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Comprehensive reanalysis for CNVs in ES data from unsolved rare disease cases results in new diagnoses

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We report the results of a comprehensive copy number variant (CNV) reanalysis of 9171 exome sequencing datasets from 5757 families affected by a rare disease (RD). The data reanalysed was extremely heterogeneous, having been generated using 28 different enrichment kits by 42 different research groups across Europe partnering in the Solve-RD project. Each research group had previously undertaken their own analysis of the data but failed to identify disease-causing variants. We applied three CNV calling algorithms to maximise sensitivity, and rare CNVs overlapping genes of interest, provided by four partner European Reference Networks, were taken forward for interpretation by clinical experts. This reanalysis has resulted in a molecular diagnosis being provided to 51 families in this sample, with ClinCNV performing the best of the three algorithms. We also identified partially explanatory pathogenic CNVs in a further 34 individuals. This work illustrates the value of reanalysing ES cold cases for CNVs.

Rare diseases (RD) are defined in Europe as conditions that affect <1 in 2000 individuals. Nevertheless, it is estimated that more than 30 million people across the European Union are affected by one of ~6000–8000 different RDs^{[1,2](#page-18-0)}. As 80% of RD are expected to have a genetic aetiology, massively parallel sequencing approaches, in particular exome sequencing (ES), have been widely applied over the last decade to identify variants in DNA that cause RD. However, despite many advances in technology during this period, more than half of all individuals affected by an RD remain without a molecular diagnosisfollowing such analyses, thus extending their diagnostic odyssey. While the accurate detection of single nucleotide variants (SNV) and short (<50nt) insertions and deletions (InDels) from ES data has become relatively robust in recent years^{[3](#page-18-0)}, the reliable detection of larger variants, including copy number variants (CNVs), remains a challenge, and it is likely that undetected pathogenic CNVs account for a proportion of undiagnosed individuals.

CNVs comprise losses, which may be heterozygous or homozygous in autosomes, or hemizygous in gonosomes, and gains of genetic material, which we refer to here as *deletions* and *duplications*, respectively. Identification of CNVs from short-read ES data (i.e. 100–150nt paired-end reads) is complicated by several factors, the most important of which being that read length is usually shorter than variant length, and that the boundaries of the CNV, referred to as breakpoints, are unlikely to be captured directly by the enrichment targets, since they represent only ~1–2% of the genome. An exacerbating factor is a marked variability in the enrichment process, in which targets for ~200,000 exons undergo DNA hybridisation and PCR amplification prior to sequencing, both between kits and between experiments. Many methods have been developed for CNV detection from ES data, most of which use the comparison of depth of coverage (DoC) between the observed number of reads covering a particular exon/target in a sample of interest and the normalised coverage for the same exon/target in a large reference batch of matched experimental samples^{4-[9](#page-18-0)}. For such methods to be successful, the sequencing data needs to be as homogenous as possible, particularly with respect to the evenness of coverage¹⁰, which is the key factor in CNV detection since it directly affects the signal-to-noise ratio.

As reviewed recently in Gordeeva et al.¹¹, these methods differ from each other primarily in terms of the approach taken for read count normalisation, assumptions regarding read-depth distribution, and the segmentation process, i.e. identification of the boundaries of a variant. Despite

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the application of sophisticated normalisation techniques, the correct separation of the signal of true CNVs from background noise remains challenging, particularly for short CNVs that only impact one or a few exons. This is illustrated by numerous cross-tool comparisons in which the intersection of CNVs detected by different methods is limited, ranging from ~1–20% concordance when three or more tools are compared across samples $12-14$. Indeed, a recent benchmarking initiative involving sixteen tools showed that the number of raw CNVs called on a single ES sample ranged from just two to over a thousand¹¹, reflecting differing optimisation of algorithms for specificity or sensitivity. Therefore, following identification of a list of potential CNVs, subsequent filtering steps are required, including determining which CNVs are technically valid (i.e. bona fide biological events), and whether any of the valid CNVs are of clinical relevance with respect to the phenotype of the affected individual. Hence, both technical expertise and expert clinical knowledge are required if disease-causing CNVs are to be correctly identified.

This complexity may explain why the detection of CNVs has often been omitted from diagnostic ES workflows, with array comparative genome hybridisation (aCGH) continuing to be the preferred method in the clinic over the last decade, despite limitations in its sensitivity and resolution, particularly with respect to short CNVs. However, recent studies have indicated that ES may be a suitable replacement as a first-tier diagnostic test^{15-[17](#page-18-0)}, with the added benefit that SNVs and InDels are detected simultaneously.

A key goal of the EU Horizon 2020 Solve-RD project is to raise the diagnostic rate of individuals with an RD for whom ES analysis and variant interpretation have previously been undertaken, but without a conclusive diagnosis having been reached. This is being achieved by undertaking massive pan-European data collation and complete reanalysis of raw data, followed by expert technical and clinical inter-pretation and validation of variants^{[18](#page-18-0)}. The CNV analysis conducted here, was an integral part of a larger re-analysis effort undertaken on the same dataset, covering most other variant types (Laurie et al.¹⁹). Here we describe the workflow applied in a comprehensive reanalysis of this heterogeneous sample of ES data from 9171 individuals pertaining to 5757 families, including 6143 individuals affected by an RD, to identify (likely) pathogenic CNVs. The ES data was generated using 28 different enrichment kits in multiple sequencing centres. Hence, to maximise the accuracy and sensitivity of CNV detection we applied three different algorithms, ClinCNV, Conifer, and ExomeDepth, and analysed experiments in 28 different batches, comprising data generated using the same enrichment kit. We filtered the raw call set, initially consisting of over two million CNV calls (average of ~300 per individual), to a manageable number of 0–2 potentially pathogenic rare CNVs per affected individual requiring interpretation by the clinical experts who submitted the cases to Solve-RD. This extensive endeavour has led to the closure of many diagnostic odysseys, some of which had been ongoing for decades, of which we provide some illustrative examples.

Results

Technical results

Prior to the initiation of CNV calling, minimal quality control was undertaken, which took the form of requiring that data from each submitted family included at least one affected individual with accompanying Human Phenotype Ontology (HPO) terms. Furthermore, following the alignment of sequencing reads, it was required that at least 70% of the target region of the enrichment kit had a depth of coverage (DoC) of ten reads. After the removal of 143 experiments that did not meet these criteria, CNV calling was undertaken on data from a total of 9171 individuals from 5757 families, of whom 6143 had a rare condition. Initial investigations indicated the presence of a large variance in sequencing depth both within and between the 28 enrichment kit batches, reflecting the heterogeneity of the sequencing data submitted to Solve-RD (Fig. 1).

Following the identification and removal of likely false positive calls based upon tool-specific QC metrics, the removal of commonly observed events, and restriction to events overlapping genes in the custom gene lists from the corresponding European Reference Network (ERN), a total of 7849 calls in 3436 affected individuals from 3300 families remained for interpretation (Table [1](#page-2-0)). The number of probands with at least one CNV call to be interpreted by clinical specialists from the ERN ranged from 113 for GENTURIS (33% of families) to 1239 for ITHACA (69% of families) (Supplementary Table 3). No CNV of interest was detected in 2707 affected individuals from the remaining 2457 families. In addition, a further 393 pairs of potential CNV-SNV double-hit compound heterozygous variants in 226 affected individuals were returned to clinical experts for interpretation. Overall, a mean of 1.3 CNVs per proband was returned for interpretation. However, as CNVs of potential interest were only identified in 55% of

Fig. 1 | Violin plot of the median depth of coverage by kit for 9351 ES experiments pertaining to 28 different enrichment kits. The number of experiments pertaining to each kit is shown above the plots. Coverage is shown on the Y-axis. Thickness of the plotted shape indicates the proportion of experiments that have a particular coverage.

Table 1 | Table showing overall number of CNV calls submitted for clinical interpretation following filtering, separated by type and caller used

Numbers in brackets denote the subset of calls detected on sex chromosomes.

Fig. 2 | Distribution of lengths of 7849 CNV calls detected in 3436 affected individuals, separated into deletions (Panel a) and duplications (Panel b). The x-axis represents the length of calls identified (log₁₀ scale), and the y-axis the number of events observed. Note that the y-axis scale is different in panel a from panel b.

probands, this equated to 2.4 variants per proband that required interpretation.

