAF)

spectrum, from rare (MAF<0.1%) to common (MAF>5%) variants. To accommodate large numbers of genotypes, they depend on distributed storage systems and require numerous software packages, hindering deployment. We developed a database schema, the 'Rareservoir,' for working with rare variant genotypes and patient phenotypes flexibly and efficiently. We deployed a Rareservoir only 5.5GB in size of the 100KGP data and applied the Bayesian statistical method BeviMed⁹ to identify genetic associations between coding genes and each of the 269 rare disease classes assigned to patients by clinicians. Out of the previously unknown associations that we identified, we followed up the most plausible subset in confirmatory analytical and experimental work.

Results

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The 'Rareservoir'

Relational databases (RDBs) provide a unified, centralised structure for storing, querying and modifying data of multiple underlying types. In principle, an RDB could provide a convenient foundation for the analysis of genotypes, variants, genes, participants and statistical results, but they cannot accommodate tables of the scale required to store exome or genome-wide genotypes in a moderately sized cohort. An RDB can, however, accommodate a sparse representation of genotypes corresponding to rare variants only, which encompass almost all variants having a large effect on rare disease risk. We developed an RDB schema, the 'Rareservoir', and build procedure for the analysis of rare diseases, which, by default, stores genotypes corresponding to variants for which all population-specific MAFs are likely to be <0.1%. This reduces the number of stored genotypes in a large study by about 99% (Extended Data Fig. 1). The Rareservoir encodes variants as 64-bit integers ('RSVR IDs', Extended Data Fig. 2), which can represent 99.3% of variants encountered in practice without loss of information. RSVR IDs occupy a single column and increase numerically with respect to genomic position, allowing fast location-based queries within a simple database structure. To support the build process of a Rareservoir, we developed a complementary software package called 'rsvr' (Extended Data Figs. 2-3). The package includes tools to annotate variants with MAF information from control databases (e.g., gnomAD¹⁰), pathogenicity scores (e.g. combined annotation dependent depletion (CADD) scores¹¹) and predicted Sequence Ontology (SO)¹² consequences with respect to a set of transcripts. We use a 64-bit integer ('CSQ ID') to record the consequences for interacting variant/transcript pairs, where each bit encodes one of the possible consequences, ordered by severity. Encoding the consequences in this way is efficient and enables succinct queries that threshold or sort based on severity of impact. The Rareservoir also contains a table with genetically derived data for each sample (including ancestry, sex and membership of a maximal set of unrelated participants (MSUP)), and a table of 'case sets' storing the rare disease classes assigned to each participant.

BeviMed infers 241 known and 19 unknown genetic associations

We built a Rareservoir, 5.5GB in size, containing 11.9 million rare exonic and splicing single nucleotide variants (SNVs) and short insertions or deletions (indels) affecting canonical transcripts of protein-coding genes in Ensembl v104¹³ from a merged variant call format file (VCF) containing genotype calls for 77,539 participants, including 29,741 probands, in the Rare Diseases Main Programme of the 100KGP (Data Release Version 13) (**Extended Data Fig. 4**). During enrolment to the 100KGP, expert clinicians used the clinical characteristics of each affected participant to assign them to one or more of 220 *Specific Diseases*. The Specific Diseases are hierarchically arranged into 88 *Disease Sub Groups*, each of which belongs to one of 20 *Disease Groups*. Whereas the eligibility criteria for many specific diseases aligned

to the same or closely related rare diseases, for others such as 'intellectual disability,' the criteria were broader and encompassed diverse genetic aetiologies. We generated 269 analytical case sets corresponding to all distinct Specific Diseases and Disease Sub Groups, ranging in size from 5,809 to one proband, and stored them in the Rareservoir (**Fig. 1a, Extended Data Figs. 5–6**). We included these two levels of the phenotyping hierarchy to account for heterogeneity in presentation or diagnosis among cases sharing the same genetic aetiology, with the aim of boosting power to identify statistical genetic associations.

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Using the Bayesian statistical method BeviMed⁹, we obtained a posterior probability of association (PPA) between each of the 19,663 protein-coding genes and each of the 269 rare disease classes. BeviMed computes posterior probabilities over a baseline model of no association and six competing association models, each of which assumes a particular mode of inheritance (MOI, dominant or recessive) and consequence class of aetiological variant (high-impact, moderate-impact or 5' UTR). The PPA is obtained by summing the posterior probabilities over all six association models. The association model with the greatest posterior probability (the modal model) determines the inferred MOI and class of aetiological variant. Conditional on an association model, BeviMed models the pathogenicity of each included rare variant. In the model, participants with at least one pathogenic allele (under a dominant MOI), or at least as many pathogenic alleles as the ploidy (under a recessive MOI), have a pathogenic configuration of alleles, which determines their risk of case status. For each rare disease class, we selected a set of unrelated cases based on pedigree information provided by the 100KGP and compared them to participants not in the case set who belonged to different pedigrees and to an MSUP, also provided by the 100KGP. To account for correlation between case sets, we only recorded the association for each gene having the highest PPA within a given Disease Group. Using a significance threshold of PPA>0.95, we identified 260 significant associations, 241 of which were documented by the PanelApp gene panel database, 14 an expert-curated and annotated resource containing gene lists with high, medium or low levels of prior supporting evidence of causality for rare diseases (Fig. 1b). Out of the 241 known associations that we identified, 43 (17.8%) were with Disease Sub Groups. For example, within each of the nine known genes associated with the Disease Sub Group 'Posterior segment abnormalities.' the set of cases explained by variants with a posterior probability of pathogenicity >0.8 comprised a mixture of participants with five different Specific Diseases (Extended Data Fig. 7). This demonstrates that participants with different Specific Diseases belonging to the same Disease Sub Group sometimes share defects in the same gene, which confirms that treating Disease Sub Groups, not just Specific Diseases, as case sets, boosts statistical power.

Out of the 241 associations identified as previously known according to PanelApp, 237 (98.3%) had an inferred MOI that was consistent with the MOIs listed for the relevant gene. Of these, the consistent MOI was found in the matched panel (223 associations), in the notes for the matched panel (five associations) or in the MOIs listed for an alternative relevant panel (nine associations) in PanelApp (**Source data for Fig. 1**). This provided independent evidence that the genetic associations we labelled as known (without reference to MOI information) are genuinely supported by evidence in the literature, further demonstrating the accuracy of BeviMed's inference. Of the four known associations with an inferred MOI that was incongruous with PanelApp, two had supporting evidence for the inferred MOI in the literature that was absent from PanelApp: *EDA* with dominant 'Ectodermal dysplasia without a known gene mutation' and *AICDA* with dominant 'Primary immunodeficiency' 16. The two associations with an MOI

that was unsupported in the literature were between *UCHL1* and dominant 'Inherited optic neuropathies' and between *SLC39A8* and dominant 'Intellectual disability'.

Among 5,253 of the probands included in our analysis, the table of clinically reported variants available from the 100KGP Rare Diseases Main Programme at the time of this study comprised 4,907 distinct variants that had been classified as pathogenic or likely pathogenic in 1,863 genes. For 855 of these genes, aetiological variants had been reported for only one family, suggesting that many genes which are aetiological in the 100KGP are not identifiable by statistical association. Nevertheless, across the 260 associations identified by BeviMed, 2,536 distinct rare variants had a posterior probability of pathogenicity >0.8 conditional on the modal model and were observed as part of a pathogenic configuration of alleles in a case (**Source data for Fig. 1**). Interestingly, among the subset of 2,485 variants contributing to the 241 known associations, only 1,604 featured in the table of clinically reported variants.

We found 19 previously unidentified genetic associations. To select a shortlist for further investigation. we assigned a plausibility score (range 0-3) based on three sources of additional evidence (**Table 1**). Firstly, we considered evidence of purifying selection from gnomAD v2.1.1. Any dominant associations with high-impact variants in a gene having a probability of loss-of-function intolerance (pLI) >0.9 or with moderate-impact variants in a gene having a Z-score >2 were considered to be supported by population genetic metrics of purifying selection. To avoid disadvantaging recessive associations, which are unlikely to leave a detectable signature of purifying selection in gnomAD even if genuine, they were considered to be supported by default. Secondly, we considered co-segregation data: any association for which variants having a posterior probability of pathogenicity conditional on the modal model >0.8 tracked with case status in at least three additional family members and for which no affected relatives lacked the pertinent variants were considered to be supported by co-segregation. Thirdly, we performed a comprehensive review of the literature for each gene and made a subjective assessment of whether an association was supported by biological function or previously known disease associations for related genes. In total, three genetic associations had a plausibility score of 3 and were therefore investigated further by gathering additional experimental evidence and looking for replication in other sequenced rare disease collections.

Variants in ERG are responsible for primary lymphoedema

BeviMed identified a dominant genetic association between high-impact variants in *ERG* and the Specific Disease 'Primary lymphoedema,' a group of genetic conditions caused by abnormal development of lymphatic vessels or failure of lymphatic function^{17,18}. Three such variants were responsible for the high PPA, with locations ranging from codon 182 to 463 on the canonical Ensembl transcript ENST00000288319.12. One of the probands had two unaffected parents without the variant allele—one sequenced by the 100KGP and the other by Sanger sequencing—suggesting the truncating heterozygous variant had appeared *de novo*. A participant in a fourth family who had been enrolled to the 100KGP for an unrelated condition also carried a predicted loss-of-function variant in *ERG*. Upon manual chart review, this participant had features associated with this unrelated condition, but additional features consistent with primary lymphoedema, providing internal replication within the discovery cohort (**Fig. 2a**).

The affected father of the proband with the variant encoding p.S182Afs*22 was called homozygous for the reference allele, initially suggesting a lack of co-segregation of the variant with the disease in that pedigree. However, a review of the GS read alignments for the father revealed that two out of the 48 reads overlapping that position supported the alternative allele. Specifically, these reads contained a deletion of a single G within the central poly-G tract of the motif "AGCTGGGGGTGAG." To assess whether this could be the result of erroneous sequencing, we counted the number of such reads in the 77,539 genomes in the 100KGP and found that the proband and the father were the only two with more than one such read. This indicated that these reads in the father were unlikely to be erroneous but instead that he was mosaic (**Fig. 2b**), consistent with the observation that his lymphoedema became clinically apparent over two decades later than his daughter, indicating milder disease. A further 130 samples collected through the 100KGP had a single read containing the deletion. This number was consistent with observations in the 80 other exonic loci that contain the same 13bp motif (mean: 99.67 samples, range: 4 to 149 samples), suggesting that, rather than being mosaic, the 130 samples contained individual sequencing errors. Furthermore, none of the participants who gave these samples had been assigned the Specific Disease 'Primary lymphoedema.'

ERG encodes a critical transcriptional regulator of blood vessel endothelial cell (EC) gene expression¹⁹ that is essential for normal vascular development²⁰. However, little is known about the contribution of ERG to lymphatic development or how primary lymphoedema could arise from loss-of-function ERG variants which affect different parts of the ERG protein (Fig. 2c). Total cellular expression of ERG detected by real-time quantitative polymerase chain reaction (PCR) in purified RNA and by immunoblotting of protein extracts was the same in primary human dermal lymphatic EC (HDLEC) as human umbilical vein EC (HUVEC) (Fig. 2d and Fig. 2e respectively). Moreover, immunofluorescence microscopy of cultured HDLEC showed that ERG expression co-localised with the lymphatic EC nuclear marker PROX1 (Fig. 2f) a finding confirmed in vivo by immunostaining whole mounts of ear skin from mice at three weeks after birth (Fig. 2q). The positions of the p.S182Afs*22 and p.T224Rfs*15 variants suggest nonsense mediated decay and haploinsufficiency as a possible disease mechanism. The other two variants, however, are located in the final exon of ERG and may therefore evade nonsense mediated decay. We studied both types of variant in more detail to explore potential disease mechanisms. In HEK293 cells, which do not express endogenous ERG, overexpression of wild type ERG cDNA recapitulated the nuclear expression pattern observed in the HDLEC and mouse ear skin models. However, overexpression of each of the ERG mutant cDNAs resulted in mislocalisation of ERG outside of the nucleus, in the cytosol (Fig. 2h-i, Extended Data Fig. 8), preventing it from binding to DNA and exerting its function as a transcription factor²¹. Together, these data confirm high levels of ERG expression within the nuclei of the lymphatic endothelium consistent with a transcription regulatory function during lymphangiogenesis. They also suggest that in the primary lymphoedema cases, defective lymphangeogenesis may result from reduced ERG availability in the nucleus either because of haploinsufficiency resulting from nonsense mediated decay or mislocalisation.

