Semantic Similarity Analysis Reveals Robust Gene-Disease Relationships in Developmental and Epileptic Encephalopathies

Peter D. Galer,1,2,3,14 Shiva Ganesan,1,2,3,14 David Lewis-Smith,4,5 Sarah E. McKeown,1,2 Manuela Pendziwiat,6 Katherine L. Helbig,1,2,3 Colin A. Ellis,2,7 Annika Rademacher,6 Lacey Smith,8 Annapurna Poduri,8,9 Simone Seiffert,10 Sarah von Spiczak,6,11 Hiltrud Muhle,6 Andreas van Baalen,6 NCEE Study Group, EPGP Investigators, EuroEPINOMICS-RES Consortium, Genomics Research and Innovation Network, Rhys H. Thomas,4,5 Roland Krause,12 Yvonne Weber,10,13 and Ingo Helbig1,2,3,7,*

Summary

More than 100 genetic etiologies have been identified in developmental and epileptic encephalopathies (DEEs), but correlating genetic findings with clinical features at scale has remained a hurdle because of a lack of frameworks for analyzing heterogeneous clinical data. Here, we analyzed 31,742 Human Phenotype Ontology (HPO) terms in 846 individuals with existing whole-exome trio data and assessed associated clinical features and phenotypic relatedness by using HPO-based semantic similarity analysis for individuals with de novo variants in the same gene. Gene-specific phenotypic signatures included associations of SCN1A with “complex febrile seizures” (HP: 0011172; p = 2.1 × 10−5) and “focal clonic seizures” (HP: 0002266; p = 8.9 × 10−6), STXBP1 with “absent speech” (HP: 0001344; p = 1.3 × 10−11), and SLC6A1 with “EEG with generalized slow activity” (HP: 0010845; p = 0.018). Of 41 genes with de novo variants in two or more individuals, 11 genes showed significant phenotypic similarity, including SCN1A (n = 16, p < 0.0001), STXBP1 (n = 14, p = 0.0021), and KCNIB (n = 6, p = 0.011). Including genetic and phenotypic data of control subjects increased phenotypic similarity for all genetic etiologies, whereas the probability of observing de novo variants decreased, emphasizing the conceptual differences between semantic similarity analysis and approaches based on the expected number of de novo events. We demonstrate that HPO-based phenotype analysis captures unique profiles for distinct genetic etiologies, reflecting the breadth of the phenotypic spectrum in genetic epilepsies. Semantic similarity can be used to generate statistical evidence for disease causation analogous to the traditional approach of primarily defining disease entities through similar clinical features.

Introduction

In 1954, Dr. Andreas Rett, a pediatrician in Vienna, Austria, noticed two girls with unusual repetitive hand-washing motions in his waiting room. Rett concluded that these unusual features may be the presentation of a new disease entity and subsequently identified additional girls with similar features and related developmental trajectories. This initial observation laid the foundation for recognizing a neurodevelopmental disorder that came to bear Dr. Rett’s name.1,2 In 1999, MECP2 (MIM: 300005) was eventually discovered as the causative genetic etiology for Rett syndrome (MIM: 312750), which is thought to affect 1 in 10,000 girls worldwide.3–5 Similar observations on related clinical features led to discoveries of other genetic neurodevelopmental disorders and childhood developmental and epileptic encephalopathies, including Dravet syndrome (MIM: 607208) and epilepsy of infancy with migrating focal seizures (MIM: 614959).5,7

Although the syndrome-based approach is the time-proven, established method of defining disease entities in the epilepsies, it has several shortcomings that are particularly relevant in the era of large-scale genomics.3,9 First, the recognition of clinical symptoms is often fortuitous, depending on individuals with shared features to be seen by the same clinician or at the same center. Second, only a subset of clinical syndromes is linked to unique genetic etiologies, whereas many clinical entities, such as infantile spasms or Lennox-Gastaut syndrome, are associated with a wide range of underlying genetic causes.10–16 Third, the recognition, documentation, and comparison of clinical features is a manual, non-scalable process requiring significant human resources in contrast to the industrial scale of massive parallel sequencing that