The total number of CNV calls in affected individuals returned for interpretation was highest for ExomeDepth ($n = 4205$), while ClinCNV called about two-thirds of this number (2782), and Conifer approximately one-fifth (862), reflecting different predilections of the underlying algorithms with respect to sensitivity and specificity of CNV detection. While Conifer and ExomeDepth showed a significant bias toward calling duplications, the reverse pattern was observed for ClinCNV, which identified more deletions ($p < 0.00001$ in all cases, Fisher exact test; Supplementary Table 4). We assessed the distribution of the length of CNVs returned for interpretation as identified by each tool. Notably, the average length of CNVs detected by Conifer was approximately an order of magnitude larger than that of ExomeDepth, which in turn was longer than that of ClinCNV. This pattern held for both duplications and deletions and again reflects differences in the way the tools identify and segment CNVs (Fig. 2, Supplementary Table 5).

Diagnostic results

Following expert interpretation, 105 potentially pathogenic CNVs of interest in 103 affected probands were identified, of which 52 have been confirmed as disease-causing in 51 individuals (Table [2\)](#page-3-0). The diseasecausing CNVs included three "double-hit" instances where an SNV and CNV affecting different alleles of the same gene were identified, resulting in a compound heterozygous diagnosis and one instance where two CNVs affecting different genes provided a dual genetic diagnosis for a complex phenotype. Parent–child trios account for 18 out of the 51 solved cases (35%), and 13 of these cases are caused by de novo CNVs. A further 25 CNVs are regarded as pathogenic by the clinical experts but not sufficient to explain the full phenotype observed in the affected individual, including seven complete gonosomal aneuploidies ("Partially explanatory" in Tables [2](#page-3-0) and [3](#page-10-0)). A further 26 potentially pathogenic CNVs were identified for which further validation is not logistically possible due to lack of access to DNA and/or the patient (referred to as candidates below). While 81% (42 of 52) of confirmed disease-causing CNVs are deletions, only 39% (7 of 18) of the partially explanatory pathogenic CNVs are deletions, even when disregarding the gonosomal duplications. Of the 26 candidate CNVs, 54% (14) are deletions (Fig. [3](#page-11-0) and Table [2\)](#page-3-0).

Of the 77 confirmed pathogenic CNVs, 40 (52%) were initially identified by all three callers (Fig. [3](#page-11-0) and Table [2\)](#page-3-0). However, in the case of ten of the 40, the Conifer call was subsequently discarded due to it being below the applied SV-RPKM threshold, and one of the ten was also discarded by the ExomeDepth workflow due to a low BF. Of the remaining 37 pathogenic CNVs, 36 (97%) were identified by ClinCNV, two of which subsequently failed ClinCNV quality control thresholds, while 25 (68%) were identified by ExomeDepth, five of which were subsequently discarded due to a low BF. Interestingly one of the 37, a duplication in PIEZO2 was identified by Conifer alone.

Belowwe provide an example of an RD case solved through the analysis of CNVs undertaken here, from each of the four ERN partners in Solve-RD.

Example of successful new diagnosis from ERN EURO-NMD

This male in his thirties first came to clinical attention in his adolescence, affected by poor balance, recurrent falls, and difficulty rising from the floor. Prior to this, he had been able to run and play sports normally. His symptoms worsened slowly over time, and he is currently unable to walk or stand without assistance. He also has mild facial weakness and mildly elevated serum creatine kinase. His family history is negative, having several unaffected siblings. Muscle biopsy showed clear features of muscular dystrophy, and immunohistochemical analysis suggested reduced expression of

dystrophin. Exome sequencing was initially undertaken in 2017, but no diagnosis was reached at that point.

As a result of reanalysis of the ES data undertaken here, a three-exon deletion affecting exons 45 through 47 of the DMD gene (NC_000023.10:g.(?_31947661)_(32053731_?)[0]) was detected by both ExomeDepth and ClinCNV, consistent with the suspected diagnosis of Becker Muscular Dystrophy. This hemizygous deletion was subsequently con firmed using multiplex ligation-dependent probe ampli fication (MLPA). Con firmation of the molecular diagnosis in this individual has enabled enhanced genetic counselling, as any future daughter he may have would be an obligate, and possibly manifesting, carrier of the CNV, thus requiring clinical management.

Example of successful new diagnosis from ERN GENTURIS

This family first came to clinical attention in 2003, meeting the criteria for hereditary diffuse gastric cancer $(HDGC)^{20}$, as several family members had developed diffuse gastric cancers prior to 30 years of age. HDGC typically results from CDH1 loss of function^{21[,22](#page-18-0)}. However, Sanger sequencing of CDH1 performed proved negative, as did a subsequent investigation in the form of MLPA, and ES, at which point no potentially explanatory SNVs, InDels, or CNVs were identified in CDH1, nor other candidate genes²³.

Following these negative findings, the ES data was submitted to Solve-RD for two affected, and four unaffected siblings. The comprehensive reanalysis of the ES data resulted in the identification of a ~116 kb heterozygous deletion impacting half of the CDH1 gene (from intron 7 forwards) and the start of the downstream gene TANGO6 (as far as intron 14) on chromosome 16 (NC_000016.9:g.(?_68846035)_(68961985_?)del) in four of the six siblings (Fig. [4](#page-12-0)). The CNV was detected by both ClinCNV and ExomeDepth and further supported by split-reads and abnormally paired reads observed in data from one of the affected individuals. Visualisation in IGV and subsequent MLPA validated this large event. Of note, one of the unaffected siblings, a female carrier in her 40s, has not developed gastric cancer to date, in accordance with previously reported incomplete penetrance among $CDH1$ mutation carriers²⁴. Another of the unaffected siblings was a carrier but never developed gastric cancer as a result of having undergone prophylactic total gastrectomy due to the high incidence of cancer in the family. The remaining unaffected siblings were found not to harbour the deletion, but unfortunately, both have also already undergone prophylactic gastrectomy. Nevertheless, as a result of their inclusion in Solve-RD, the family has since been recontacted and enroled in a clinical pathway of care, and their 20-year diagnostic odyssey has now come to an end. Importantly, targeted genetic testing has now been made available to their offspring to avoid unnecessary prophylactic gastrectomy in subsequent generations. The functional analysis and clinical implications of this CNV are described in more detail in São José et al.²⁵.

Example of successful new diagnosis from ERN ITHACA

This girl was first referred to paediatric neurology in her first year of life, presenting with generalised tonic-clonic seizures. During her infancy, mild global developmental delay became evident, with delays in speech and language acquirement and in gross-motor skill acquisition. Seizures were controlled with lamotrigine monotherapy, which could be discontinued during childhood following prolonged seizure-free periods. Apart from polyhydramnios, pregnancy and delivery were uncomplicated. Medical history comprised constipation and eczema, and family history was unremarkable. Physical examination revealed no additional phenotypic features, i.e. no congenital anomalies, no facial dysmorphisms, and no growth abnormalities. Investigations, including cerebral MRI and general metabolic screening were negative. Singleton ES was performed, followed by trio ES, which revealed a heterozygous de novo SNV of uncertain significance (VUS) in STIP1 (STIP1; chr11(GRCh37):g.63961718C>T; NM_001282652.1:c.418C>T; p.(Arg140*)). Within this diagnostic trajectory, no analysis dedicated to CNV detection was performed.

The systematic reanalysis of ES data reported here led to the identification of a heterozygous 27 kb deletion on chromosome 6p21

Table 2 (continued) | Table listing the 105 potentially pathogenic CNVs discovered in this study

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Table 3 | Table showing success rates in identification of pathogenic CNVs from each of the four ERNs (European reference Networks)

ERN	Solved	Partially solved (families)		Candidates	Total	Pathogenic CNV	Solved families
	Families	Sex chromosome aneuploidies	Other	Families	Families	$\frac{0}{0}$	$\frac{0}{0}$
EURO-NMD	18		4	10	1.461	1.5	1.2
GENTURIS				Ω	340	1.2	1.2
RND	13		◠	12	2.168	0.7	0.6
ITHACA	16		12	$\mathbf 4$	1.788	2.0	0.9
Totals	51		18	26	5.757	1.3	0.9

The table shows the number and proportion of families found to have disease-causing variants which fully or partially explain the affected individual's phenotype, and how many have candidate CNVs requiring further invetigation.