Variants in *PMEPA1* result in Loeys-Dietz syndrome

BeviMed identified a dominant genetic association between high-impact variants in *PMEPA1* and the Specific Disease 'Familial Thoracic Aortic Aneurysm Disease' (FTAAD). The variant with the highest conditional probability of pathogenicity was an insertion of one cytosine within a seven-cytosine stretch in the last exon of the canonical Ensembl transcript ENST00000341744.8. This variant, which is predicted

to induce a p.S209Qfs*3 frameshift, was observed in three FTAAD pedigrees of European ancestry in the 100KGP discovery cohort. We replicated the association in three additional collections of cases. Firstly, the same variant was identified independently in eight affected members of three pedigrees of Japanese ancestry in a separate Japanese patient group. Secondly, a single-cytosine deletion within the same poly-cytosine stretch as the previous variant, and encoding p.S209Afs*61, was found in an FTAAD case enrolled in a separate collection of 2,793 participants in the 100KGP Pilot Programme. Lastly, we identified a family in Belgium wherein the affected members carried a five base-pair deletion in the same stretch of poly-cytosines inducing a frameshift two residues upstream of the other two variants (p.P207Qfs*3).

All pedigrees exhibited dominant inheritance of aortic aneurysm disease with incomplete penetrance and skeletal features including pectus deformity, scoliosis and arachnodactyly with complete penetrance, which co-segregated with the respective variants in genotyped participants (**Fig. 3a**). To assess whether *PMEPA1* families affected by FTAAD form a phenotypically distinct subgroup, we analysed the HPO terms assigned to the 593 FTAAD families in both programmes of the 100KGP. Using a permutation-based method^{22,23} based on Resnik's semantic similarity measure²⁴, we found that the four 100KGP *PMEPA1* families were significantly more similar to each other than to other FTAAD families chosen at random (*p*=5.7x10⁻³). To characterise the *PMEPA1* phenotype in greater detail, we compared the prevalence of each of the HPO terms in the minimal set of terms present in at least three of the four families with the prevalence in the other FTAAD families. We identified four HPO terms related to the musculoskeletal system that were significantly enriched (**Fig. 3b**), echoing the phenotypic characteristics of the syndromic aortopathy Loeys-Dietz syndrome^{25,26}.

To understand the molecular mechanisms underlying this defect, we examined the protein-protein interactions²⁷ for *PMEPA1* and the complete set of high-confidence genes in the 'Thoracic aortic aneurysm or dissection' PanelApp panel. *PMEPA1* encodes a negative regulator of Transforming Growth Factor β (TGF β) signalling²⁸, a pathway previously implicated in multiple aortopathies, including Loeys-Dietz syndrome²⁹. The genes underlying known forms of Loeys-Dietz syndrome encode part of a tightly interacting subgroup of proteins in the TGF β pathway, in which there is a direct interaction between the proteins encoded by *SMAD2*, *SMAD3* and *PMEPA1* (**Fig. 3c**). As the two candidate variants occur in the last exon of the transcript, they are likely to evade nonsense-mediated decay³⁰. However, their truncating effects are predicted to remove a PPxY interaction motif, while leaving the SMAD interaction motif intact (**Fig. 3d**), possibly affecting binding between PMEPA1 and SMAD2/3, and altering TGF β signalling through a gain-of-function mechanism.

Variants in *GPR156* lead to recessive congenital hearing loss

BeviMed identified a recessive genetic association between high-impact variants in *GPR156* and the Specific Disease 'Congenital hearing impairment'. Two high-impact variants in *GPR156* were responsible for the strong evidence of association: a one base pair deletion predicting p.S207Vfs*113 and a one base pair insertion predicting p.P718Lfs*86 with respect to the canonical Ensembl transcript ENST00000464295.6. One family contained two affected siblings who were both homozygous for the p.S207Vfs*113 variant inherited from heterozygous parents. In a second family, there were also two affected siblings, in this case compound heterozygous for the same p.S207Vfs*113 variant that was maternally inherited and a different p.P718Lfs*86 variant that was paternal. Using GeneMatcher³¹, we

identified a third pedigree from Saudi Arabia with biallelic truncating variants in *GPR156*. This consanguineous pedigree contained four siblings with hearing impairment, all of whom were homozygous for a variant predicting p.S642Afs*162 (**Fig. 4a**). The eight affected individuals in these three families all had congenital non-syndromic bilateral sensorineural hearing loss (see **Extended Data Fig. 9** for illustrative audiograms).

GPR156 encodes probable G-protein coupled receptor 156, which has sequence homology to the class C GABAB receptors³². Although previously designated as an orphan receptor, *GPR156* has recently been identified as a critical regulator of stereocilia orientation on hair cells of the auditory epithelium and other mechanosensory tissues³³. Its expression is highly restricted to hair cells in the inner ear³⁴. Disruption of stereocilia is a common pathogenic mechanism underlying many human Mendelian hearing loss disorders³⁵ and the over-expression of *GPR156* in hair cells relative to surrounding cells was commensurate with the over-expression of the 21 genes currently implicated in hearing impairment having a Gene Ontology (GO) term relating to stereocilia (**Fig. 4b**). By immunostaining of the Corti and vestibular system from wild type mice, we found that GPR156 strongly co-localises with actin at the apical surface of the outer and inner hair cells of the organ of Corti (**Fig. 4c**).

The p.S207Vfs*113 variant is located in the sixth of 10 exons of *GPR156* and therefore predicts absent expression through nonsense mediated decay of the *GPR156* mRNA. In contrast, the p.S642Afs*162 and p.P718Lfs*86 variants both occur within the final *GPR156* exon and likely result in expression of abnormal GPR156 with an altered amino acid sequence and premature truncation of the cytoplasmic tail (**Fig. 4d**). To determine the effect of the variants on protein expression, we transfected Cos7 cells, which do not express *GPR156* endogenously, with constructs containing cDNAs for wild type *GPR156* or *GPR156* containing each of the three mutant alleles, tagged with a green fluorescent protein (GFP) reporter. While cells transfected with wild type sequence expressed GPR156-GFP fusion protein robustly, cells transfected with the mutant constructs either did not express the protein appreciably or exhibited markedly reduced expression, suggesting that all three of the truncated proteins are degraded (**Fig. 4e**). These data suggest that the biallelic chain truncating variants in *GPR156* cause a congenital hearing loss by preventing expression of GPR156 protein, thereby disrupting stereocilia formation in the auditory epithelium.

Discussion

The standardisation of GS within a healthcare system, together with powerful frameworks for genetic and phenotypic data processing and statistical analysis, promises to advance the resolution of the remaining unknown aetiologies of rare diseases. We have developed a lightweight and easily deployable relational database, the Rareservoir, for genetic analysis of rare diseases using approaches such as BeviMed. In one unified analysis, we identified 260 associations, of which 241 had been published previously in a body of work spanning several decades of genetics research. Our results give an upper bound on the false discovery rate (FDR) of 7.3%. In contrast, a recent analysis of 57,000 samples in the 100KGP reported 249 known and 579 previously unidentified associations³⁶, giving an upper bound on the FDR of 70%, which suggests that our analytical approach has a greater specificity for a given sensitivity. The associations spanned 86 disease classes across a wide range of organ systems. Interestingly, only 64% of the variants contributing substantially to the known associations were present in the table of clinically reported variants available at the time of this study. This suggests that, as cohorts grow larger, the

results of statistical inference could help guide the clinical reporting process. The case sets we used in our genetic association analysis were based on the formal disease classifications used by the 100KGP. Some of the case sets, such as 'Intellectual disability' (5,529 probands), are particularly large and likely to be highly genetically heterogeneous, potentially limiting the power of our analyses. Careful partitioning of heterogeneous case sets using individual-level HPO terms⁶ has the potential to boost power. Of the 19 previously unidentified associations, we shortlisted, replicated and validated three. These three aetiologies involve genes that had not previously been implicated in any of these human diseases. The remaining 16 associations include further plausible hypotheses. For example, LRRC7, which we identified to be associated with intellectual disability, encodes a brain-specific protein in post-synaptic densities³⁷, and Lrrc7-deficient mice exhibit a neuro-behavioural phenotype³⁸. USP33, which we found to be associated with early-onset hypertension, encodes a deubiquitinating enzyme implicated in regulating expression of the $\beta2$ -adrenergic receptor regulation³⁹. These and other candidates will require replication and validation before they can be considered causative genes.

The present study has several limitations. Firstly, approximately 82% of the participants in the 100KGP are of European ancestry. While this percentage is in line with the proportion of residents in England and Wales reporting their ethnic group as White in the 2011 UK census (86%), its large magnitude constrains power to identify causative variants specific to other ancestry groups. Secondly, of the 260 case sets analysed, 28 contained fewer than 5 probands, limiting power to identify the causes of the corresponding disease classes and highlighting the need for continued enrolment of patients with ultra-rare disorders. Thirdly, we have only considered SNVs and indels in coding genes. The exploration of rare variation in non-coding genes and in regulatory elements of the genome may help identify further etiologies. Lastly, we focused our attention on monogenic models of rare disorders, even though the genetic etiologies of certain rare diseases may be polygenic. In addition, important variation in clinical presentation of monogenic disorders may be explained by polygenic effects. These limitations point towards multiple promising avenues of future research to uncover the remaining unknown genetic determinants of rare diseases.

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Author contributions

 D. Greene developed software, conducted analyses and co-wrote the paper. G.E.R.C. provided genetic and phenotypic data and access to the Genomics England Research Environment. C. Thys performed experiments and interpreted results. B. D. Gelb provided biological interpretation and feedback on the manuscript. K. Freson designed and supervised experiments, provided biological interpretation and contributed to writing the paper. A. Mumford provided clinical oversight, provided biological interpretation and contributed to writing the paper. E. Turro oversaw the study and co-wrote the paper. The following contributions relate to the three gene-specific vignettes. ERG: D. Pirri, K. Frudd and E. Sackey performed experiments and interpreted results. S. Mansour and C. L. S. Turner provided additional clinical information. P. Ostergaard coordinated validation and contributed to writing the paper. G. Birdsey designed and supervised experiments and contributed to writing the paper. PMEPA1: I. Yamanaka and N. Boeckx conducted experiments and interpreted results. P. Brennan, V. Hartill, J. Harvengt, T. Kosho, M. Masuno and T. Ohata provided clinical information. T. Morisaki and B. Loeys oversaw clinical and experimental studies. H. Morisaki recruited the Japanese cases, conducted experiments, interpreted and analysed results, and oversaw genetic studies. GPR156: H. Stewart provided additional clinical information for the compound heterozygous family. K. Taibah clinically evaluated and recruited the p.S642Afs*162 family, A. Giese, K. Ramzan and S. Riaz conducted experiments and interpreted results. M. Al-Owain assisted with experiments, interpreted results and contributed clinical information. S. Riazuddin, F. Imtiaz and Z. M. Ahmed designed and supervised experiments, analysed results, and provided reagents and tools.

Competing interests No authors have competing interests.

Gene	Case set	Lev el	Cas es	Contr ols	Varia nt class	M OI	p LI	z	Co-segregation evidence	Biological function and existing disease associations	Sco re	Replicati on
									Co-segregation	ETS family transcription		Internal
									in 2 affected and	factor ERG is a critical		(case
									1 unaffected	regulator of endothelial		enrolled
									relatives	lineage specification,		for a
									(mosaicism in	vascular development,		different
	Primary					Do	0.	2.5	one affected	angiogenesis, and endothelial		Specific
<u>ERG</u>	lymphoedema	SD	94	55,400	High	m	96	3	parent).	homeostasis.40,20.	3	Disease)