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1Division of Neurology, Children’s Hospital of Philadelphia, Philadelphia, PA 19104, USA; 2The Epilepsy NeuroGenetics Initiative (ENGIN), Children’s Hospital of Pennsylvania, Philadelphia, PA 19104, USA; 3Department of Biomedical and Health Informatics (DBHi), Children’s Hospital of Philadelphia, Philadelphia, PA 19146, USA; 4Translational and Clinical Research Institute, Newcastle University, Newcastle-upon-Tyne NE1 7RU, UK; 5Royal Victoria Infirmary, Newcastle-upon-Tyne NE1 4LP, UK; 6Department of Neuropediatrics, Christian-Albrechts-University of Kiel, 24105 Kiel, Germany; 7Department of Neurology, University of Pennsylvania, Philadelphia, PA 19104, USA; 8Epilepsy Genetics Program, Department of Neurology, Boston Children’s Hospital, Boston, MA 02115, USA; 9Department of Neurology, Harvard Medical School, Boston, MA 02115, USA; 10Department of Neurology and Epileptology, Hertie Institute for Clinical Brain Research, University of Tübingen, 72076 Tübingen, Germany; 11DKR-Northern German Epilepsy Centre for Children and Adolescents, 24223 Schwentinental-Raisdorf, Germany; 12Luxembourg Centre for Systems Biomedicine, University of Luxembourg, 4367 Belvaux, Luxembourg; 13Department of Epileptology and Neurology, University of Aachen, 52074 Aachen, Germany
14These authors contributed equally to this work
*Correspondence: helbigi@email.chop.edu
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can be performed on DNA from tens of thousands of individuals.\textsuperscript{17}

Large collaborative studies that are designed primarily for genetic discovery also collect descriptive clinical data, and these phenotypic data can be exploited for clinical discovery.\textsuperscript{18,19} Following the logic of primarily defining disease entities through shared clinical features, we reasoned that applying computational algorithms to available phenotype datasets might detect disease entities by identifying individuals with rare, overlapping phenotypic features that share the same genetic etiology. However, phenotype data is typically sparse and unstructured, which impedes the comparison of clinical features between individuals.

The Human Phenotype Ontology (HPO) is a standardized biomedical representation of the semantic relationships among over 14,000 phenotypic terms with defined relationships, enabling the mapping of heterogeneous clinical features to a common framework.\textsuperscript{20–22} Consequently, the value of a phenotypic feature can be weighted on the basis of its position in the ontological tree and frequency in the overall cohort. We and others have previously developed algorithms to identify individuals with significant phenotypic similarities on the basis of HPO terms within patient cohorts.\textsuperscript{18,23}

Here, we translated clinical findings in 846 individuals with developmental and epileptic encephalopathies (DEEs) with available trio whole-exome data to 31,742 HPO terms. We then assessed whether individuals with \textit{de novo} variants in the same genetic etiology had phenotypic features that were more similar than expected by chance and identified 11 genetic etiologies with significant phenotypic similarity. Our results demonstrate that phenotype data in HPO format represents a valuable resource in providing statistical evidence in gene-disease relationships and reconstructs meaningful disease patterns from sparse clinical data.

\section*{Material and Methods}

\subsection*{Participant Recruitment}

Clinical and phenotypic data included in this study were derived through local studies and data obtained through dbGaP (dbGaP Study Accession: phs000653.v1.p1, n = 335). For local cohorts, informed consent for participation in this study was obtained from parents of all probands in agreement with the Declaration of Helsinki and completed per protocol with local approval by the respective institutional review boards (IRBs). These cohorts included individuals from the EuroEPINOMICS-RES cohort (RES, n = 319), Epi4K cohort (EPG, n = 335), and a cohort of individuals recruited through the Epilepsy Genetics Research Project at the Children’s Hospital of Philadelphia (EGRP, n = 192). A subcohort of 320 individuals from the RES and EGRP populations were included in a previous study.\textsuperscript{18} Phenotypes for these cohorts were collected through standardized phenotyping and questionnaires to physicians and healthcare providers. Description of the recruitment and phenotyping of the Epi4K dbGaP cohort (phs000653.v1.p1) has been reported previously.\textsuperscript{14,25}

\subsection*{Translation to HPO Terms, Information Content (IC)}

For the various phenotyping forms and databases provided for the individuals included in this project, we manually generated dictionaries to map phenotyping terms to HPO terms (HPO version 1.2; release format-version: 1.2; data-version: releases/2019-11-08; downloaded on 1/23/20). The phenotype of each individual from the EGRP dataset was manually coded by expert reviewers. Phenotypes were first extracted by research staff with clinical and biomedical knowledge and experience with the HPO by using all available clinical and research notes for an individual and by using the most specific HPO terms applicable. These assigned terms were then reviewed and verified by domain experts in the field of epilepsy, i.e., either epilepsy genetic counselors or specialist physicians. In cases of ambiguity and uncertainty, the higher level HPO term was coded (e.g., if autism spectrum disorder was not clearly diagnosed but mentioned, we assigned the higher level “autistic behavior” [HP: 0000729]).

For each individual, all higher-level (ancestral) HPO terms were derived, followed by de-duplication of HPO terms for each individual. We refer to this method as “propagation,” resulting in a base and propagated set of HPO terms for each individual. The propagated HPO dataset from the entire cohort was used to generate baseline frequencies \( f \) for all HPO terms. Information content (IC) of each term was defined as the \(-\log_2(f)\) with a higher IC value, reflecting a more specific and less frequently encountered HPO term in the cohort. In the current manuscript, we use a compact internationalized resource identifier (CURIE) to refer to HPO terms, i.e., “HP: 0001250” (“seizures”) abbreviates “https://hpo.jax.org/app/browse/term/HP:0001250” in accordance with the Open Biological and Biomedical Ontologies (OBO) Citation and Attribution Policy.