(NC_000006.11:g.(?_31630124)_(31657924_?)del) in the proband. This deletion was detected by all three tools, and visual inspection of sequence alignment files in IGV clearly indicated the presence of the variant in the affected daughter, and its absence in both parents, thus confirming that it is a de novo deletion. The deletion fully removes CSNK2B, LY6G5B and LY6G5C, and its breakpoints affect GPANK1 and ABHD16A. GPANK1, LY6G5B and LY6G5C currently have no disease association, and while ABHD16A is associated with autosomal recessive spastic paraplegia-86 (MIM#619735), there is no apparent second hit in ABHD16A, and the phenotype of the proband does not comprise spastic paraplegia. CSNK2B, on the other hand, has recently been shown to be associated with autosomal dominant Poirier-Bienvenu neurodevelopmental syndrome (POBINDS; MIM#618732), in which truncating variants in CSNK2B result in haploinsufficiency, leading to early-onset seizures and highly variable impairments of intellectual functioning²⁶⁻²⁸. As the de novo deletion observed in this proband results in haploinsufficiency of CSNK2B, and her phenotypic description fits within the CSNK2B-associated phenotypic spectrum, this 27 kb deletion on chromosome 6p21 is regarded as explanatory for her rare condition, thus ending a seven-year diagnostic odyssey for this family.

Example of successful new diagnosis from ERN RND

This teenage female was first evaluated in paediatric neurology as a child, presenting with global developmental delay and behavioural and learning problems. Retrospectively, the first symptoms had become apparent in her infancy, consisting of mild delayed development of fine and gross motor skills. Additionally, she had delays in language and speech development and was diagnosed with attention deficit disorder, for which she is being treated with methylphenidate and responding well. No obvious dysmorphic features were observed upon physical examination, but mild hypertonia of the triceps surae, hyperreflexia, kinetic tremor, mirror hand movement, and a tiptoeing gait were observed. Subsequent cerebral MRI showed ventriculomegaly, corpus callosum hypoplasia, prominent cerebellar folia, and thin middle cerebellar peduncles. Genetic testing, consisting of aCGH (median resolution 180 kb), targeted testing for Fragile X syndrome, and ES did not pinpoint a molecular cause.

Systematic reanalysis of the ES data undertaken here led to the identification of a heterozygous deletion of ~200 kb at chromosome 4q31.1 (NC_000004.11:g.(?_140187697)_(140394334_?)del), encompassing part of the MGARP gene (not known to be associated with disease), and the entire NAA15 gene, which encodes the catalytic subunit in the N-terminal acetyltransferase A complex (MIM: 608000). The deletion was identified by all three tools and subsequently validated using high-resolution aCGH (median resolution 60 kb). Following the review of the prior results, the absence of recall of the variant in the initial aCGH analysis was attributed to its limited resolution. The patient's mother, who had had similar learning problems and has mild cognitive disability, was subsequently also found to be positive for the deletion. No further family testing was possible. Echocardiography was normal in both cases. Loss-of-function variants in NAA15 and heterozygous deletion of this gene and nearby genes are associated with

'Intellectual developmental disorder, autosomal dominant 50, with behavioural abnormalities' (MIM: 617787)^{20,29}. This disorder has the features of a wide spectrum of neurodevelopmental severity and variable association of congenital anomalies, thus confirming that the observed CNV was causative in this case, and ending this family's seven-year diagnostic odyssey.

Discussion

Rigorous detection of CNVs from ES requires sequencing data that has been generated as uniformly as possible, in order that the test experiment can be compared against a similarly generated batch of matched control samples. However, the ES data submitted to Solve-RD had been generated using 28 different enrichment kits and sequenced with different short-read technologies to different depths of coverage in multiple sequencing centres across Europe. Hence the primary challenge encountered during this analysis was data heterogeneity. Similarly, from the perspective of diagnosis, it is essential to have a clear clinical description of the affected individual to be able to determine which genes and variants, if encountered, may explain the observed phenotype. This was achieved here firstly through the use of the HPO to capture a deep phenotypic description of affected individuals from the referring clinicians, and secondly using the curated set of genes of interest provided by each ERN. Together these significantly reduced the search space for potentially disease-causing CNVs.

The interpretation of raw CNV calls is challenging due to the initial high number of calls most tools report. We applied a robust filtering strategy to remove calls that were clearly unlikely to be of relevance for RD and benefited from the curated lists of genes of interest provided by each ERN. Nevertheless, visual inspection of the affected region using IGV was key for assessing the technical validity of calls, prior to, or in parallel with, their biological interpretation. For interpretation purposes, we routinely provided the following images: (1) Image of normalised coverage across the whole genome, (2) Close-up images of apparent breakpoints, and (3) Image of the variant itself and the surrounding neighbourhood. It is likely that this is an aspect where an AI-based tool for automated IGV-image analysis would be of significant benefit, potentially saving many hours of human expert review time. We believe that a Machine Learning/AI tool could be trained to discriminate between whether a variant called by one of the algorithms is clearly a false positive or likely to be a bona fide biological event, in the same manner that the human eye can, when presented with the same images.

The clinical researchers representing each ERN applied their own prioritisation strategy when interpreting CNV calls according to the specific pathologic and phenotypic characteristics of their patients. When used as a first-tier analysis, CNV detection from ES has been reported to result in diagnostic yields as high as $7-19\%$ ^{[30](#page-18-0)-[32](#page-19-0)}. The overall rate of novel diagnoses reached here through reanalysis was 0.9%, ranging from 0.6% for RND and 0.9% for ITHACA to 1.2% for GENTURIS and EURO-NMD. Notably, nine of the sixteen CNVs established as being disease-causing in ITHACA cases could be confirmed as de novo mutations due to ES data being available from the proband's parents. While our values are lower than those of prior

Fig. 3 | Heat maps illustrating the length of confirmed disease-causing CNVs (Panel a), partially explanatory disease-causing CNVs (Panel b) and candidate disease-causing CNVs (Panel c) identified in this study. Duplications are shown in blue, and deletions in red. Cyan and pink, represent duplication and deletion calls, respectively, which were initially QC filtered in the workflow for the respective tool,

and identified post hoc. The approximate length of the event is indicated in the top layer using a log_{10} scale. The affected gene is indicated along the bottom. Where more than one gene was unaffected, it is shown as multiple, with the affected chromosome indicated.

reports, where yield from reanalysis efforts, have resulted in increases in diagnostic yield with respect to CNVs in the range of $1.6-2.0\%^{24,33,34}$ $1.6-2.0\%^{24,33,34}$ $1.6-2.0\%^{24,33,34}$ in those studies, the prior CNV analyses had largely consisted of only chromosomal microarray (CMA) analyses, which lack sensitivity for short CNV events, which were hence identified in the subsequent ES-based CNV analyses. Our results reflect several factors: the likelihood that detailed CNV analysis of the ES data had been undertaken prior to submission to Solve-RD; the role that CNVs are likely to play in the respective class of disease; the time passed since the initial analysis, which would affect the number of genes known to be associated with a particular class of disease. Interestingly, the number of genes of interest in each of the custom ERN gene lists does not appear to be a

factor, given that GENTURIS had by far the shortest list, and RND and ITHACA the longest.

There was a clear bias towards deletions vis-à-vis duplications being identified as pathogenic, with 49 of 77 (64%) confirmed pathogenic CNVs being deletions and 42 of 52 (81%) disease-causing CNVs. This reflects the fact that duplications are more challenging to detect, and even when detected by ES, with DoC data alone it is invariably unclear as to whether they are tandem duplications, possibly inverted, or inserted elsewhere in the genome, each of these scenarios being likely to result in a different biological consequence, making interpretation challenging. Furthermore, long duplications appear to be under less evolutionary constraint than similarly

Fig. 4 | Family pedigree and MLPA confirmation results for a Mexican family extensively affected by Hereditary Gastric Cancer. a Family tree of the family of proband P0014615 (represented by an arrow). Exome Sequencing data from six individuals of the family was submitted to Solve-RD for re-analysis, following prior analysis in 2015 for both SNVs and CNVs, which did not identify any variants of interest. Three of the sequenced family members were affected by diffuse gastric cancer (DGC, black symbols: P0014616, P0014615, P0014613), while the other three were unaffected (P0014617, P0014614, P0014612). Individual III-3 (P0014617) is currently a healthy carrier, perhaps due to incomplete penetrance previously

sized deletions 35 , suggesting that they are less likely to result in disease. Accordingly, the ACMG guidelines for the interpretation of constitutional $CNVs³⁶$, require more supporting evidence for a duplication to be confirmed as pathogenic than is required for a deletion.