<u>GPR156</u>	Congenital hearing impairment	SD	510	54,739	High	Re c	0	1.0	Co-segregation in 2 affected and 4 unaffected relatives.	G protein-coupled receptor that regulates hair cell orientation in mechanosensory epithelia including in murine auditory epithelium ³³ .	3	Riyadh
PMEPA1	Familial Thoracic Aortic Aneurysm Disease	SD	574	54,858	High	Do m	0. 94	1.2	Co-segregation in 3 affected relatives and distinctive phenotypic features.	Negative regulator of Transforming Growth Factor β (TGFβ) signalling ²⁸ . Aberrant TGFβ signalling is implicated in multiple Mendelian aortopathies ²⁹ .	3	100KGP pilot, Antwerp, Tokyo
<u> </u>	Dioddo	OB	07.1	01,000	riigii		-		Toutur oo.	Brain-specific scaffold		Tokyo
LRRC7	Intellectual disability	SD	5,52 9	46,401	High	Do m	1	3.6		protein in post-synaptic densities ³⁷ . LRRC7- inactivated mice have neuro- behavioural phenotype ³⁸	2	
	Extreme early-									Deubiquitinating enzyme implicated in multiple cellular processes, including regulation of expression of the β2-adrenergic receptor ³⁹ , a critical regulator of		
USP33	onset hypertension	SD	182	55,305	High	Do m	0. 86	2.1		circulatory function and blood pressure ⁴¹ .	2	
03733	Hypertension	30	102	33,303	riigii	111	80	2.1		Component of the Arp2/3 complex that regulates polymerisation of F-actin,	2	
ARPC3	Charcot-Marie- Tooth disease	SD	549	54,856	Moder ate	Do m	0. 22	0.3		abundant in axonal neurofilaments. Multiple Mendelian axonal filamentopathies manifest as Charcot-Marie-Tooth disease ⁴² . ArpC3-inactivation in mice causes axon dysfunction ⁴³ .	1	
FMN1	Congenital hearing impairment	SD	510	54,738	High	Re c	0	- 1.5 3	Co-segregation in 2 unaffected relatives.	Formin family protein involved in linear actin and microtubule polymerisation ⁴⁴ . Pathogenic variants in the formin DIAPH1 cause hearing loss via cytoskeletal disruption in auditory stereocilia ⁴⁵ .	1	
TIVIIVI	Familial	30	310	34,730	riigii		0	J	Co-segregation in	Small GTP-binding proteins that	1	
RAB35	Hypercholestero laemia	SD	469	55,033	High	Do m	0. 98	2.3	1 affected relative.	are a regulator of endosomal transport and function.	1	
RAB3A	Hereditary ataxia	SD	905	54,504	Moder ate	Do m	0. 95	2.3		Small GTP-binding proteins that regulate exocytosis and secretion. Although abundant in brain synaptic vesicles, rab3A-inactivated mice have no neuromuscular phenotype ⁴⁶ .	1	
	Epidermolysis					Re			Co-segregation in 1 affected and 4 unaffected	Acidic protein that mediates		
TUFT1	bullosa Ultra-rare	SD	32	55,459	High	С	0	0.9	relatives.	dental enamel mineralisation.	1	
FAM222 B	undescribed monogenic disorders	SD	1,20 5	53,681	Moder ate	Do m	0. 29	0.4		Uncharacterised nucleosomal protein.	0	
INSL4	Rod Dysfunction Syndrome	SD	58	55,425	Moder ate	Do m	0	1.4		Insulin-like growth factor implicated in trophoblast and bone development.	0	
KRT14	Young onset tumour syndromes	DS G	256	55,207	Moder ate	Re c	0	0.8	Co-segregation in 2 unaffected relatives.	Component of keratin intermediate filaments in epithelial cells. Pathogenic variants cause Epidermolysis	0	

										bullosa simplex !A-D(AD/AR); Dermatopathia pigmentosa reticularis (AD); Naegeli- Franceschetti-Jadassohn syndrome (AD).		
MPPE1	Primary ciliary dyskinesia	SD	105	55,360	High	Re c	0	0.3 5	Co-segregation in 2 unaffected relatives.	Metallophosphoesterase required for transport of GPI-anchor proteins from the endoplasmic reticulum to the Golgi.	0	
PKMYT1	Single autosomal recessive mutation in rare disease	SD	51	55,429	Moder ate	Re c	0. 22	0.0	Co-segregation in 2 unaffected relatives.	Serine/threonine protein kinase that is a negative regulator of cell entry into mitosis.	0	
RPL10A	Milroy disease	SD	20	55,470	High	Do m	0. 85	2.0		Component of the large ribosomal subunit that mediates protein translation.	0	
SERPIN B3	Autosomal recessive congenital ichthyosis	SD	46	55,437	Moder ate	Re c	0	- 1.6 6	Co-segregation in 2 unaffected relatives.	Cysteine endopeptidase inhibitor implicated in autocrine/paracrine signalling and cell protein metabolism	0	
SRP9	Ductal plate malformation	SD	54	55,445	High	Do m	0. 42	1.1		Component of the signal recognition particle that targets secretory proteins to the endoplasmic reticulum.	0	
	Gastrointestinal	DS			Moder	Re		- 4.4	Co-segregation in 1 unaffected	Short-chain dehydrogenase/reductase that acts as a tumour suppressor and apoptosis regulator. Pathogenic variants cause developmental and epileptic encephalopathy 28 and		
WWOX	disorders	G	59	55,413	ate	С	0	4	relative.	spinocerebellar ataxia 12.	0	

Table 1 | Plausibility scoring of the 21 genetic associations identified by BeviMed. Each row corresponds to a genetic association between a gene and a case set in the 100KGP Main Programme without prior supporting evidence in PanelApp. Each column gives additional information for each association. Cells contributing to the final score are shown in bold. Rows are sorted by score in descending order and the genes corresponding to associations with a score of three are underlined. The level of the case set in the disease label hierarchy (DSG: Disease Sub Group, SD: Specific Disease), the class of variants and the MOI corresponding to the model with the greatest posterior probability are shown (Dom: dominant; Rec: recessive). A recessive association contributes one point to the score. A pLI >0.9 contributes one point to the score providing the inferred class of aetiological variants is high-impact variants. A Z-score >2 contributes one point to the score providing the inferred class of aetiological variants is moderate-impact variants. Evidence of co-segregation in ≥3 relatives in the 100KGP data contributes one point to the score (including mosaicism supported by ≥2 reads containing the alternate allele). Prior evidence of a relevant biological function or disease association contributes one point to the score. The 'Replication' column specifies cohorts in which additional cases were confirmed.

FIGURE LEGENDS

Fig. 1 | BeviMed analysis of the 100KGP. a, Bars showing the size of each case set used for the genetic association analyses, grouped by Disease Group and coloured by type (Disease Sub Group or Specific Disease). Case sets smaller than 5 are shown as having size 4 to comply with 100KGP policy on limiting participant identifiability. Below, the names and sizes of the case sets for an exemplar Disease Sub Group, 'Cardiovascular disorders', is shown. **b,** BeviMed PPAs >0.95 arranged by Disease

Group. Only the strongest association for each gene within a Disease Group is shown. Associations are coloured by their PanelApp evidence level (green, amber or red). Associations that were mapped to PanelApp by manual review, rather than using our automatic matching algorithm, are marked with an asterisk (**Source data for Fig. 1**). Previously unidentified associations are shown in grey. The shape of the points shows whether the association was with a Disease Sub Group (square), or Specific Disease (circle).

> Fig. 2 | Loss-of-function variants in ERG are responsible for primary lymphoedema. a, Pedigrees for the four probands with loss-of-function variants in the canonical transcript of ERG. ENST00000288319.12. b, Truncated barchart showing the distribution of the number of reads supporting the p.S182Afs*22 alternate allele in the 100KGP. The embedded windows show the read pileups at this position in the two affected members of the family with the variant encoding p.S182Afs*22. The reads supporting the reference allele are in blue and those supporting the variant allele are in red. c. Schematic showing the effects of each variant at the cDNA and amino acid level, and on the protein product with respect to the canonical transcript, d. Reverse transcription-PCR amplification of ERG mRNA in HDLEC relative to HUVEC. Data are normalised to GAPDH. Statistical significance was assessed using a twosided Student's t-test, n.s.: not significant (p=0.39). e, Immunoblot (representing two replicates) of HUVEC and HDLEC protein lysates identified several bands corresponding to ERG isoforms expressed at similar intensities in both cell types. f, Immunofluorescence microscopy (representing three replicates) of HDLEC shows ERG (green) nuclear co-localisation with lymphatic endothelial cell nuclear marker PROX1 (violet) and DAPI (blue). HDLEC junctions are shown using an antibody to VE-cadherin (yellow). Scale bar, 50µm. **g,** En face immunofluorescence confocal microscopy (representing five replicates) of mouse ear skin. Vessels are stained with antibodies to the lymphatic marker PROX1 (violet) and ERG (green). Scale bar, 100µm. h, Exemplar immunofluorescence microscopy image of HEK293 cells overexpressing wild type ERG and the p.S182Afs*22 variant ERG. Cells were stained for ERG (green) and nuclear marker DAPI (blue). Scale bar, 20µm. The brightness was optimised for print. i, Dot plot of estimated proportion of ERG not overlapping the nuclear marker DAPI in each of a set of immunofluorescence microscopy images of HEK293 cells overexpressing different ERG cDNAs (20 replicates for wild type (WT), 17 replicates per tested mutant). The estimated proportions were significantly higher in each of the variants compared to wild type: p=1.52x10⁻¹¹, 4.10x10⁻¹³ and 3.03x10⁻⁵ for each of p.S182Afs*22, p.T224Rfs*15 and p.A447Cfs*19, respectively (two-sided Student's t-test).

Fig. 3 | Truncating variants in *PMEPA1* **result in Loeys-Dietz syndrome. a,** Pedigrees for the three probands in the 100KGP (discovery cohort) heterozygous for the frameshift insertion predicting p.S209Qfs*3 and probands from replication cohorts, including: one from the 100KGP pilot programme heterozygous for the frameshift deletion predicting p.S209Afs*61, three of Japanese ancestry heterozygous for p.S209Qfs*3 and one Belgian pedigree heterozygous for a frameshift deletion encoding p.P207Qfs*3. All variant consequences are shown with respect to the canonical transcript of *PMEPA1*, ENST00000341744.8. **b,** HPO terms present in at least three of the four *PMEPA1* FTAAD families, excluding redundant terms within each level of frequency, alongside their frequency in four *PMEPA1* FTAAD families and the other 589 unexplained FTAAD families. Terms are ordered by *p*-value obtained by a Fisher's exact test of association between the term's presence in an FTAAD family and whether the family is one of the four *PMEPA1* families. Terms were declared significant (indicated by an asterisk), or not significant (n.s.) by comparing their Fisher test *p*-values and rank to a null distribution of equivalent

pairs obtained by permutation (10,000 replicates). For each rank, the p-value of the term on the 5th percentile was used as an upper bound for declaring an association significant, provided all terms at higher ranks were also significant. The p-values for each term were as follows. Dolichocephaly: p=2.9x10⁻⁴, Abnormal axial skeleton morphology: p=6.7x10⁻³, Striae distensae: p=0.013, Pes planus: p=0.014, Ascending tubular aorta aneurysm: p=0.62. \mathbf{c} , Graph showing PMEPA1 and genes with high evidence (green) of association with FTAAD in PanelApp. Edges connect genes where the string-db v11.5²⁷ confidence score for physical interactions between corresponding proteins was >0.6. Genes known to be associated with Loeys-Dietz syndrome are highlighted in blue. PMEPA1 is highlighted yellow. \mathbf{d} , Schematic showing the effects of each variant at the cDNA and amino acid level, and on the protein product.

Fig. 4 | Loss-of-function variants in GPR156 give rise to recessive congenital hearing loss. a, Schematic of the three pedigrees with cases homozygous or compound heterozygous for loss-of-function variants in the canonical transcript of GPR156, ENST00000464295.6. Blank symbols indicate individuals with an unknown genotype. b, Histograms of expression log fold changes for different sets of genes in mouse hair cells compared to surrounding cells: all genes (left) and genes homologous to the human counterparts in the 'Hearing loss' PanelApp panel with and without a stereocilia-related GO term (i.e. a term whose name contained 'stereocilia' or 'stereocilium', or the descendant of such a term) (right). The log fold change for Gpr156 is shown as a horizontal line. c. Maximum intensity projections of confocal Zstacks in the organ of Corti and vestibular system of a P20 wild type mouse immunostained with GPR156 antibody (green) and counterstained with phalloidin (red). Top row: overview of the organ of Conti and vestibular system. Middle and bottom rows: magnified images of outer hair cells (OHC) and inner hell cells (IHC), respectively. No stereociliary bundle staining was observed. The punctate staining observed in the organ of Corti was absent or significantly decreased in the utricle of the vestibular system. Scale bars: 10 µm (each image representative of three replicates). d, Schematic showing the effects of each variant at the cDNA and amino acid level, and on the protein product. e, Exemplar western blot taken from three replicates of GFP-GPR156 using anti-GPR156 antibody in untransfected Cos7 cells (Cos7), Cos7 cells transfected with the wild type construct (W) and Cos7 cells transfected with the constructs containing each of the mutant alleles p.S642Afs*162 (S642), p.P718Lfs*86 (P718) and p.S207Vfs*113 (S207).

References

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- 1. Boycott KM et al. International Cooperation to Enable the Diagnosis of All Rare Genetic Diseases. Am J Hum Genet. 2017; 100(5):695--705.
- 2. Ferreira CR. The burden of rare diseases. Am J Med Genet A. 2019; 179(6):885--892.
- 3. Turro E et al. Whole-genome sequencing of patients with rare diseases in a national health system.
- 532 Nature. 2020; 583(7814):96--102.
- 4. Wang Q et al. Rare variant contribution to human disease in 281,104 UK Biobank exomes. Nature.
- 534 2021; 597(7877):527--532.
- 535 5. Kaplanis J et al. Evidence for 28 genetic disorders discovered by combining healthcare and research data. Nature. 2020; 586(7831):757--762.