\subsection*{Genetic Analysis}

Trio-based whole-exome sequencing was performed as previously described,\textsuperscript{18,26} including research sequencing within the EuroEPINOMICS-RES project (n = 335) performed at the Wellcome Trust Sanger Institute (Hinxton, UK) with the Illumina TruSeq DNA Sample Preparation Kit, the Agilent Technologies SureSelect Human All Exon 50 Mb Kit, and the Illumina HiSeq2000 per manufacturer’s protocols.\textsuperscript{11,26,27} Research sequencing at the Institute of Clinical Molecular Biology at the University of Kiel and the Cologne Center for Genomics with NimbleGen SeqCap EZ Human Exome Library v2.0, Nextera Rapid Capture Exome, Nextera Rapid Capture Expanded Exome, Agilent SureSelect Human All Exon V5, and Agilent SureSelect Human All Exon 50 Mb; research sequencing at the Broad Institute with Nextera Rapid Capture Exome kit; sequencing in a diagnostic setting at GeneDx (n = 69) with SureSelect Human All Exon V4 (50Mb) kit; and sequencing at the Division of Genomic Diagnostics at the Children’s Hospital of Philadelphia (n = 49) with SureSelect Clinical Research Exome kits.

All genetic data on individuals included in the overall cohort were re-analyzed via a standardized pipeline as previously described.\textsuperscript{18,26} The Burrows Wheeler Alignment (v 0.7.12) MEM algorithm was used to align the raw data to the HS37d5 human reference genome, and Sambler (v 0.1.20) was used to add mate tags (MC and MQ) to the paired-end lines. Base quality score recalibration (BQSR) was performed with GATK tools (v4.0.0.0), followed by SNP and indel calling via HaplotypeCaller with intervals specific to the exome enrichment kit used for each sample. GVCF files for each trio were combined with PICARD tools.
Phenotypic Similarity Analysis

We used two similarity measures to determine phenotypic similarity (sim score): the previously reported sim\textsubscript{max} algorithm\textsuperscript{18} and a novel sim\textsubscript{cm} algorithm (Figure S1). The sim\textsubscript{max} was used as the primary algorithm for this study. The basic concept of both phenotypic similarity algorithms is the generation of symmetric phenotypic similarity scores between two individuals on the basis of the similarity between the phenotypic concepts represented by their HPO terms. The greater the similarity score, the more similar the individuals' phenotypes. This similarity score of a pair of individuals is derived from the summation of the IC of the most informative common ancestor (MICA) terms of all pairwise comparisons of the base HPO terms of the two individuals.\textsuperscript{29}

\[
\text{sim}_{\text{max}}(P_1, P_2) = \frac{1}{2} \left( \sum_{i=1}^{n} \max_{S \in S_1} S_i + \sum_{j=1}^{n} \max_{S \in S_2} S_j \right).
\]

(Equation 1)

A matrix is formed with the \(n\) base HPO terms, \(i\) of individual \(P_1\) as rows, and the \(n\) base HPO terms, \(j\) of individual \(P_2\) as columns. Each \(S_g\) corresponds to the IC of the MICA of HPO terms \(i\) and \(j\), that is the maximum information content within the set of propagated terms shared by \(i\) and \(j\). In summary, the sim\textsubscript{max} algorithm sums over all rows and columns of a matrix that holds all base HPO terms in individual \(P_1\) (\(n\) terms as rows) and all HPO terms in individual \(P_2\) (\(n\) terms as columns; Equation 1).

The faster sim\textsubscript{cm} algorithm operates on the propagated HPO terms of each individual and determines the intersect of propagated HPO terms between individual \(P_1\) and individual \(P_2\), summing up the IC of all ancestral HPO terms shared by both individuals. All computations were performed with the R Statistical Package.\textsuperscript{30}

Although more computationally costly, this study used sim\textsubscript{max} as the primary similarity measure because this algorithm has been successfully utilized previously.\textsuperscript{18} However, results from both similarity measures are highly correlated (Figure S1).

Expected Phenotypic Similarity Score per Gene

All genetic etiologies with \(de\ novo\) variants in two or more individuals were included in the primary analysis. The expected phenotypic similarity per gene with \(n\) individuals was determined by comparing distribution of the median similarities of \(n\) individuals that were randomly selected with 100,000 permutations from the overall cohort, resulting in an exact \(p\) value via the comparison of observed versus expected phenotypic similarity. For example, only 10 out of 100,000 permutations of 16 randomly selected individuals showed a median sim score that was greater than or equal to the observed median phenotypic similarity in the 16 individuals with \(de\ novo\) variants in SCN1A (MMR: 182:389), resulting in an exact \(p\) value of \(<1.0 \times 10^{-5}\) for SCN1A (median sim score = 17.69).