It is noteworthy that, in comparison with the other two tools, Conifer called very few CNVs under 20 kb in length, and indeed failed to successfully identify 18 of 20 deletions <20 kb that were determined to be diseasecausing, and the remaining two fell below the calling threshold. Notably, Conifer also failed to identify duplications over 1 Mb in length, including seven sex-chromosome aneuploidies, a limitation mentioned in the original paper⁴. It is this failure at the two extremes of CNV length that largely contributes to the inferior performance of Conifer. It should also be highlighted that we required a Z-score in excess of ±1.75 for a CNV called by Conifer to be returned for interpretation, whereas had we used ± 1.5 , Conifer would have successfully identified a further eight events of the diseasecausing CNVs, all but two of which were over 20 kb in length. ClinCNV performed best of the three callers with this highly heterogeneous dataset, which is likely due to its more adaptive DoC calculation whereby it subsegments target regions into overlapping 120 bp tiles, significantly improving resolution, particularly for short CNVs, most of which were also detected by ExomeDepth but some of which fell below the minimal calling threshold. Indeed, only ClinCNV was sensitive enough to be able to identify the three events affecting only one or two exons in APC, MEIS2, and NFIB, respectively.

In addition to cases of de novo dominant inheritance resolved by an individual CNV, we also identified eight cases where an SNV and CNV were

reported for CHD1. The age shown below affected individuals indicates the age of disease onset, while that below healthy individuals represents their current age. b MLPA validation results using SALSA MLPA-Probemix P083 CDH1 (MRC Holland) in the healthy-carrier III-3, and in the proband, III-5. A ratio above the blue line indicates an elevated number of copies, while a ratio below the red line indicates a decrease in copy number. The shaded blue area represents the position of probes for CDH1 and two neighbouring genes, while the grey area represents reference probes.

affecting different alleles of the same gene, potentially forming a diseasecausing compound heterozygote. Two of these have been confirmed as being explanatory for the individuals' conditions, with the remaining six requiring further validation. These findings underline the importance of having all data relevant to the interpretation of an affected individual's condition readily at hand, as had the SNV and CNV analyses been undertaken independently, these individuals would have been unlikely to have received a diagnosis. Furthermore, in one affected individual, we identified two pathogenic CNVs affecting different genes, each of which explains unique features of the individual's complex phenotype, i.e. a dual diagnosis 37 . We are confident that many of the CNVs that we currently classify as candidates are likely pathogenic in the affected individuals, but complete follow-up has not yet been possible. The complete expert-curated dataset of deletions and duplications, together with the detailed phenotypes and pedigrees and the aligned sequence files (BAM/CRAMs), are available to the entire RD community via the European Genome–Phenome Archive (EGA[\)38](#page-19-0), allowing for new discoveries (see Data Availability section, below).

There are many reasons why a pathogenic CNV identified here may not have been found in prior analysis of the ES data. Firstly, there may have been no attempt to identify CNVs by the respective clinical research team, due to a lack of resources or expertise. However, we know that some form of prior CNV analysis had been undertaken for the majority of affected individuals analysed here. Secondly, the tool(s) applied previously for CNV detection may not have identified the relevant CNV, or though identified, it may have been discarded due to local quality control parameters applied, e.g. ~10% of all the experiments submitted to Solve-RD were of sufficiently poor quality such that one of the centres involved in the reanalysis undertaken here would have routinely QC-failed the sample in their diagnostic workflow and thus not attempted to identify CNVs. Thirdly, while the CNV may have been identified, there may not have been any known association between the affected gene(s) and the clinical presentation of the patient at the time of the initial analysis, resulting in, at best, classification of the CNV as a variant of uncertain significance (VUS), and the individual remaining undiagnosed.

We would emphasise that any observations of potential tendencies in the results presented here must be interpreted prudently since this was an extremely heterogeneous dataset both in terms of the breadth and the quality of the data and in terms of the time and expertise that had been applied to the interpretation of the ES data in analyses undertaken prior to submission to Solve-RD. As we gather more information about the role of CNVs in RD through projects that share data widely, such as Solve-RD, hopefully, the accuracy of CNV detection will improve, and the entire process of identification and interpretation of this important class of variants, from sequencing data to identification of pathogenic variants can be automated, resulting in families affected by RD receiving a diagnosis sooner rather than later.

The work presented here has several clear limitations vis-a-vis reaching a diagnosis for individuals affected by an RD. Firstly, given that the data was from ES and that we only considered events affecting one of between 230 and 1944 genes of interest identified by each of the ERNs, we will obviously miss any non-exonic events or CNVs affecting genes not in the list of genes of interest. However, undertaking this work without using gene lists would result in a currently insurmountable load of data for interpretation, and novel gene discovery was not the goal of the work undertaken here. However, such discoveries are enabled by the sharing of data with the wider RD community via the EGA, which we hopewill enable more cases to be solved. Different approaches in interpretation undertaken by the ERN experts may have resulted in some biologically relevant events being discarded as uninteresting, which may be particularly true for duplications, for which evidence of biological relevance in RD is currently relatively scarce. It is also possible that the application of other tools designed to find CNVs affecting only single exons, such as VarGenius-HZD³⁹, may have allowed the identification of shorter events missed by the tools applied. With the future adoption of long-read genome sequencing technologies such as those provided by Oxford Nanopore Technologies and Pacific Biosciences, it is likely that the accuracy of CNV detection, and hence ease of interpretation, will improve markedly.

Despite these limitations, we have successfully provided diagnoses to at least 51 families who had previously undergone extensive genetic testing and, in many cases, multiple hospital visits over many years, some even decades, without having been provided with a diagnosis. Within the larger Solve-RD reanalysis of all variant types, these 51 CNVs were the second most common type of disease-causing variant identified, after SNVs/InDels, contributing to ~9% of the successful diagnoses (Laurie et al.¹⁹). The ending of a diagnostic odyssey has many benefits to patients and their families, beyond changes in medical management and genetic counselling of relatives. It also allows a better understanding of disease progression, access to disease-specific online communities, and psychological closure, amongst other benefits⁴⁰. The work undertaken here indicates the value of comprehensive (re)-analysis of copy number variants in undiagnosed RD cases, even from historic ES data, and has resulted in patients and their families being given an accurate diagnosis, finally ending their diagnostic odysseys.

Based upon our findings, we suggest the following recommendations for future (re)-analyses of ES data with respect to the identification of disease-causing CNVs.

- 1. Know your enrichment kit. Investigate how well and how evenly it captures your genes of interest.
- 2. Choose your tools wisely. While Conifer has been shown to work with homogenous datasets, e.g., thousands of ES datasets generated using

the same kit in the same sequencing centre, it does not perform with the heterogeneous dataset analysed here. Furthermore, it identified very few CNVs <20 kb in length, missing many disease-causing variants.

- 3. Identifying regions that are commonly copy-number variants. In this way any CNVs observed in such regions can be excluded from being potentially disease-causing.
- 4. Use an in silico candidate gene list when possible. This will greatly accelerate the process of interpretation. If the list is very short, then any signal of a CNV in a gene of interest should be examined further, since the sensitivity of tools remains low, and the prior probability of the gene being variant is high. However, as lists grow longer, this probability reduces, and calls will have to be filtered by quality thresholds.
- 5. Visualisation of CNV calls using a tool such as IGV is essential to assure that they are likely to be real biological events, prior to expending time and effort on further interpretation, investigation, and/or confirmation using orthologous techniques.

Methods

Data collation

The ES data reanalysed here comprises previously inconclusive ES experiments submitted for reanalysis as part of the Solve-RD project by 42 different research groups based in 12 countries across Europe and Canada (range of 1–2111 experiments submitted per group). Each experiment was submitted via one of four European Reference Networks (ERN) partnering in Solve-RD, each focusing on a particular group of RD: EURO-NMD (rare neuromuscular diseases); GENTURIS (rare genetic tumour risk syndromes); ITHACA (rare malformation syndromes, intellectual and other neurodevelopmental disorders); RND (rare neurological diseases).