- 6. Greene D, Richardson S, Turro E. Phenotype Similarity Regression for Identifying the Genetic
- 538 Determinants of Rare Diseases. Am J Hum Genet. 2016; 98(3):490--499.
- 7. Hail Team. (2022). Hail 0.2. https://github.com/hail-is/hail.
- 8. Lopez J et al. HGVA: the Human Genome Variation Archive. Nucleic Acids Res. 2017; 45(W1):W189-
- 541 W194.
- 9. Greene D, Richardson S, Turro E. A Fast Association Test for Identifying Pathogenic Variants Involved
- 543 in Rare Diseases. Am J Hum Genet. 2017; 101(1):104--114.
- 10. Karczewski KJ et al. The mutational constraint spectrum quantified from variation in 141,456
- 545 humans. Nature. 2020; 581(7809):434--443.
- 11. Rentzsch P, Schubach M, Shendure J, Kircher M. CADD-Splice-improving genome-wide variant
- effect prediction using deep learning-derived splice scores. Genome Med. 2021; 13(1):31.
- 12. Eilbeck K et al. The Sequence Ontology: a tool for the unification of genome annotations. Genome
- 549 Biol. 2005; 6(5):R44.
- 13. Howe KL et al. Ensembl 2021. Nucleic Acids Res. 2021; 49(D1):D884-D891.
- 14. Martin AR et al. PanelApp crowdsources expert knowledge to establish consensus diagnostic gene
- 552 panels. Nat Genet. 2019; 51(11):1560--1565.
- 15. Korber L, Schneider H, Fleischer N, Maier-Wohlfart S. No evidence for preferential X-chromosome
- inactivation as the main cause of divergent phenotypes in sisters with X-linked hypohidrotic ectodermal
- 555 dysplasia. Orphanet J Rare Dis. 2021; 16(1):98.
- 16. Kasahara Y et al. Hyper-IgM syndrome with putative dominant negative mutation in activation-
- induced cytidine deaminase. J Allergy Clin Immunol. 2003; 112(4):755--760.
- 17. Martin-Almedina S, Mortimer PS, Ostergaard P. Development and physiological functions of the
- lymphatic system: insights from human genetic studies of primary lymphedema. Physiol Rev. 2021;
- 560 101(4):1809--1871.
- 18. Gordon K et al. Update and audit of the St George's classification algorithm of primary lymphatic
- anomalies: a clinical and molecular approach to diagnosis. J Med Genet. 2020; 57(10):653--659.
- 19. Kalna V et al. The Transcription Factor ERG Regulates Super-Enhancers Associated With an
- 564 Endothelial-Specific Gene Expression Program. Circ Res. 2019; 124(9):1337--1349.
- 565 20. Shah AV, Birdsey GM, Randi AM. Regulation of endothelial homeostasis, vascular development and
- angiogenesis by the transcription factor ERG. Vascul Pharmacol. 2016; 86:3--13.
- 567 21. Hoesel B et al. Sequence-function correlations and dynamics of ERG isoforms. ERG8 is the black
- sheep of the family. Biochim Biophys Acta. 2016; 1863(2):205--218.
- 569 22. Westbury SK et al. Human phenotype ontology annotation and cluster analysis to unravel genetic
- defects in 707 cases with unexplained bleeding and platelet disorders. Genome Med. 2015; 7(1):36.
- 571 23. Greene D, Richardson S, Turro E. ontologyX: a suite of R packages for working with ontological data.
- 572 Bioinformatics. 2017; 33(7):1104--1106.
- 573 24. Resnik P, Others. Semantic similarity in a taxonomy: An information-based measure and its
- application to problems of ambiguity in natural language. J. Artif. Intell. Res.(JAIR). 1999; 11:95--130.
- 575 25. Ciurica S et al. Arterial Tortuosity. Hypertension. 2019; 73(5):951--960.
- 576 26. Loeys BL et al. A syndrome of altered cardiovascular, craniofacial, neurocognitive and skeletal
- development caused by mutations in TGFBR1 or TGFBR2. Nat Genet. 2005; 37(3):275--281.
- 578 27. Szklarczyk D et al. STRING v11: protein-protein association networks with increased coverage,
- 579 supporting functional discovery in genome-wide experimental datasets. Nucleic Acids Res. 2019;
- 580 47(D1):D607-D613.

- 581 28. Watanabe Y et al. TMEPAI, a transmembrane TGF-beta-inducible protein, sequesters Smad proteins
- from active participation in TGF-beta signaling. Mol Cell. 2010; 37(1):123--134.
- 583 29. Creamer TJ, Bramel EE, MacFarlane EG. Insights on the Pathogenesis of Aneurysm through the
- 584 Study of Hereditary Aortopathies. Genes (Basel). 2021; 12(2).
- 585 30. Thermann R et al. Binary specification of nonsense codons by splicing and cytoplasmic translation.
- 586 EMBO J. 1998; 17(12):3484--3494.
- 31. Sobreira N, Schiettecatte F, Valle D, Hamosh A. GeneMatcher: a matching tool for connecting
- investigators with an interest in the same gene. Hum Mutat. 2015; 36(10):928--930.
- 32. Ellaithy A, Gonzalez-Maeso J, Logothetis DA, Levitz J. Structural and Biophysical Mechanisms of
- 590 Class C G Protein-Coupled Receptor Function. Trends Biochem Sci. 2020; 45(12):1049--1064.
- 33. Kindt KS et al. EMX2-GPR156-Gai reverses hair cell orientation in mechanosensory epithelia. Nat
- 592 Commun. 2021; 12(1):2861.
- 593 34. Scheffer DI, Shen J, Corey DP, Chen ZY. Gene Expression by Mouse Inner Ear Hair Cells during
- 594 Development. J Neurosci. 2015; 35(16):6366--6380.
- 595 35. Miyoshi T et al. Human deafness-associated variants alter the dynamics of key molecules in hair cell
- 596 stereocilia F-actin cores. Hum Genet. 2022; 141(3-4):363--382.
- 36. Smedley D et al. 100,000 Genomes Pilot on Rare-Disease Diagnosis in Health Care Preliminary
- 598 Report. N Engl J Med. 2021; 385(20):1868--1880.
- 599 37. Thalhammer A, Trinidad JC, Burlingame AL, Schoepfer R. Densin-180: revised membrane topology,
- domain structure and phosphorylation status. J Neurochem. 2009; 109(2):297--302.
- 38. Chong CH et al. Lrrc7 mutant mice model developmental emotional dysregulation that can be
- alleviated by mGluR5 allosteric modulation. Transl Psychiatry. 2019; 9(1):244.
- 39. Berthouze M, Venkataramanan V, Li Y, Shenoy SK. The deubiquitinases USP33 and USP20
- 604 coordinate beta2 adrenergic receptor recycling and resensitization. EMBO J. 2009; 28(12):1684--1696.
- 40. Birdsey GM et al. The endothelial transcription factor ERG promotes vascular stability and growth
- 606 through Wnt/Beta-catenin signaling. Dev Cell. 2015; 32(1):82--96.
- 41. Motiejunaite J, Amar L, Vidal-Petiot E. Adrenergic receptors and cardiovascular effects of
- 608 catecholamines. Ann Endocrinol (Paris). 2021; 82(3-4):193--197.
- 42. Munoz-Lasso DC, Roma-Mateo C, Pallardo FV, Gonzalez-Cabo P. Much More Than a Scaffold:
- 610 Cytoskeletal Proteins in Neurological Disorders. Cells. 2020; 9(2).
- 43. Zuchero JB et al. CNS myelin wrapping is driven by actin disassembly. Dev Cell. 2015; 34(2):152--
- 612 167.

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- 44. DeWard AD, Eisenmann KM, Matheson SF, Alberts AS. The role of formins in human disease.
- 614 Biochim Biophys Acta. 2010; 1803(2):226--233.
- 45. Ninoyu Y et al. The integrity of cochlear hair cells is established and maintained through the
- localization of Dia1 at apical junctional complexes and stereocilia. Cell Death Dis. 2020; 11(7):536.
- 46. Geppert M et al. The role of Rab3A in neurotransmitter release. Nature. 1994; 369(6480):493--497.

METHODS

621 Ethics

- 622 The 100,000 Genomes project was approved by East of England-Cambridge Central REC REF
- 623 20/EE/0035. Only participants who provided written informed consent for their data to be used for
- research were included in the analyses. The study at the University of Maryland was approved by the

Institutional Review Board (RAC#2100001) and written informed consent was obtained by clinicians at King Faisal Hospital in Saudi Arabia from the participating individuals. The study of the Japanese ancestry pedigrees bearing *PMEPA1* truncating alleles was approved by the Institutional Review Board of the National Cerebral and Cardiovascular Centre (M14-020) and Sakakibara Heart Institute (16-035), and written informed consent was obtained from the participating individuals.

Motivation for developing a sparse relational database

Computational approaches for discovering the aetiologies of rare diseases typically depend on the analysis of a heterogeneous set of files, each of which can be very large and follow a distinct convention. Genotypes, for example, are ordinarily stored in VCFs containing data for one sample or for multiple samples. In the latter case, the data are usually distributed in files covering many different "chunks" of the reference genome. Variant-level information, such as consequence predictions or pathogenicity scores, are typically encoded in strings that require extensive parsing to decode, either from within the VCFs containing the genotypes, or in separate files. Modifying genotype or annotation files, for example in order to incorporate newly generated data, requires rewriting files in their entirety. Phenotype data, pedigree data and the results of statistical inference are stored in a further set of files. Consequently, analyses are often burdensome to conduct and prone to error. Frameworks such as Hail⁷ and OpenCGA⁸ afford greater flexibility but they depend on the centrally organised deployment of a distributed storage system, hindering usability and portability.

Relational databases are widely used, mature technologies, well known for their speed, reliability, flexibility, structure and extensibility. In the context of rare diseases, a relational database can in principle render the modification, combination and addition of data on samples, variants, genes and other entities efficient, reliable and straightforward to implement using a single query language. Unfortunately, the performance of relational databases degrades substantially when the number of records in a table reaches several billion, and the number of genotypes in a cohort the size of the 100KGP easily surpasses this threshold. However, the MAFs of pathogenic variants with strong effects on rare disease risk are typically kept below 1/1,000 by negative selection, and the proportion of non-homozygous reference genotypes for variants within that MAF stratum is only about 1% of the total (Extended Data Fig. 1). Consequently, it is possible to construct a compact relational database that includes virtually all the pathogenic variants even in a large cohort such as the 100KGP. This provides an opportunity for exploiting the benefits of a single unified relational database containing the non-homozygous genotypes of rare variants upon which to conduct the entirety of the aetiological discovery process. Furthermore, it provides a natural foundation for developing web applications for the multidisciplinary review of genetic, phenotypic, statistical and other data.

Rareservoir

The Rareservoir is a relational database schema and a complementary software package 'rsvr' for working with rare disease data. The database stores data including rare variant genotypes, variant annotations, phenotypes, sample information and pedigrees (**Extended Data Fig. 1**) but it can be extended arbitrarily. A Rareservoir is built through a series of steps from a set of input data and parameters (**Extended Data Fig. 3**). The 'bcftools' program⁴⁷ extracts ('bcftools view') and normalises ('bcftools norm') variants from either a set of single sample genome VCF files (gVCFs) or from a merged VCF. In all steps of the procedure, variants are encoded as RSVR IDs using the 'rsvr enc' tool (see