A total of 9351 ES experiments from 9314 individuals (6224 affected individuals and 3090 unaffected relatives) were initially submitted for reanalysis. After the removal of samples sequenced with enrichment kits for which the available control cohort was <30 and thus not large enough to allow accurate CNV identification, data from 9171 individuals from 5757 families were analysed (see Technical Results). While 1320 of 1788 (74%) families from ITHACA were composed of parent–child trios, facilitating identification of de novo mutations, only 239 of the remaining 3969 (6%) probands from other ERNs were trios. ES had been performed using 28 different enrichment kits (range of 4–2078 experiments per kit), and each of the 42 research groups had followed their own DNA library preparation, target enrichment, and short-read sequencing protocol in their local labs, or via external DNA-sequencing providers. Furthermore, each group had previously undertaken its own historic analysis and interpretation of the resulting ES data to identify disease-causing variants, which had proven inconclusive. The date at which the initial ES analysis and interpretation had been undertaken ranged from 6 months to 8 years prior to the experimental data being submitted to Solve-RD for reanalysis; however, this information was not collected systematically for individual data sets.

In addition to sequencing data, a phenotypic description for each affected individual was recorded in the PhenoStore module of the RD-Connect GPAP⁴¹, consisting of a minimum of five Human Phenotype Ontology terms (HPO^{42}) wherever possible, and disease classification using Orphanet Rare Disease Ontology (ORDO) ORPHA codes [\(http://www.orphadata.org/cgi-bin/index.php\)](http://www.orphadata.org/cgi-bin/index.php), and/or OMIM identifiers^{[43](#page-19-0)} (<https://www.omim.org/>) where appropriate, together with family pedigrees. A detailed description of this data set can be found in Laurie et al. 19 .

Ethics statement

The Ethics committee of the Eberhard Karl University of Tubingen gave ethical approval for this work. Written informed consent for data sharing within Europe for the purpose of research was obtained from all recruited individuals or their parents/legal guardians where appropriate. The responsibility of checking the data is suitable for submission to the RD-Connect GPAP and Solve-RD, including informed consent, lies within the data submitter as required by their Code of Conduct and Data Sharing Policy, respectively. In some cases, individuals had to be re-consented prior to data submission. This study adheres to the principles set out in the Declaration of Helsinki.

Alignment and definition of capture regions of interest

Sequencing data was submitted in BAM, CRAM, or FastQ format. Where data was submitted in BAM or CRAM format, it was reconverted to FastQs at read-group level prior to being realigned to the hs37d5 human genome reference version, as used in phase 2 of the 1000 genomes project^{[44](#page-19-0)} with BWA-MEM^{[45](#page-19-0)} (v0.7.8-r455). As GC-rich enrichment targets are known to amplify poorly, resulting in unreliable CNV calling⁴⁶, the GC-content for each target in each enrichment kit was calculated, and any targets in which the GC-content was >80% were removed from the corresponding target BED file prior to CNV calling. This resulted in the removal of $\leq 0.5\%$ of target regions per kit. Ensembl version 75 was used for gene and transcript definition.

With the goal of maximising the probability of detecting potentially disease-causing CNVs, three different algorithms which identify CNVs based on DoC were applied. Two of these, Conifer $\mathrm{^4},$ and ExomeDepth $\mathrm{^6},$ have been widely applied to ES data with success previously, while the third, ClinCNV, was developed recently by a Solve-RD partner^{[47](#page-19-0)}. Each of these tools offers the practical advantage of separating the DoC calculation for each individual experiment from the CNV calling step, and thus CNVs were subsequently called in batches by enrichment kit. The processing took on average 1 CPU hour per experiment per tool, e.g. a batch of 500 samples was processed in around 32 h on a machine with 16 cores. Furthermore, each algorithm provides an estimate of the likelihood that calls produced are biologically real, and the most likely false positive calls were excluded based on these metrics.As primary filters, in the case of Conifer, a value in excess of ±1.75 SV-RPKM was required for a CNV call to be taken forward for biological interpretation, while for ExomeDepth a Bayes factor (BF) > 15 was required, and for ClinCNV, a minimum log likelihood estimation of twenty was applied.

CNV call filtering and visualisation

As the focus of Solve-RD is diagnosing RD cases, through the identification of rare variants that are potentially disease-causing, any apparent CNV call observed in a region where more than 1% of individuals in the whole sample had a similar type of call (i.e. a deletion or duplication) were discarded as being too common to be clinically relevant with respect to RD. Furthermore, CNVs returned for interpretation by clinical experts were restricted to those that overlapped with at least part of a gene in a predefined list of curated genes of interest provided by the respective ERN: EURO-NMD ($n = 615$), GENTURIS (230), ITHACA (1944), RND (1820). The full list of ERN curated genes is provided in Supplementary Table 1 and details as to how these lists were determined in Laurie et al.¹⁹. Potential CNVs of interest were subsequently categorised into six nonredundant classes to aid interpretation: Long CNVs (>500 kb in length); Homozygous deletions; Heterozygous CNVs affecting genes known to cause disorders with an autosomal dominant mode of inheritance; Regions with apparent copy numbers of four or more; Gonosomal CNVs; Potential compound-heterozygous double-hits in the form of a CNV affecting the second allele of a gene in which biallelic variants are known to be disease-causing, and in which a potentially pathogenic SNV has been previously identified in Solve-RD. For each class recommendations were provided for interpretation, for example, computationally detected consanguinity status was used for prioritising short homozygous deletions (<500 bp) and short regions with copy number four or more, which would otherwise have been filtered due to the minimum size threshold. To provide support for the interpretation of the technical validity of CNV calls, images of regions containing CNV calls were generated automatically using the Integrative Genomics Viewer $(IGV)^{48}$. A variety of custom tracks, including call tracks for each of the three algorithms, BAM DoC, and gene tracks for ERN genes of interest, were incorporated, among others.

ClinCNV Workflow

Analysis was performed separately for experiments generated by different exome enrichment kits. Initially, ClinCNV calculates the average read coverage of targeted regions of the enrichment kit divided into 120 bp windows. As the first step of preprocessing, coverage is corrected for GCcontent and library size for each sample individually. Following normalisation, systematically poorly covered regions (i.e.where 90% of samples had a normalised coverage < 0.3) were excluded, followed by the application of variance stabilisation of read counts (square root transformation). To ameliorate the potential impact of batch effects on coverage calculation, samples were further clustered based on their global coverage profiles. In generating these clusters, target regions in the top and bottom quintiles for a variance were excluded to minimise the potential impact of polymorphic regions on cluster generation and coverage profiles were smoothed using the rolling median. Uniform manifold approximation and projection $(UMAP)^{35}$ was performed for the mapping of smoothed coverage profiles. Samples were clustered into subgroups with a minimum size of 15 using dbscan⁴⁹. Finally, the coverage of each 120 bp window was normalised using the median of coverages within the cluster. Different potential copy numbers are modelled using the theoretically expected value and estimated variance, and the log likelihood of normalised coverage under different expected copy-number models is calculated for each window. Calling is performed analogously to Circular Binary Segmentation⁵⁰ using a Maximum Subarray Sum algorithm³⁸, i.e. the segment with the highest evidence supporting an alternative copy-number to that of the model is identified at each step of the segmentation, rather than the segment with the largest difference in mean.

Resulting CNV calls were filtered according to measures of within-kit allele frequency of the CNV and the noisiness of the coverage at the CNV site, requiring a minimum log likelihood ratio of 20 to be considered worthy of biological interpretation. A robust regression model is fitted, taking the 75% percentile rank of the per-chromosome number of CNVs as a response variable, and median read depth, enrichment kit, and predicted ancestry determined using SampleAncestry [\(https://github.com/imgag/ngs-bits/](https://github.com/imgag/ngs-bits/blob/master/doc/tools/SampleAncestry) [blob/master/doc/tools/SampleAncestry](https://github.com/imgag/ngs-bits/blob/master/doc/tools/SampleAncestry)) as predictors. A sample was assessed as QC failed if the response variable was outwith the 99.5% prediction interval of the regression. The 75% percentile of the perchromosome number of CNVs was chosen to overcome cases where long CNVs may have been segmented into many separate calls, and thus, an otherwise good sample could be falsely identified as QC failed if only the total number of CNV calls was used as a response. Where parents of a case were available (i.e. family trios), copy-number information from the parents was also provided to assist in interpretation and to confirm if CNVs represented de novo events.

Conifer workflow

Conifer⁴ [\(http://conifer.sourceforge.net/\)](http://conifer.sourceforge.net/) uses singular value decomposition (SVD) to identify rare CNVs from exome sequencing data. Samples with similar read lengths were analysed in the same batch, and sex-specific sample pools were created to generate accurate X-Chromosome calls. Reads Per Kilobase per Million mapped reads (RPKM) values were calculated independently by enrichment kit for all corresponding targets. Following SVD to identify biases in coverage introduced by batch effects, 3–15 components were removed from each group based on manual inspection of the inflection points of scree plots generated by the programme.