Encoding RSVR IDs). Merged VCFs typically contain cohort-wide variant quality information in the FILTER column, which can be used to select variants for processing. However, this is not readily obtained from single qVCFs. To address this, we developed the 'rsvr depth' tool, which computes variant quality pass rates at all positions in the genome based on a random subsample of gVCFs. If the input is a merged VCF, an internal (i.e. within-VCF) allele frequency threshold is applied with bcftools to filter out internally common variants. If the input is a set of single-sample qVCFs, internally common variants are filtered out in two steps, for computational efficiency. Firstly, a set of variants that are statistically almost certain to be common based on a random sample of gVCFs is identified—by default, the variants for which a one-sided binomial test under the null hypothesis that the MAF=0.01 is rejected at a significance level of 10⁻⁶ (done using the 'rsvr tabulate' tool). Secondly, all gVCFs are read sequentially, filtering out the variants identified in the previous step (using the 'rsvr mix' tool) and those for which the pass rates identified with 'rsvr depth' do not meet the threshold. Retained genotypes are then loaded into a temporary genotype table in the database in order to apply the final internal allele frequency filter by executing an SQL 'DELETE' statement. These variants are then annotated with gnomAD 'probabilistic minor allele frequency' (PMAF) scores³ using the 'rsvr pmaf' tool. The PMAF score is calculated with respect to a given allele frequency threshold t, by evaluating a binomial test (at a significance threshold of 0.05) on the observed frequency of the variant under the null hypothesis that the variant has an allele frequency of t. If, in any gnomAD population, the null is rejected for t=0.001 and the allele count is at least 2, the score is set to 0. If the null is rejected for t=0.0001, the score is set to 1. If the null is not rejected, the score is set to 2. Finally, if the variant is absent from gnomAD, the score is set to 3. For the non-pseudo autosomal dominant regions of chromosome X, only allele counts for males are used in calculations. Variants are then additionally annotated with their CADD phred scores using the 'rsvr ann' program, and loaded into the VARIANT table. At this point, variants in the VARIANT and GENOTYPE table which have a PMAF score of 0 may be deleted because they are unlikely to be involved in rare diseases. We then annotate the retained variants with predicted transcript consequences for a given set of transcripts specified in a Gene Transfer Format (GTF) file. The 100KGP Rareservoir, uses Ensembl v104 canonical transcripts with a protein-coding biotype, of which >90% are Matched Annotation from NCBI and EMBL-EBI (MANE)⁴⁸ transcripts. The 'rsvr segfx' program determines a set of SO terms for each interacting transcript-variant pair and encodes them as a CSQ ID, which is added to the CONSEQUENCE table. This table can also hold LOFTEE scores corresponding to a transcript-variant pair. Note that, as LOFTEE scores on the Genomics England Research Environment correspond to Ensembl v99 transcripts, we mapped Ensembl v104 canonical transcripts to the most similar v99 transcripts having an identical CDS in order to obtain the LOFTEE scores for the 100KGP Rareservoir, finding a match for >98% of transcripts. The contents of the GTF file are also imported into the database to create tables of transcript features (FEATURE), transcripts (TX) and genes (GENE). Optionally, VARIANT, GENOTYPE and CONSEQUENCE may be filtered for RSVR IDs that have CSQ IDs meeting particular criteria, for instance, in order to retain only variants with protein-coding consequences. The SAMPLE table of metadata and genetic statistics for each sample represented in the input VCF(s) must then be added to the database, including mandatory columns containing the ID, sex, family, and an indicator of inclusion in the maximal unrelated set of samples in the database. The VARIANT, GENOTYPE and CONSEQUENCE tables are indexed by RSVR ID, in order to support fast lookups by genomic location. The SAMPLE table and GENOTYPE table are indexed by sample ID allowing fast lookups by sample. The CONSEQUENCE, TX and GENE tables are indexed by transcript and gene ID, allowing fast lookups of variants based on gene/transcript specific consequences. If sample phenotypes

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have been encoded using phenotypic terms (e.g. ICD10 codes or HPO terms), terms from the relevant coding systems can be added to a generic PHENOTYPE table mapping code IDs to descriptions, and codes assigned to samples can be added to the SAMPLE PHENOTYPE table. Disease labels may be added to the CASE SET table. The majority of the compute time required for building the database is taken by reading the genotype data from the input VCF, which may be executed in parallel over separate regions against a merged VCF or over single qVCFs. The rsvr tool, implemented in C++, executes rapidly, with 'rsvr segfx' capable of assigning CSQ IDs for all Ensembl v104 canonical transcripts to all variants (over 685M) in gnomAD v3.0 in under 40 minutes on a single core. The 100KGP Rareservoir. which is stored in a SQLite database, returns complex gene-specific gueries in under one second. For example: (1) a table with 628 rows containing the moderate and high-impact variants with a PMAF score ≥1 in TTN, along with the corresponding SegFx consequence predictions and CADD scores takes 0.57 seconds; (2) a table with 1,498 rows containing, for each variant, the samples and genotypes for individuals who carry an alternate allele takes 0.61 seconds; and (3) a classification for each of the 77,539 participants into proband with Dilated Cardiomyopathy, relative of such a proband, unrelated control, or relative of a control takes 0.65 seconds. Specific details on implementation of the workflow, code for encoding data as SQL statements compatible with Rareservoir and the mapping between bits in the 64 bit CSQ ID and each SO term assigned by 'rsvr seqfx' can be found in the rsvr software package (see Code availability). Software packages rsvr 1.0, bcftools 1.9 and perl 5 were used to build the 100KGP Rareservoir.

Encoding RSVR IDs

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SNVs and indels may be encoded as 64-bit integers called RSVR IDs. In order to compute an RSVR ID for a given variant, the following expression is evaluated:

$$c \times 2^{58} + p \times 2^{30} + |r| \times 2^{24} + |a| \times 2^{18} + \sum_{i=1}^{|A|} A_i \times 4^{i-1},$$

where c is the chromosome number (using 23, 24 and 25 respectively to represent X, Y and MT), p is the position, and |r| and |a| are the lengths of the reference and alternate alleles, respectively. A is a sequence identical to the alternate allele, a, when its length is less than 10, and otherwise equal to the first five followed by the last four elements of a. In the summation, nucleotides are assigned values: A= 0, C = 1, G = 2 and T = 3. The expression evaluates to integers that can be represented using 63 bits, setting the most significant bit to 0 when encoding as 64-bit integers. The chromosome, position, reference and alternate allele lengths and alternate allele bases are thereby encoded respectively by the subsequent 5, 28, 6, 6 and 18 bits (with two bits per base for the alternate allele). This procedure and its inverse are implemented in the 'rsvr enc' and 'rsvr dec' programs respectively. The reference and alternate alleles of input variants are first normalised by removing any redundant identical sequence from the starts and then the ends. The proportion of variants in gnomAD 3.0 weighted by allele count that can be encoded losslessly is 99.3%, while 99.8%can be represented by a distinct RSVR ID. The full variant information corresponding to any encountered ambiguous RSVR ID may be stored in full in a dedicated table. Structural variants that can be represented by a position and length may also be encoded using distinct 64-bit RSVR IDs alongside SNVs and indels by setting the most significant bit to 1, and subsequently encoding the type of structural variant using 2 bits (Deletion 0, Duplication 1, Inversion 2, Insertion 3), the chromosome using 5 bits (as done for SNVs and indels), and the start and length consecutively using 28 bits.

Genetic association analysis of 100KGP data

We constructed a Rareservoir in the Genomics England Research Environment containing the PASSing⁴⁹ variants in the merged VCF of 77,539 consented participants in the 100KGP rare diseases programme. This Rareservoir only included variants with a PMAF >0 according to GnomAD v3.0, an internal MAF <0.002 and at least one predicted consequence on a canonical transcript in Ensembl v104. Variants with a greater MAF are unlikely to be highly penetrant for diseases eligible for inclusion in the 100KGP and are likely to have, at most, small effects on risk, making them challenging to validate. Variants with a median genotype quality <35 and SNVs with a CADD Phred score <10 were also excluded from the analyses.

For each of the 269 rare disease classes (**Extended Data Figs. 5–6**), we applied the BeviMed⁹ association test to rare variants extracted from the Rareservoir database in each of the 19,663 canonical transcripts belonging to a gene with a 'protein_coding' biotype. The analysis was carried out using R 3.6.2, making use of functionality from packages: Matrix 1.2-18, dplyr 0.8.5, bit64 0.9-7, bit 1.1-14, DBI 1.1.0, RSQLite 2.1.4 and BeviMed 5.7. The case set for a given disease class and gene was constructed by selecting one case from each pedigree containing at least one person affected with the disease class. For the purposes of the association analysis, participants were labelled 'explained' by a given gene if they had variants in that gene classified as 'pathogenic_variant' or 'likely_pathogenic_variant' in the 'gmc_exit_questionnaire' table in the Genomics England Research Environment. To boost power, we used this information to reassign cases who were explained by variants in a different gene to the control group.

Using BeviMed, we performed a Bayesian comparison of a baseline model of no association and each of six association models defined by a mode of inheritance and a class of aetiological variant:

- 1. No association (prior probability: 0.99),
- 2. Dominant association with "high"-impact variants having a PMAF ≥2 (i.e., corresponding to a target MAF <0.01%) (prior probability: 0.002475),
- 3. Dominant association with "moderate"-impact variants having a PMAF ≥2 (prior probability: 0.002475),
- 4. Dominant association with "5' UTR" variants having a PMAF ≥2 (prior probability: 0.00005).
- 5. Recessive association with "high"-impact variants having a PMAF ≥1 (i.e., corresponding to a target MAF <0.1%) (prior probability: 0.002475),
- 6. Recessive association with "moderate"-impact variants having a PMAF ≥1 (prior probability: 0.002475),
- 7. Recessive association with "5' UTR" variants having a PMAF ≥1 (prior probability: 0.00005). Thus the overall prior probability of association was 0.01 and there was an equal prior probability of dominant and recessive inheritance. The PPA was the sum of the posterior probabilities of models 2 through 7. We imposed a stricter PMAF threshold under a dominant MOI than under a recessive MOI because, ceteris paribus, dominant variants are under stronger negative selection than recessive variants. The three groups of variants were selected as follows:
 - 5' UTR variants: those with a 5 prime UTR variant consequence,
 - High-impact variants: those with any consequence amongst start_lost, stop_lost, frameshift_variant, stop_gained, splice_donor_variant or splice_acceptor_variant, excluding variants with a "low-confidence" LOFTEE score¹⁰.

 Moderate-impact variants: those with any consequence amongst start_lost, stop_lost, frameshift_variant, stop_gained, splice_donor_variant or splice_acceptor_variant, missense variant or inframe deletion.

The rationale for embedding variants from the high-impact class in the moderate-impact class is that both types of variant are capable of inducing a loss of function. The prior on the probability that a modelled rare variant is pathogenic, conditional on either the association model mediated by 5' UTR variants or the association model mediated by moderate-impact variants, was set to Beta(2,8). This encodes a prior conditional expectation that 20% of rare variants are pathogenic, which is well suited to missense and 5' UTR variants. However, we specified a distribution with a greater mean for the high-impact models. Specifically, the prior on the probability that a modelled high-impact variant is pathogenic was set to Beta(3,1), which reflects a prior conditional expectation that 75% of rare variants are pathogenic because loss-of-function variants tend to be functionally equivalent to each other. BeviMed reports the posterior probability that each variant is pathogenic conditional on the mode of inheritance and the class of aetiological variant. The methodology is described in further detail in the original BeviMed publication⁹.

We applied the following post-processing of BeviMed results with a PPA >0.95:

- We re-ran BeviMed including all samples (i.e. with relatives of cases and controls). Associations
 for which the analysis with all samples caused the PPA to fall below 0.9 were filtered out due to
 conflicting evidence for the association within families.
- We re-ran BeviMed after removing variants absent from affected relatives of the cases.
 Associations for which this removal caused the PPA to drop below 0.25 were filtered out because they depended on variants that were not shared by affected cases within families.
- To guard against false positives due to incorrect pedigree data, population structure or cryptic relatedness, we applied the following algorithm. We obtained the distribution of the number of rare variants in the Rareservoir shared by pairs of individuals within each assigned ancestry in the 100KGP. The top percentile in each of these distributions was used to indicate potential relatedness between participants in the same population. We re-ran BeviMed after removing cases so as to ensure that no more than one case from any set of potentially related cases sharing a variant were included in the analysis. Associations for which this analysis caused the PPA to fall below 0.25 were filtered out.

To account for correlation between case sets, for each gene, we removed all but the most strongly associated disease class within each Disease Group before reporting the 260 associations remaining (**Source data for Fig. 1**). Without the post-processing, the number of reported associations would have been 302. Conditional on the modal model underlying each of the 260 associations, we recorded the variants with a posterior probability of pathogenicity >0.8 accounting for at least one case in the 100KGP (**Source data for Fig. 2**).

PanelApp annotation

Significant associations were coloured according to PanelApp¹⁴ (**Fig. 1b**) evidence levels for panel—gene relations (green for high evidence, amber for moderate evidence, and red for low evidence) for panels of type 'Rare Disease 100K', which are organised hierarchically by Disease Sub Group and Disease Group, or of type 'GMS Rare Disease'. Given an association between a gene and a case set (corresponding either to a Specific Disease or a Disease Sub Group), we searched for panels which contained the gene

and had the same name as the case set (ignoring case). If such a match was not found, we searched for panels which contained the gene and which belonged to a Disease Sub Group with the same name as the Disease Sub Group of the case set. When this matching rule generated multiple matches, we selected the panel(s) with the highest evidence. If multiple panels still remained, we selected the panel with the smallest number of genes. Associations for which no matching panel in PanelApp could be found were inspected manually to assess whether PanelApp contained an alternative suitable panel (marked with an asterisk in **Fig. 1b**).

Shortlisting previously unidentified genetic associations for validation

Several sources of independent evidence were used to shortlist significant associations for validation. For each source, a score of one was awarded if the evidence was supportive, and zero otherwise. Scores were then added over the different sources and used to rank the associations. Associations for which at least three sources of evidence were supportive were taken forward for further investigation. The sources of evidence and qualifying criteria for being considered supportive are listed below. Note that here we refer to variants which had a probability of pathogenicity >0.8 conditional on the modal model as 'probably pathogenic'.