Within each analysis batch, if all experiments had <30 calls, the results were considered ready for further filtering. On the contrary, where any experiment in a batch had more than 30 calls, then if the median number of calls per experiment in the batch was less than 10, any experiment with more than 30 calls was discarded as failing QC, and the results from the remaining experiments were considered ready for filtering. However, if the median number of calls within the batch was more than 10 per experiment, then the SVD value was increased, and the batch analysis was rerun, until either all experiments had <30 calls or the median number of calls was <10, at which point any experiment with more than 30 calls was discarded as described

above. CNVs with an SVD-ZRPKM value >1.75 or less than −1.75 were considered bona fide duplication or deletion calls, respectively, worthy of biological interpretation. Conifer does not provide any guidance as to the exact copy number identified at a particular locus and provides no further indicators of the quality of a detected event other than the SVD-RPKM metric.

ExomeDepth workflow

ExomeDepth⁶ applies a beta-binomial model to the genome-wide distribution of read-depth data, aiming to compare a test sample to a similar reference set selected by the tool. For the implementation of the Exome-Depth workflow, the generation of read count data was separated from that of identifying candidate CNVs. Thus, for each experiment, read depth was initially calculated for all targets of the respective capture kit and stored as a Bioconductor iRanges object^{44,[45](#page-19-0),51}. In the second step, all iRanges objects from experiments generated using the same enrichment kit were analysed as a batch to generate raw CNV call sets. In this second step, ExomeDepth automatically identifies an independent background reference set for each test sample by selecting the most closely correlated samples in terms of coverage from within the batch. Copy-number prediction is provided by the ratio of observed/expected reads over a set of targets. We interpreted these ratios in diploid chromosomes as follows:

- O/E ratio <0.10—likely homozygous deletion i.e. copy number $(CN) = 0$
- $0.10 < O/E$ ratio < 0.75—likely heterozygous deletion; CN = 1
- $0.75 < O/E$ ratio <1.25—likely copy number neutral; CN = 2, i.e. No CNV to report
- $1.25 < O/E$ ratio <1.75—likely heterozygous duplication; CN = 3
- $1.75 < O/E$ ratio $< 2.25 CN = 4$
- O/E ratio >2.25—CN OTHER

ExomeDepth provides two indicators of quality. The first is a samplelevel indicator of the correlation between the test sample and the background reference, which should be >0.97 for the results to be regarded as reliable. Secondly, regarding call quality, ExomeDepth provides a Bayes factor (BF) based on the ratio of observed/expected reads over a set of apparently copy-number variant targets. Experiments with a correlation <0.97 were considered failing QC, and any calls with a BF < 0.15 were discarded as being unreliable.

CNV classes

To aid downstream interpretation, each CNV call was categorised into one of six classes.

- 1. Putative CNVs longer than 500 kb in length were initially identified regardless of the presence or absence of genes of interest in the ERN gene lists. The recent release of large CNVs catalogues, such as DECIPHER, as well as the presence of a large number of case reports with chromosomal changes of this size and larger, allowed us to hypothesise that such variants could be interpreted successfully, even if the reported phenotypes of the patients exhibiting such variants may differ from the phenotypes expected for affected genes.
- 2. Homozygous deletions are generally rare, and the presence of a homozygous deletion needs to be interpreted very cautiously due to potentially incorrect enrichment kit reporting, or poor-quality library preparation. An important indicator that a putative homozygous deletion call is likely to be bona fide is the consanguinity status of the patient.
- 3. Heterozygous CNVs occurring in genes with a described autosomaldominant mode of inheritance reported in OMIM.
- 4. Duplications with apparent copy number > 3. These may represent cases where alleles on both chromosomes are duplicated or cases where only the allele on one chromosome has been duplicated multiple times.
- 5. Gonosomal CNVs: As gonosomal CNVs require a mixed workflow depending on the sex of the participant, a separate set of calls was generated for CNV calls on chromosomes X and Y. In the case of the Y-

Chromosome, only "Long"CNVs that would fall into category 1 above were reported for interpretation since there were no genes of interest on the Y-Chromosome on any of the ERN gene lists.

6. Potential compound heterozygote SNV/CNV "double-hits". For a short list of experiments in which a single candidate SNV had been identified by the Solve-RD SNV working group, which was either listed in ClinVar as Pathogenic/Likely Pathogenic or predicted to have a high impact in a gene of interest, affecting an individual where the mode of inheritance was suspected to be recessive, (see Laurie et al.¹⁹) we investigated whether a potentially pathogenic CNV affecting the second allele of the same gene could explain the case as a compound heterozygote.

Call filtering and visualisation

As the focus of Solve-RD is diagnosing RD cases, through the identification of rare variants that are potentially disease-causing, any apparent CNV call observed in a region where more than 1% of individuals in the whole sample had a similar type of call (i.e. a deletion or duplication) were discarded as being too common to be clinically relevant with respect to RD. Furthermore, CNVs returned for interpretation by clinical experts were restricted to those that overlapped with at least part of a gene in a predefined list of curated genes of interest provided by the respective ERN: EURO-NMD $(n = 615)$, GENTURIS (230), ITHACA (1944), RND (1820). The full list of ERN curated genes is provided in Supplementary Table 1, and details as to how these lists were determined is described in Laurie et al.^{[19](#page-18-0)}. Potential CNVs of interest were subsequently categorised into six nonredundant classes to aid interpretation: Long CNVs (>500 kb in length); Homozygous deletions; Heterozygous CNVs affecting genes known to cause disorders with an autosomal dominant mode of inheritance; Regions with apparent copy numbers of four or more; Gonosomal CNVs; Potential compound-heterozygous double-hits in the form of a CNV affecting the second allele of a gene in which biallelic variants are known to be disease-causing, and in which a potentially pathogenic SNV has been previously identified in Solve-RD. For each class, we gave recommendations for interpretation; for example, computationally detected consanguinity status was used for prioritising small homozygous deletions (<500 bp) and small regions with copy number four or more, which would otherwise have been filtered due to the minimum size threshold.

To provide support for interpretation of the technical validity of CNV calls, screenshots for regions containing CNV calls were generated automatically using the Integrative Genomics Viewer^{[48](#page-19-0)} (IGV), incorporating a variety of custom-built tracks (see Fig. [5](#page-16-0)). These included call tracks for each of the three callers in SEG format, normalised coverage tracks for ClinCNV and Conifer, beta-allele frequency, BAM DoC, Institute of Medical Genetics and Applied Genomics (Tübingen) inhouse polymorphic CNV regions, and gene tracks from RefSeq genes, ERN candidate genes, and DECIPHER microdeletion and duplication syndromes^{[52](#page-19-0)}.

For each CNV returned for interpretation, we generated IGV screenshots of both the whole sample (chr1-22 and chrX/Y) to allow evaluation of overall sample quality, and the region around the individual CNV (±10 kb). Specifically in the case of long CNVs, the observation of clear deviations from the expected ratio of 50/50 in beta-allele frequencies provided strong additional support of variant validity. For rare cases in which a signal of unusual read pairing was observed, suggesting that a breakpoint may have been captured, a screenshot was generated, including the suspected breakpoint.

Clinical interpretation

Further annotations to aid interpretation (Supplementary Table 2) were added to the results using AnnotS $V⁵³$ (Version 3.0.7), and fully annotated CNV call sets generated for all tools together with accompanying customised IGV visualisations were distributed to clinical experts in each ERN for

diagnostic interpretation. Some annotations, such as that of the ENCODE blacklist for high-signal regions, were used to quickly discard overlapping CNVs by all ERNs, whereas other information, such as evidence of consanguinity, provided further support that homozygous deletions were likely to be relevant in affected cases. For the interpretation of heterozygous deletions, pLI scores from G nom $AD⁵⁴$ and haploinsufficiency gene lists from the DDD project⁵⁵, aided interpretation. Each ERN prioritised calls for further investigation based on their expert knowledge of underlying disease mechanisms in their respective patients. The full workflow is illustrated in Fig. [6](#page-17-0). On average the clinical experts spent 5 min on interpretation per CNV with less than two CNVs of interest on average per sample. Many CNV calls could be rapidly discarded based upon a lack of match between the gene potentially affected and the phenotype of the affected individual, and/or segregation patterns within the family. Others were rejected when visual inspection of the IGV tracks indicated that they were likely falsepositive calls, and thus unlikely to be bona fide biological events. Where deemed necessary and when feasible, CNVs believed to be diagnostically relevant were validated at local centres using orthologous approaches. The

OD2 CTRL ESRP2 ZFP90 CDH1 $HAS3$ PDF NFAT5 WWP2 POBINDS. d GENTURIS: Inherited heterozygous deletion affecting CDH1 and TANGO6, resulting in autosomal dominant HDGC. Images show customised coverage tracks and the position of the identified CNV (red bar). Blue dots above the midline indicate elevated coverage, while red dots below the line indicate reduced coverage. The position of genes is indicated at the bottom of the image, while the chromosomal position is indicated at the top of the image.

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final decision as to whether a CNV was determined to be pathogenic or not was taken by the respective clinical experts from the ERN (see below for further details).

The filtering strategy of ERN EURO-NMD

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The filtering strategy undertaken by EURO-NMD was determined per analysis (see the section"Callfiltering and visualisation" above). In general, a balance had to be upheld whereby clinical researchers would interpret as many CNVs as possible while maintaining a feasible interpretation load. Thus the following analyses were shared directly given the relative number of CNVs to be analysed: homozygous deletions, high copy number duplications, gonosomal CNVs, and potential compound heterozygote second hits, whereas heterozygous CNVs were split between CNVs of copy number one (CN1, i.e. deletions) and those of copy number three (CN3 i.e. duplications).

For CN1, CNVs for genes with DDD Haploinsuffiency scores > 90 or a GnomAD pLi < 0.1 were discarded, as these indicate that the gene is likely tolerant of heterozygous deletions. For both CN1 and CN3, CNVs identified

returning calls to clinical experts for interpretation. The first line shows the preprocessing generation of coverage profiles for each experiment, prior to these

collation of CNVs of diferent types which were then annotatd and filtered appropriately before being passed to the respective ERNs for prioritisation.

through ClinCNV with a log likelihood <30 were discarded, as these are likely false positives. CNVs identified in genes only known to have recessive inheritance patterns were discarded, as were CNVs reported in Conrad et al.⁵⁶. For long CNVs, CNVs found in the Encode blacklist were discarded. Following these filtering steps, experts from the submitting groups applied a phenotype-first approach. If the phenotype could potentially match with the gene affected by the CNV call, IGV tracks were checked to evaluate the likelihood of the called CNV being a true CNV.

The filtering strategy of ERN GENTURIS

Due to the small size of the ERN GENTURIS cohort, and the short gene list, only limited further filtering of calls was necessary. No additional filters were applied to call sets from Conifer. In the case of heterozygote deletions and duplications, specific filtering criteria were applied separately for ClinCNV and ExomeDepth. For ClinCNV, we first interpreted all events identified by more than one tool, independent of the ClinCNV log likelihood value. After this, we proceeded to analyse all events called only by ClinCNV with a log likelihood of at least 20. For ExomeDepth, we first interpreted all events called by more than one tool, independently of the Bayes factor (BF), and subsequently considered events called only by ExomeDepth with a BF of at least 15. For long CNVs, we first discarded all those events found in the encode blacklist and analysed the rest. For all datasets, following IGV

visualisation, only CNVs observed to be rare in control populations were considered for further interpretation.

The filtering strategy of ERN ITHACA

For ERN ITHACA, as a first step, we discarded variants that were annotated to have low QC, had been previously annotated as benign, or occurred in regions on the Encode Blacklist, as provided by the AnnotSV annotation. Additionally, to reduce the proportion of false positives, we discarded deletions shorter than 10 kb and duplications shorter than 20 kb in length, with the exception of homozygous deletion calls and variants in parent-offspring trios identified as being de novo by ClinCNV. Following this, a visual inspection of each of the remaining CNV calls in IGV images was undertaken to assess technical validity, using reads and coverage supporting the call and B-allele frequency. Based on this visual assessment, apparently, real biological CNVs were defined. For detailed clinical interpretation, prioritisation was subsequently guided by genes present on the ERN ITHACA gene list with a disease-association validity score ≥ 3 , see Laurie et al.^{[19](#page-18-0)}, consistent with the expected mode of inheritance. Of note, CNVs ≥200 kb were also investigated regardless of the presence or absence of a gene on the ERN ITHACA gene list, given the prior knowledge of large CNVs being involved in ITHACA-associated phenotypes. All CNVs passing the above criteria were returned to the submitting groups from ERN-ITHACA, for diagnostic interpretation based on the clinical relevance to the phenotype observed in the affected individual.

The filtering strategy of ERN RND

The filtering strategy of ERN RND was predominantly based on toolspecific metrics. In general, the goal was to exclude calls with a high likelihood of being false positives. For ClinCNV, we discarded all calls with a log likelihood <30 and fist prioritised calls with a log likelihood > 200. As Conifer provides no metrics for filtering, all Conifer calls were analysed. For ExomeDepth, we discarded all calls affecting less than three targets and those with a Bayes factor <30, unless there was an overlapping CNV identified by one of the other tools. Following these filtering steps, the clinical researchers who submitted the case applied a phenotype-first approach. If the phenotype could potentially match that of the called CNV, IGV tracks were checked visually to evaluate the likelihood that the called CNV was bona fide.

Data availability

All raw and processed data files are deposited at the EGA (Datasets EGAD00001009767, EGAD00001009768, EGAD00001009769, and EGAD00001009770, under Solve-RD study EGAS00001003851) and can be made available upon approval by the Data Access Committee (EGAC00001001319). The family (FAM) and participant (P) identifiers used in this manuscript are pseudonymized and known only to the researchers involved In Solve-RD.

Code availability

All the software tools used in this paper are open-source and freely available online at <https://github.com/imgag/ClinCNV> (ClinCNV 1.16.6), [https://](https://github.com/vplagnol/ExomeDepth) github.com/vplagnol/ExomeDepth (ExomeDepth 1.1.15), [https://conifer.](https://conifer.sourceforge.net/) [sourceforge.net/](https://conifer.sourceforge.net/) (CoNIFER 0.2.2), <https://github.com/lgmgeo/AnnotSV> (AnnotSV v.3.0.7). Genome-Phenome Analysis Platform used for the metadata collection is available on <https://platform.rd-connect.eu/>.