- Counting co-segregating pedigree members. The pedigrees harbouring pathogenic configurations of probably pathogenic alleles were checked for co-segregation between genotype and affection status. This evidence counted as supportive for associations for which all such pedigrees demonstrated co-segregation, and there were at least three additional relatives who had not been included in the association analysis but for whom there was co-segregation. Note that BAM files for the affected members of pedigrees who were called homozygous reference for probably pathogenic variants were checked for evidence of mosaicism to guard against the possibility that they were falsely portraying a lack of co-segregation.
- *pLI and Z-scores.* pLI and *Z*-scores for depletion of missense variants were obtained from the gnomAD v2.2.1 browser¹⁰. pLI >0.9 for associations in which high impact variants were most strongly associated were counted as supportive, whilst *Z*-scores greater than 2 for associations in which moderate impact variants were most strongly associated were counted as supportive.
- Recessive association. Population genetic metrics of purifying selection (pLI scores and Z-scores) are sensitive to depletion of high-impact variants and missense variants, respectively. They are therefore useful measures to corroborate dominant associations. However, these metrics have low sensitivity to identify the signatures of selection against recessive diseases because isolated pathogenic variants in heterozygous form do not lead to a reduction in reproductive fitness. To avoid disadvantaging recessive associations identified by BeviMed, they were assigned a contribution of one point to the score.
- Literature review. A comprehensive literature review, assessing the gene's role (if any) in biological processes relevant to the disease, other diseases, and a survey of model organisms was undertaken, and determined to be either supportive or not.

ERG: Primary endothelial cell culture

Single donor primary human dermal lymphatic endothelial cells (HDLEC) (Promocell, Heidelberg) were cultured in Endothelial Cell Growth Medium MV2 (Promocell). Pooled donor human umbilical vein endothelial cells (HUVEC) (Lonza, Slough) were grown in Endothelial Cell Growth Media-2 (EGM-2) (Lonza). HUVEC and HDLEC were grown on 1% (v/v) gelatin and used between passages 3-5.

ERG: Real-time polymerase chain reaction

HUVEC and HDLEC were grown to confluency in a pre-gelatinised 6-well dish. Total RNA was isolated using the RNeasy Mini Kit (Qiagen) and 1 μg of total RNA was transcribed into cDNA using Superscript III Reverse Transcriptase (Thermo Fisher Scientific). Quantitative real-time PCR was performed using PerfCTa SYBR Green FastMix (Quanta Biosciences) on a Bio-Rad CFX96 System. Gene expression values of ERG in HUVEC and HDLEC were normalised to GAPDH expression and compared using the ΔΔCt method. The following oligonucleotides were used: ERG, 5'-GGAGTGGGCGTGAAAGA-3' and 5'-AAGGATGTCGGCGTTGTAGC-3'; GAPDH, 5'-CAAGGTCATCCATGACAACTTTG-3' and 5'-GGGCCATCCACAGTCTTCTG-3'.

ERG: Immunoblotting analysis

Immunoblotting was performed according to standard conditions. Proteins were labelled with the following primary antibodies: rabbit anti-human ERG antibody (1:1000; ab133264, Abcam) and mouse anti-human GAPDH (1:10000; MAB374, Millipore). Primary antibodies were detected using fluorescently labelled secondary antibodies: goat anti-rabbit IgG DyLight 680 and goat anti-mouse IgG Dylight 800 (Thermo Scientific). Detection of fluorescence intensity was performed using an Odyssey CLx imaging system (Li-COR Biosciences, Lincoln) and Odyssey version 4 software.

ERG: Immunofluorescence analysis of endothelial cells and mouse tissues

Confluent cultures of HUVEC and HDLEC were fixed with 4% (w/v) paraformaldehyde for 15 minutes and permeabilised with 0.5% (v/v) Triton-X100, before incubation with 3% BSA (w/v) in PBS containing the following primary antibodies: goat anti-human PROX1 antibody (1:100; AF2727, R&D Systems), rabbit anti-human ERG antibody (1:100; ab92513, Abcam), mouse anti-human VE-cadherin (1:100; 555661, BD Biosciences). Secondary antibody incubation was carried out in 3% BSA (w/v) in PBS, using the following antibodies: donkey anti-goat IgG Alexa Fluor-488 (1:1000; A-11055), donkey anti-rabbit IgG Alexa Fluor-555 (1:1000; A-31572), donkey anti-mouse Alexa Fluor-594 (1:1000; A-21203). All secondary antibodies from Thermo Fisher Scientific. Nuclei were visualised using DAPI (4',6-diamidino-2-phenylindole) (Sigma-Aldrich). Confocal microscopy was carried out on a Carl Zeiss LSM780 confocal laser scanning microscope with Zen 3.2 software. All animal experiments were conducted with ethical approval from Imperial College London under UK Home Office Project Licence number PEDBB1586 in compliance with the UK Animals (Scientific Procedures) Act of 1986. Ear tissue was collected from euthanised 3-week old male and female C57BL/6J mice and fixed in 4% (w/v) paraformaldehyde at room temperature for 2h. Tissue was then washed with PBS followed by a blocking and permeabilization step using 3% (w/v) milk in PBST (containing 0.3% (v/v) Triton X-100 in PBS) for 1h at room temperature. The following primary antibodies were used for immunofluorescence staining: goat anti-human PROX1 antibody (1:100; AF2727, R&D Systems) and rabbit anti-human ERG antibody (1:100; ab92513, Abcam). Primary antibodies were incubated at 4°C overnight in 3% (w/v) milk in PBST. The following day, tissues were washed three times with PBST over the course of 2h at room temperature. Tissues were incubated with secondary antibodies at room temperature for 2h in 3% milk (w/v) in PBST. Primary antibodies were detected using fluorescently labelled secondary antibodies: donkey anti-goat IgG Alexa Fluor-488 (1:400; A-11055, Thermo Fisher Scientific) and donkey anti-rabbit IgG Alexa Fluor-555; A-31572, Thermo Fisher Scientific). Stained samples were mounted onto glass slides using Fluoromount G (Thermo Fisher

Scientific). Images were acquired using Zeiss LSM-780 confocal laser scanning microscope with Zen 3.2 software. All confocal images represent maximum intensity projection of Z-stacks of single tiles.

ERG: Subcloning and overexpression in HEK293 cells

We subcloned *ERG* (ENST00000288319.12) from HUVEC into the mammalian expression vector pcDNA3.1 (Thermo Fisher). *ERG* variants were generated by site-directed mutagenesis using the Quikchange Lightning kit (Agilent, Stockport, Cheshire) using the wild type *ERG* cDNA as template. Expression of wild type and mutant *ERG* was carried out using Polyethylenimine (PEI; Sigma-Aldrich) transfection reagent in HEK293 cells grown in DMEM (Thermo Fisher) with 10% (v/v) fetal bovine serum. After 24 hr, cells were fixed with 4% (w/v) paraformaldehyde for 15 minutes and permeabilised with 0.5% (v/v) Triton-X100, before incubation with 3% BSA (w/v) in PBS containing mouse monoclonal anti-ERG antibody (1:100; sc-376293, Santa Cruz Biotechnology). Secondary antibody incubation was carried out in 3% BSA (w/v) in PBS, using donkey anti-mouse Alexa Fluor-488 (1:1000; A-21202, Thermo Fisher). Nuclei were visualised using DAPI (4',6-diamidino-2-phenylindole) (Sigma-Aldrich). Confocal microscopy was carried out on a Carl Zeiss LSM780 confocal laser scanning microscope with Zen 3.2 software.

ERG: Estimation of nuclear and non-nuclear ERG in HEK293 cells

Each image was read into a pair of channel-specific 1,024 x 1,024 matrices in R 4.2.1 using the readCzi function from the readCzi R package v0.2.0. A pixel was declared to contain a nuclear region if the intensity in the blue channel exceeded 60% of the 95th percentile of blue intensities across all pixels above background (identified as exceeding 1.35x10⁻² by visual inspection of bimodal intensity histograms). A pixel was declared to contain ERG if the intensity in the green channel exceeded 30% of the 95th percentile of the green intensities within the pixels previously declared to be nuclear. To fill in intranuclear gaps, any non-nuclear pixels adjacent to at least 5 nuclear pixels were declared nuclear. The estimated proportion of ERG that was cytosolic in an image was set to the number of ERG pixels that did not overlap nuclear pixels divided by the number of ERG pixels.

GPR156: Western blots

We subcloned *GPR156* from human brain cDNA, into EGFP-N2 vector. The three mutant *GPR156* constructs were generated by mutagenesis using the QuickChange kit (Stratagene, La Jolla, CA) and a wild type GPR156-GFP as a template. For expression analysis, the WT and mutants were transfected in COS7 cells grown in DMEM (Gibco, Gaithersburg, MD, USA) with 10% fetal bovine serum. Transfections were performed with Lipofectamine 2000 reagent (Life Technologies). Cells were harvested 48hr after transfection, lysed in buffer containing 1% CHAPS, 100mM NaCl, and 25mM HEPES, pH 7.4 and clarified by centrifugation at 18,407 x g. Lysates (20µg) were run on a 4–20% SDS-PAGE gel. Membrane was blocked with 5% milk then incubated with anti-GPR156 (1:200) and immunoblots developed with HRP conjugated secondary (sheep anti-rabbit) antibody (1:1,000). Comparable loading was checked by stripping and reprobing the blots with anti-GAPDH (1:500) antibodies (Santa Cruz Biotechnology, Heidelberg, Germany).

GPR156: Whole mount immunostaining of GPR156 in mouse inner ears

All the animal work was approved by the University of Maryland, Baltimore Institutional Animal Care and use Committee (IACUC 420002). Inner ears were dissected from C57BL/6J mice with a postnatal age of 10 days and fixed in 4% paraformaldehyde (PFA) in phosphate buffered saline (PBS) overnight. For

whole mount immunostaining, the cochleae were micro-dissected and were subjected to blocking for 1 hour with 10% normal goat serum in PBS containing 0.25% tritonX100, followed by overnight incubation at 4°C with anti-GPR156 antibodies (1:200; Cat#PA5-23857; Thermo Fisher) in 3% normal goat serum with PBS. F-Actin was decorated using Phalloidin (1:300). Confocal images were acquired from Zeiss LSM710 confocal microscope and images were processed using ImageJ 1.53t software.

Data Availability

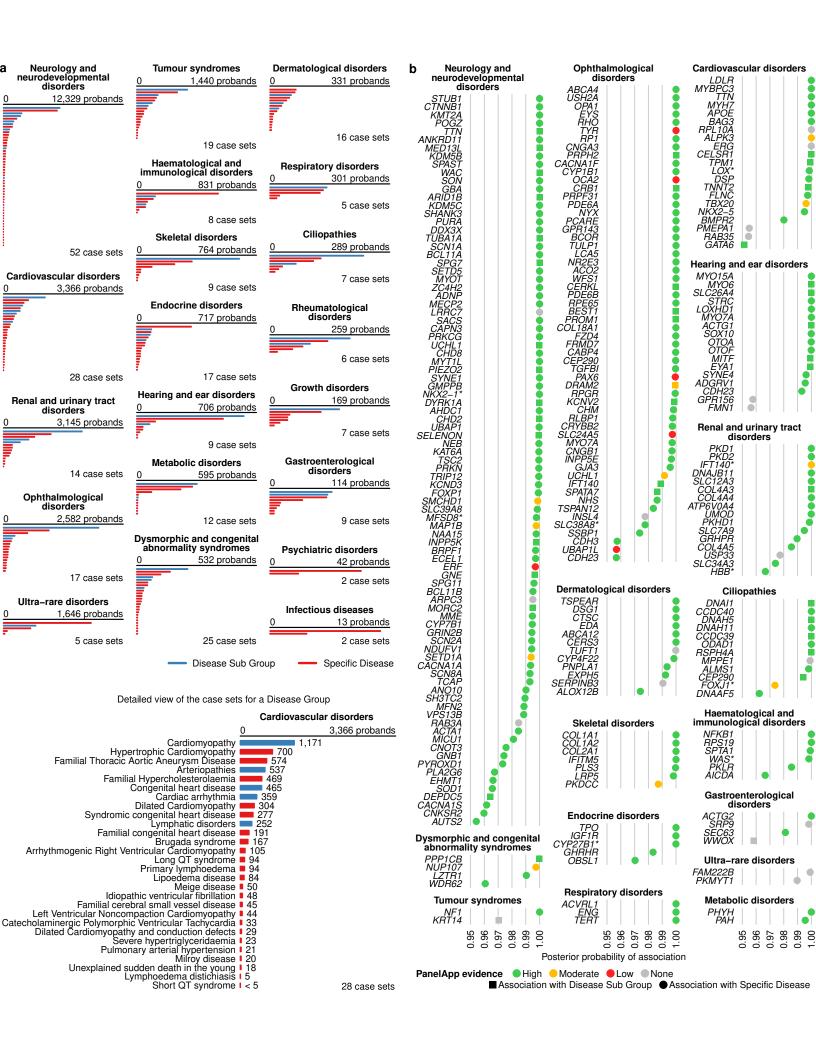
 Genetic and phenotypic data for the 100KGP study participants are available through the Genomics England Research Environment via application at https://www.genomicsengland.co.uk/join-a-gecip-domain. PanelApp gene panels and evidence of associations were obtained using the PanelApp application programming interface (https://panelapp.genomicsengland.co.uk/api/docs/) on the 20th October 2021. CADD v1.5 (https://cadd.gs.washington.edu/) and Ensembl v104 (https://cadd.gs.washington.edu/) and Ensembl v104 (https://may2021.archive.ensembl.org/index.html) were used for variant annotation.

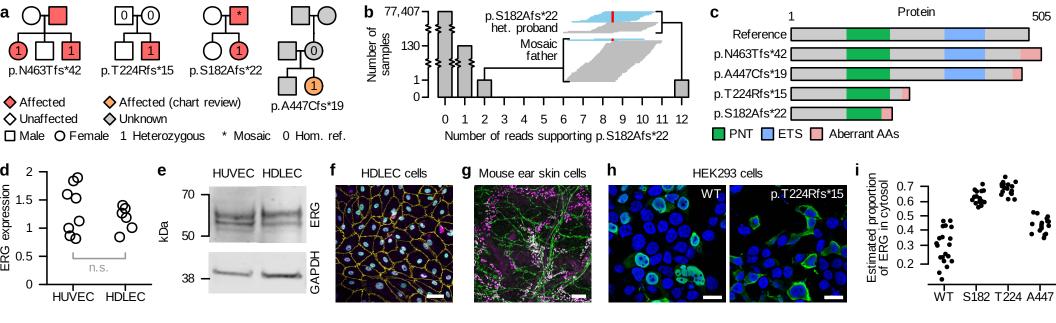
Code Availability

The rsvr tool and Rareservoir schema are available from https://github.com/turrogroup/rsvr.

Methods-only references

- 995 47. Li H et al. The Sequence Alignment/Map format and SAMtools. Bioinformatics. 2009; 25(16):2078--996 2079.
- 997 48. Morales J et al. A joint NCBI and EMBL-EBI transcript set for clinical genomics and research. Nature. 998 2022; 604(7905):310--315.
- 49. Variant QC for 100,000 Genomes Project merged VCF files (2022). https://research-
- 1000 help.genomicsengland.co.uk/display/GERE/Site+QC%2C+FILTER+and+INFO+Fields



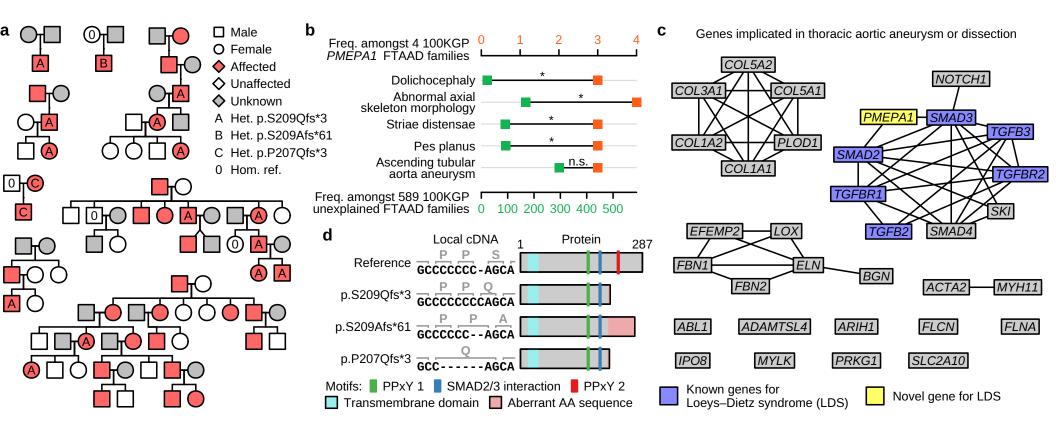


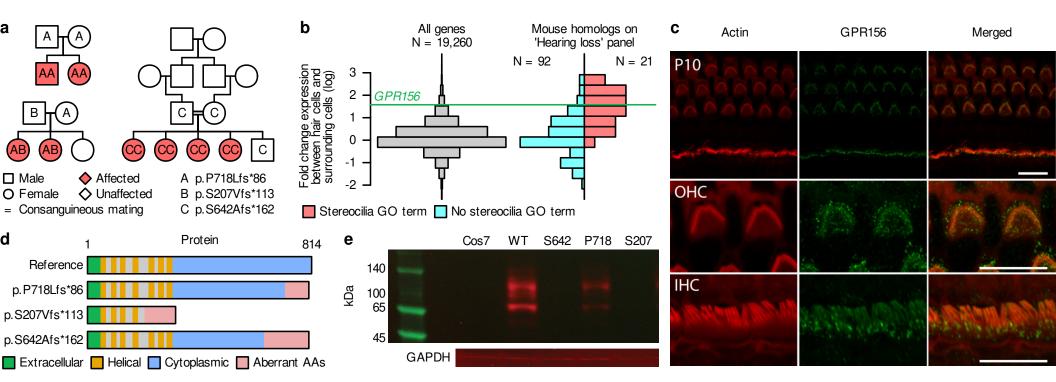
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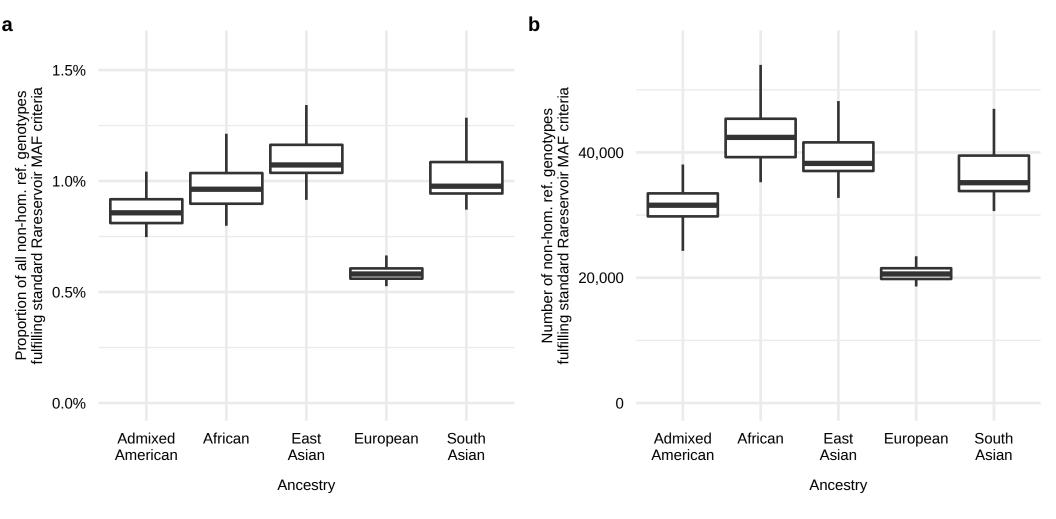
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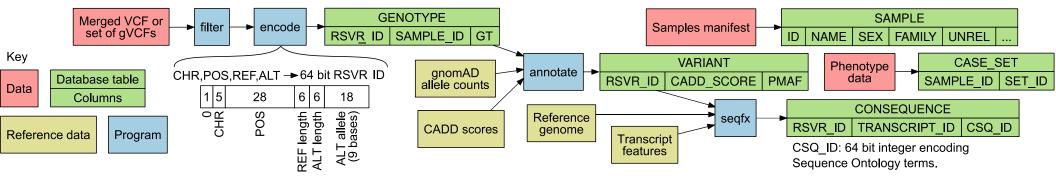
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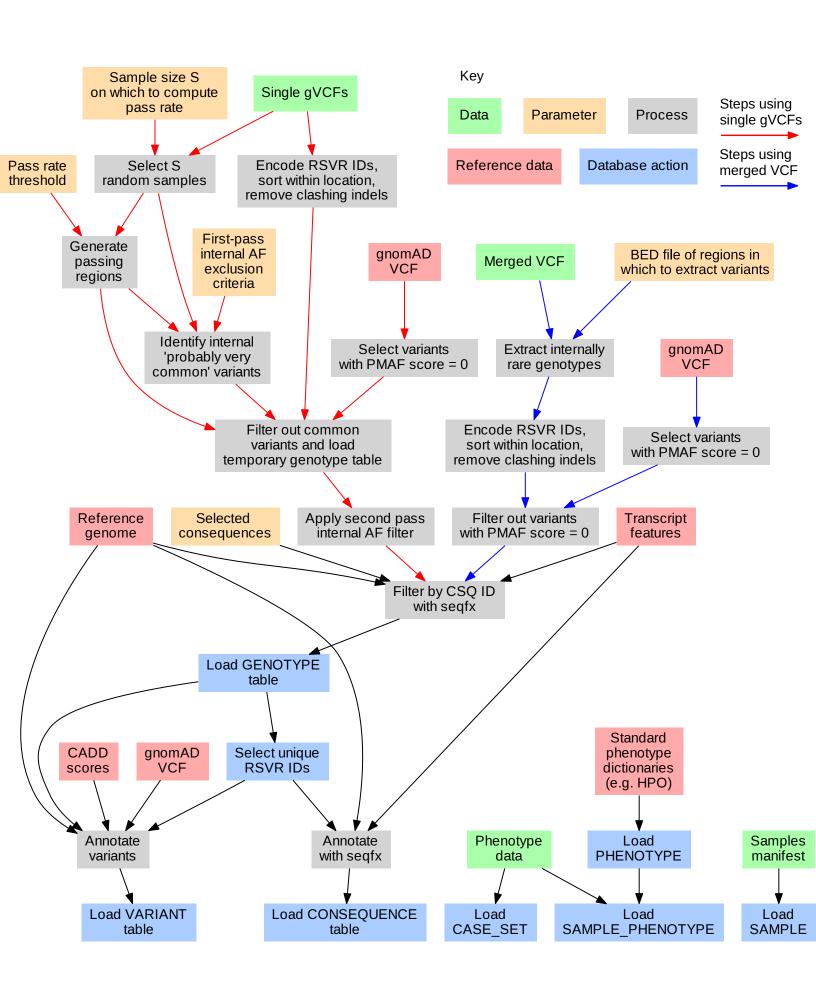
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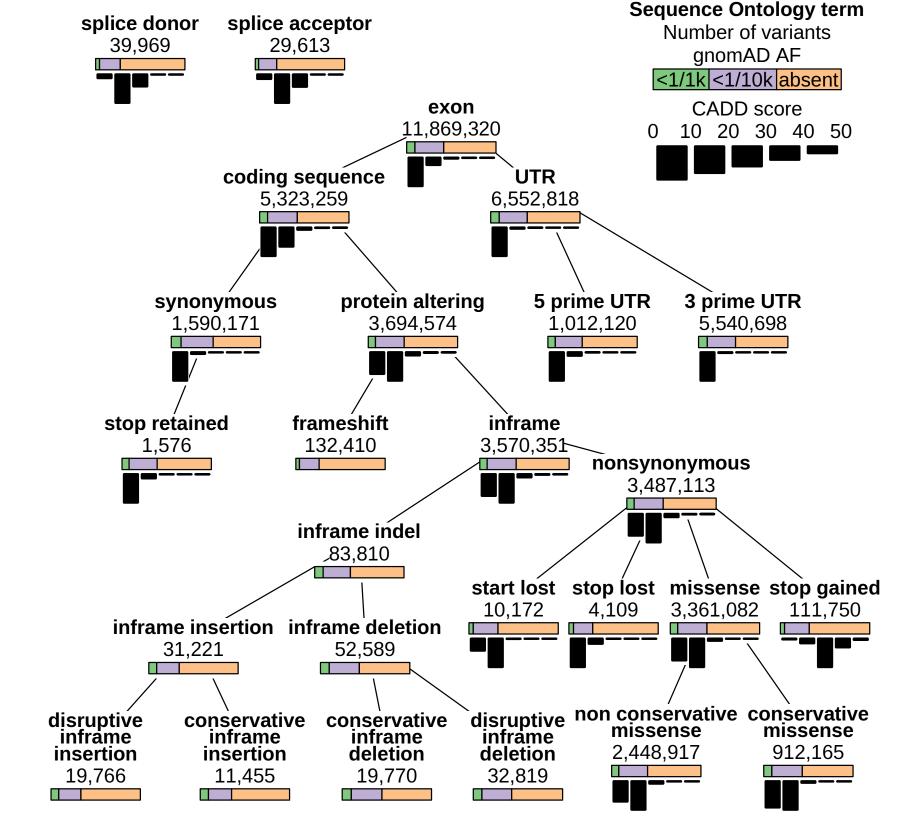