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References

- 1. Nguengang Wakap, S. et al. Estimating cumulative point prevalence of rare diseases: analysis of the Orphanet database. Eur. J. Hum. Genet. 28, 165–173 (2020).
- 2. European Commission. EU Research on Rare Diseases [https://](https://research-and-innovation.ec.europa.eu/research-area/health/rare-diseases_en) [research-and-innovation.ec.europa.eu/research-area/health/rare](https://research-and-innovation.ec.europa.eu/research-area/health/rare-diseases_en)[diseases_en](https://research-and-innovation.ec.europa.eu/research-area/health/rare-diseases_en) (2023).
- 3. Poplin, R. et al. Scaling accurate genetic variant discovery to tens of thousands of samples. Preprint at bioRxiv [https://doi.org/10.1101/](https://doi.org/10.1101/201178) [201178](https://doi.org/10.1101/201178) (2018).
- 4. Krumm, N. et al. Copy number variation detection and genotyping from exome sequence data. Genome Res. 22, 1525–1532 (2012).
- 5. Li, J. et al. CONTRA: copy number analysis for targeted resequencing. Bioinformatics 28, 1307–1313 (2012).
- 6. Plagnol, V. et al. A robust model for read count data in exome sequencing experiments and implications for copy number variant calling. Bioinformatics 28, 2747–2754 (2012).
- 7. Backenroth, D. et al. CANOES: detecting rare copy number variants from whole exome sequencing data. Nucleic Acids Res. 42, e97–e97 (2014).
- 8. Fromer, M. & Purcell, S. M. Using XHMM software to detect copy number variation in whole-exome sequencing data. Curr. Protoc. Hum. Genet. 81, 7.23.1–7.23.21 (2014).
- 9. Demidov, G., Sturm, M. & Ossowski, S. ClinCNV: multi-sample germline CNV detection in NGS data. Preprint at bioRxiv [https://doi.](https://doi.org/10.1101/2022.06.10.495642) [org/10.1101/2022.06.10.495642](https://doi.org/10.1101/2022.06.10.495642) (2022).
- 10. Yaldiz, B. et al. Twist exome capture allows for lower average sequence coverage in clinical exome sequencing. Hum. Genom 17, 39 (2023).
- 11. Gordeeva, V. et al. Benchmarking germline CNV calling tools from exome sequencing data. Sci. Rep. 11, 14416 (2021).
- 12. Tan, R. et al. An evaluation of copy number variation detection tools from whole-exome sequencing data. Hum. Mutat. 35, 899-907 (2014).
- 13. Yao, R. et al. Evaluation of three read-depth based CNV detection tools using whole-exome sequencing data. Mol. Cytogenet. 10, 1–7 (2017).
- 14. Zhao, L., Liu, H., Yuan, X., Gao, K. & Duan, J. Comparative study of whole exome sequencing-based copy number variation detection tools. BMC Bioinform. 21, 1–10 (2020).
- 15. Srivastava, S. et al. Meta-analysis and multidisciplinary consensus statement: exome sequencing is a first-tier clinical diagnostic test for individuals with neurodevelopmental disorders. Genet. Med. 21, 2413–2421 (2019).
- 16. Martinez-Granero, F. et al. Comparison of the diagnostic yield of aCGH and genome-wide sequencing across different neurodevelopmental disorders. NPJ Genom. Med. 6, 25 (2021).
- 17. Royer-Bertrand, B. et al. CNV detection from exome sequencing data in routine diagnostics of rare genetic disorders: opportunities and limitations. Genes 12, 1427 (2021).
- 18. Zurek, B. et al. Solve-RD: systematic pan-European data sharing and collaborative analysis to solve rare diseases. Eur. J. Hum. Genet. 29, 1325–1331 (2021).
- 19. Laurie et al. Genomic Reanalysis of a Pan-European Rare Disease Resource Yields >500 New Diagnoses. Nat. Med. (2024). (in press).
- 20. Cheng, H. et al. Truncating variants in NAA15 are associated with variable levels of intellectual disability, autism spectrum disorder, and congenital anomalies. Am. J. Hum. Genet. 102, 985–994 (2018).
- 21. Guilford, P. et al. E-cadherin germline mutations in familial gastric cancer. Nature 392, 402–405 (1998).
- 22. Oliveira, C. et al. Germline CDH1 deletions in hereditary diffuse gastric cancer families. Hum. Mol. Genet. 18, 1545–1555 (2009).
- 23. Fewings, E. et al. Germline pathogenic variants in PALB2 and other cancer-predisposing genes in families with hereditary diffuse gastric cancer without CDH1 mutation: a whole-exome sequencing study. Lancet Gastroenterol. Hepatol. 3, 489-498 (2018).
- 24. Pfundt, R. et al. Detection of clinically relevant copy-number variants by exome sequencing in a large cohort of genetic disorders. Genet. Med. 19, 667–675 (2016).
- 25. São José, C. et al. Combined loss of CDH1 and downstream regulatory sequences drive early-onset diffuse gastric cancer and increase penetrance of hereditary diffuse gastric cancer. Gastric Cancer <https://doi.org/10.1007/s10120-023-01395-0> (2023).
- 26. Poirier, K. et al. CSNK2B splice site mutations in patients cause intellectual disability with or without myoclonic epilepsy. Hum. Mutat. 38, 932–941 (2017).
- 27. Li, J. et al. Germline de novo variants in CSNK2B in Chinese patients with epilepsy. Sci. Rep. 9, 17909 (2019).
- 28. Nakashima, M. et al. Identification of de novo CSNK2A1 and CSNK2B variants in cases of global developmental delay with seizures. J. Hum. Genet. 64, 313–322 (2019).
- 29. Stessman, H. A. F. et al. Targeted sequencing identifies 91 neurodevelopmental-disorder risk genes with autism and developmental-disability biases. Nat. Genet. 49, 515–526 (2017).
- 30. Dong, X. et al. Clinical exome sequencing as the first-tier test for diagnosing developmental disorders covering both CNV and SNV: a Chinese cohort Diagnostics. J. Med. Genet. 57, 558–566 (2020).
- 31. Zhai, Y., Zhang, Z., Shi, P., Martin, D. M. & Kong, | Xiangdong. Incorporation of exome-based CNV analysis makes trio-WES a more

powerful tool for clinical diagnosis in neurodevelopmental disorders: a retrospective study. Hum. Mutat. 42, 990–1004 (2021).

- 32. Pennings, M. et al. Copy number variants from 4800 exomes contribute to ~7% of genetic diagnoses in movement disorders, muscle disorders and neuropathies. Eur. J. Hum. Genet. 31, 654–662 (2023).
- 33. Bullich, G. et al. Systematic collaborative reanalysis of genomic data improves diagnostic yield in neurologic rare diseases. J. Mol. Diagn. 24, 529–542 (2022).
- 34. Marchukid, D. S. et al. Increasing the diagnostic yield of exome sequencing by copy number variant analysis. PLoS ONE 13, e0209185 (2018).
- 35. McInnes, L., Healy, J. & Melville, J. UMAP: uniform manifold approximation and projection for dimension reduction. arXiv:1802.03426 (2018).
- 36. Riggs, E. R. et al. Technical standards for the interpretation and reporting of constitutional copy-number variants: a joint consensus recommendation of the American College of Medical Genetics and Genomics (ACMG) and the Clinical Genome Resource (ClinGen). Genet. Med. 22, 245–257 (2020).
- 37. Posey, J. E. et al. Resolution of disease phenotypes resulting from multilocus genomic variation. New Engl. J. Med. 376, 21–31 (2017).
- 38. Bentley, J. L. & Chan, P. Programming Pearls (Addison-Wesley, 1989).
- 39. Musacchia, F. et al. VarGenius-HZD allows accurate detection of rare homozygous or hemizygous deletions in targeted sequencing leveraging breadth of coverage. Genes (Basel) 12, 197 (2021).
- 40. Marshall, D. A. et al. The value of diagnostic testing for parents of children with rare genetic diseases. Genet. Med. 21, 2798–2806 (2019).
- 41. Laurie, S. et al. The RD-Connect Genome-Phenome Analysis Platform: accelerating diagnosis, research, and gene discovery for rare diseases. Hum. Mutat. 43, 717–733 (2022).
- 42. Köhler, S. et al. The human phenotype ontology in 2021. Nucleic Acids Res. 49, D1207–D1217 (2021).
- 43. Amberger, J. S., Bocchini, C. A., Scott, A. F. & Hamosh, A. OMIM.org: leveraging knowledge across phenotype-gene relationships. Nucleic Acids Res. 47, D1038–D1043 (2019).
- 44. Auton, A. et al. A global reference for human genetic variation. Nature 526, 68–74 (2015).
- 45. Li, H. Aligning sequence reads, clone sequences and assembly contigs with BWA-MEM. arXiv Prepr. arXiv 00, 3 (2013).
- 46. Parrish, A. et al. An enhanced method for targeted next generation sequencing copy number variant detection using ExomeDepth. Wellcome Open Res. 2, 49 (2017).
- 47. Demidov, G. Methods for Detection of Germline and Somatic Copynumber Variants in Next Generation Sequencing Data (Universitat Pompeu Fabra, 2019).
- 48. Robinson, J. T., Thorvaldsdóttir, H., Wenger, A. M., Zehir, A. & Mesirov, J. P. Variant review with the integrative genomics viewer. Cancer Res. 77, e31–e34 (2017).
- 49. Hahsler, M., Piekenbrock, M. & Doran, D. dbscan: fast density-based clustering with R. J. Stat. Softw. 91, 1-30 (2019).
- 50. Olshen, A. B., Venkatraman, E. S., Lucito, R. & Wigler, M. Circular binary segmentation for the analysis of array‐based DNA copy number data. Biostatistics 5, 557–572 (2004).
- 51. Lawrence, M. et al. Software for computing and annotating genomic ranges. PLoS Comput. Biol. 9, e1003118 (2013).
- 52. Firth, H. V. et al. DECIPHER: database of chromosomal imbalance and phenotype in humans using ensembl resources. Am. J. Hum. Genet. 84, 524–533 (2009).
- 53. Geoffroy, V. et al. AnnotSV: an integrated tool for structural variations annotation. Bioinformatics 34, 3572–3574 (2018).
- 54. Karczewski, K. J. et al. The mutational constraint spectrum quantified from variation in 141,456 humans. Nature 581, 434–443 (2020).
- 55. Huang, N., Lee, I., Marcotte, E. M. & Hurles, M. E. Characterising and predicting haploinsufficiency in the human genome. PLoS Genet. 6, e1001154–e1001154 (2010).
- 56. Conrad, D. F. et al. Origins and functional impact of copy number variation in the human genome. Nature 464, 704–712 (2010).

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