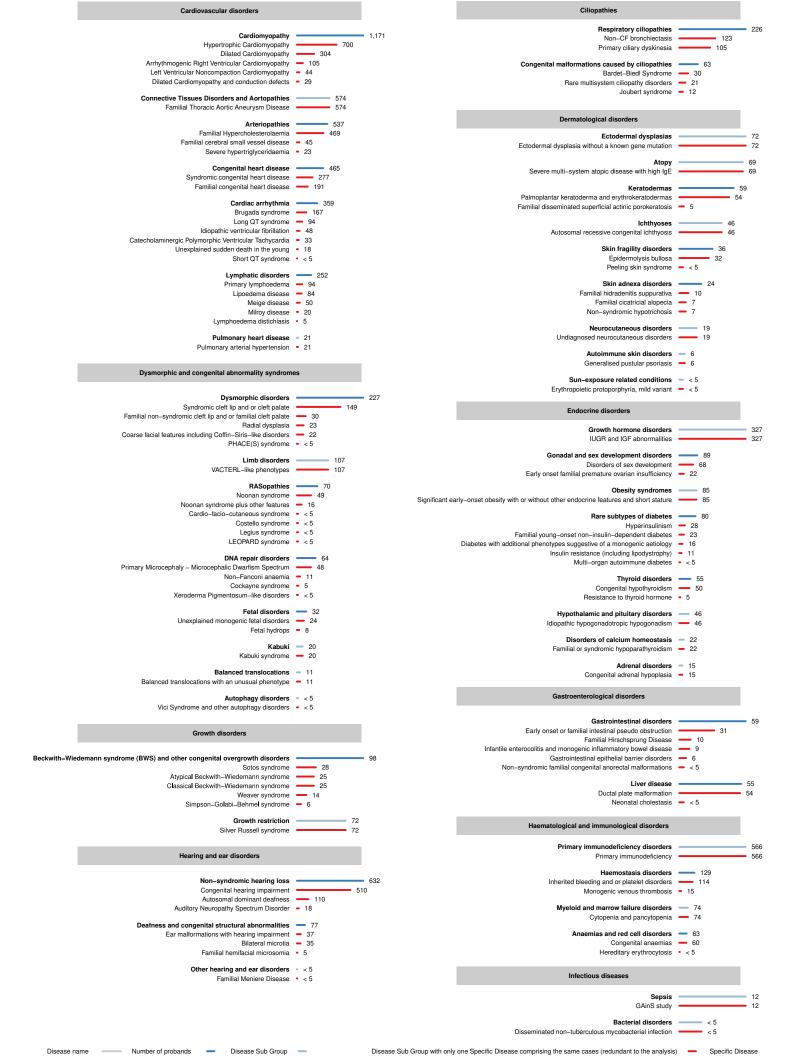


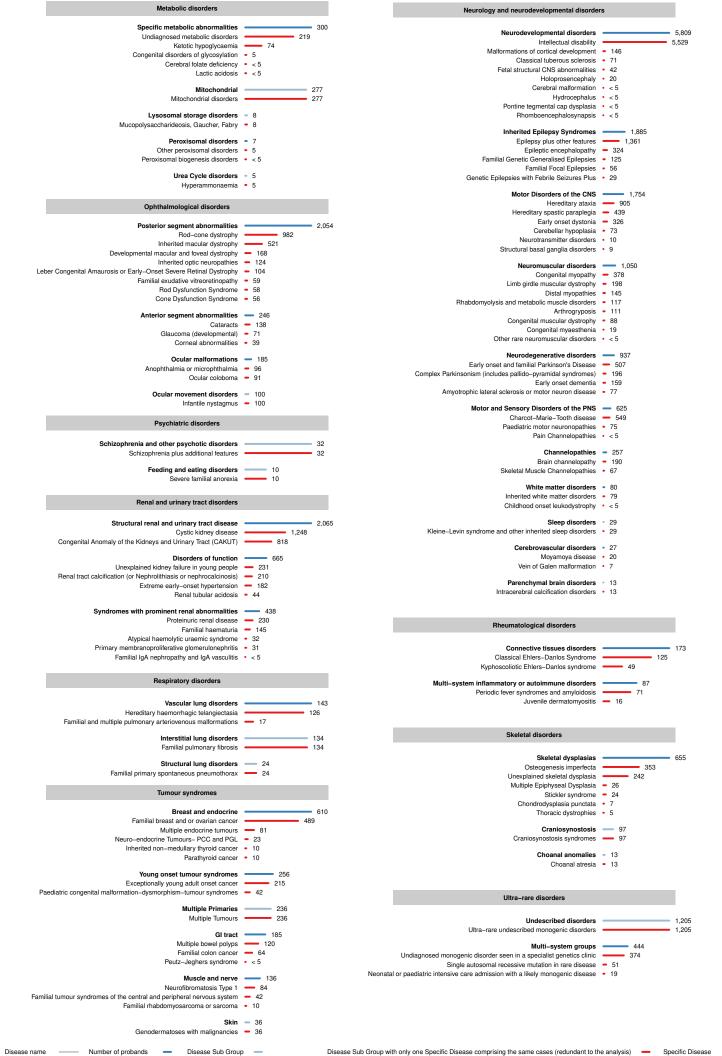


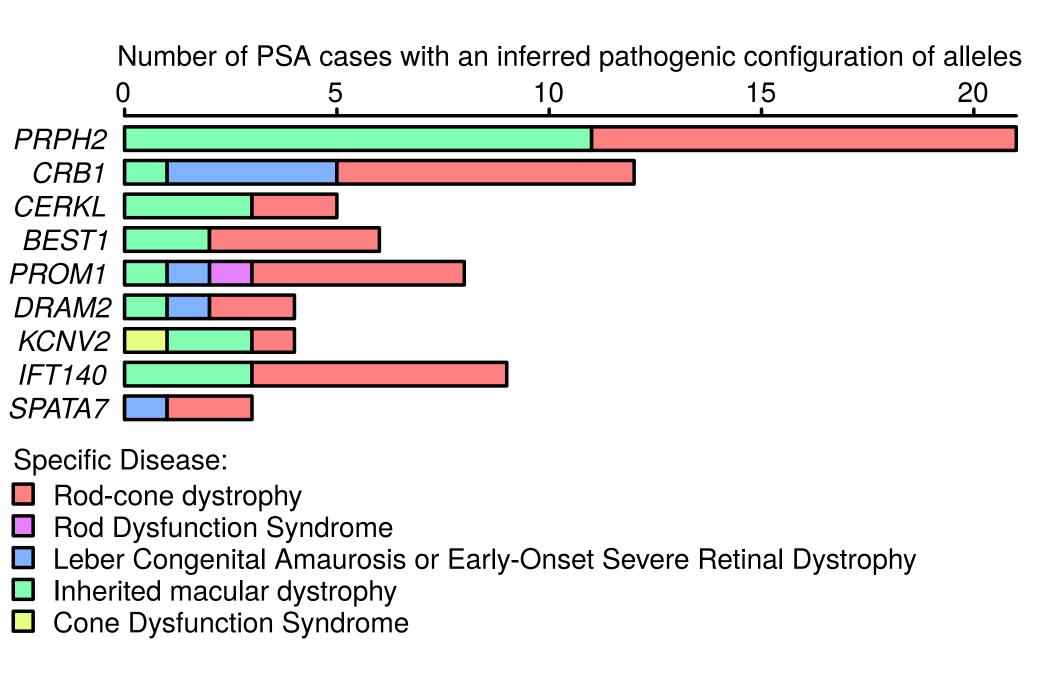


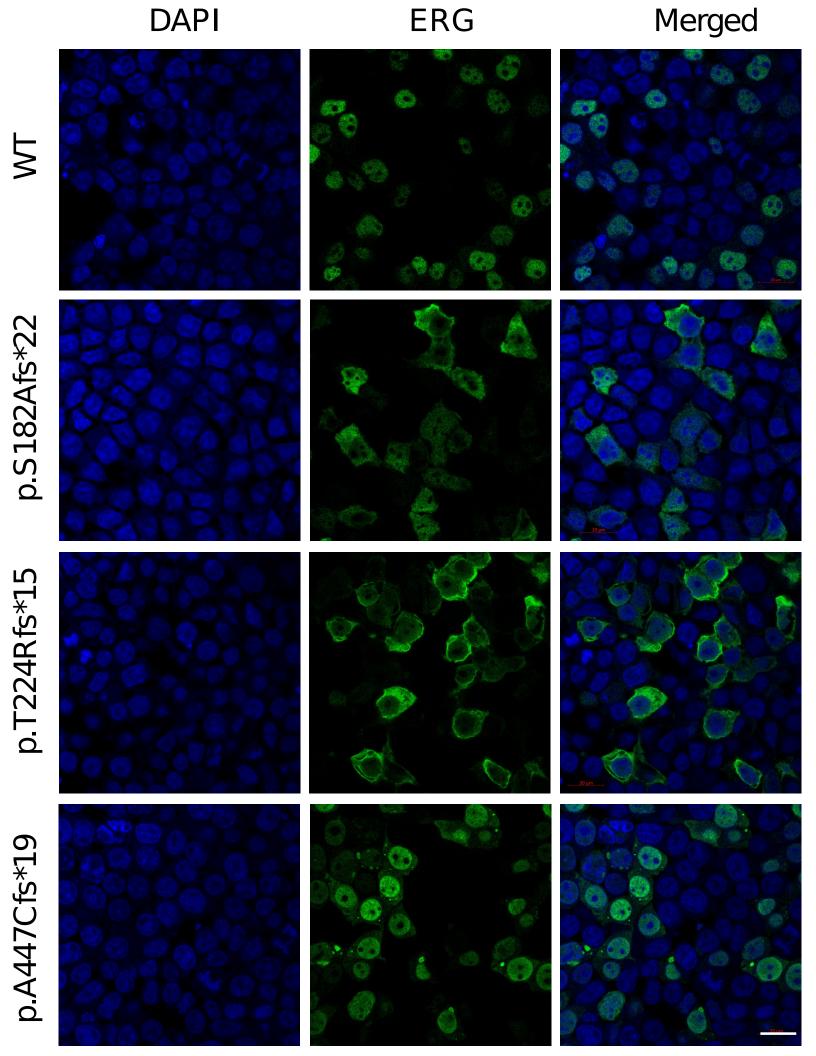


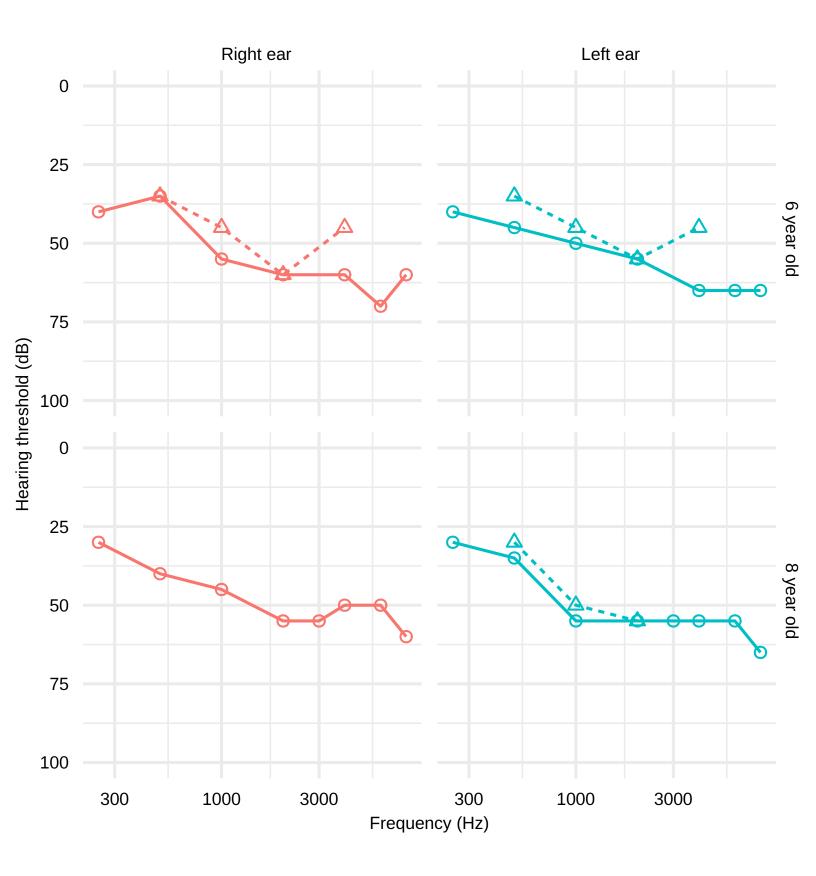












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