Phenograms and Analysis of Gene-Specific Phenotypic Signals

For each genetic etiology, the frequency of all assigned and derived (propagated) HPO terms in patients was identified and compared to the frequency in individuals without the genetic etiology deriving a \(p\) value via Fisher’s tests. We refer to the display of these frequencies as “phenograms,” which provide a visual intuition of the phenotypic spectrum of each disease. Phenograms were generated for all genes included in the analysis. We compiled \(p\) values by comparing the observed versus expected contribution for all HPO terms across all genes.

Assessment of Positive Predictive Value of HPO Term Combinations

In order assess the predictive power of the combination of HPO terms for the presence of a specific genetic etiology, we selected HPO terms associated with each genetic etiology that were more frequent in gene-positive individuals compared to gene-negative individuals by using the propagated HPO dataset. “Gene-positive individuals” refers to individuals with \(de\ novo\) variants in a given genetic etiology, whereas “gene-negative individuals” refers to individuals without \(de\ novo\) variants in a given genetic etiology. We then selected HPOs present in at least 10% of individuals of gene-negative individuals to prevent the effect of very rare HPO terms. We then used HPO term frequency in gene-positive and gene-negative individuals to assess the combined frequency of \(n\) HPO terms. For example, if three HPO terms have a frequency of 0.9, 0.85, and 0.7, the combined frequency would be 0.9 \(\times 0.85 \times 0.7 = 0.54\). Ranking HPO terms by strength of association with a given genetic etiology, we then assessed the positive predictive value (PPV) of the combination of HPO terms when successively including additional HPO terms. We used this method to determine the number of HPO terms needed for a PPV of 0.8.

Results

Phenotypic Information Translated to HPO Is Sparse with a Wide Range of Phenotypic Depth

After translation to HPO terms, the 846 individuals included in the study were coded with a total of 31,742 HPO terms, including 1,616 unique HPO terms. The overall number of HPO terms differed widely between individuals, ranging from 12 terms to 181 terms with a median of 30 terms per individual. The cohorts included in the study showed significant differences: the Epi4K cohort (median of 22 terms) demonstrated a lower number of HPO terms per individual than the remaining cohort (median of 38 terms). The distribution of HPO terms in the cohort was sparse: only 29 terms were present in 100 or more
individuals (Figure 1). “Seizures” (HP: 0001250), “infantile spasms” (HP: 0012469), and “hypsarrhythmia” (HP: 0002521) were the most common explicitly assigned HPO terms. Only 15% of all HPO terms were found in two or more individuals, and 50.1% of all HPO terms were only coded in a single individual.

Propagation of HPO Terms Enables an Accurate Assessment of Term Frequencies

Because HPO terms are interrelated within the tree-like structure of the HPO, assessing the baseline frequency of HPO terms provides a misleading estimate of the general frequencies of disease features in the cohort. For example, the higher-level term “neurodevelopmental abnormality” (HP: 0012759) was coded as an explicit term in only one individual. However, a much greater number of individuals had developmental differences consistent with “neurodevelopmental abnormality” (HP: 0012759) but had been assigned more specific terms. For example, “global developmental delay” (HP: 0001263) was coded in 272 individuals and “intellectual disability” (HP: 0001249) was coded in 62 individuals. We therefore generated the true frequency of all HPO terms by a process we referred to as “propagation.” In brief, for each individual, all higher-level HPO terms were added for the baseline HPO terms assigned to each individual, followed by de-duplication of HPO terms per individual. This method ensures that each individual coded with “global developmental delay” (HP: 0001263) was also coded with all higher-level, less specific ancestral terms, including “neurodevelopmental abnormality” (HP: 0012759) and “abnormality of the nervous system” (HP: 0012638). The propagated HPO terms allow for a meaningful estimate of the frequencies of clinical features in the cohort (Table S4). The frequencies of high-level HPO terms were particularly affected by the propagation (Figure S2), indicating that estimates derived from baseline HPO terms generally underestimate the frequency of higher-level, less specific terms for phenotypic features.

In brief, when we used the propagated HPO terms, 803/846 individuals had seizures (HP: 0001250 and child terms), 227/846 had intellectual disability (HP: 0001249 and child terms), 254/846 had movement disorders or “abnormality of central motor function” (HP: 0011442 and child terms), and 97/846 individuals had autistic behavior (HP: 0000729 and child terms).

Genetic Analysis Identifies 41 Genetic Etiologies Shared by Two or More Individuals

Using a standardized pipeline across all samples for variant calling, annotation, and inheritance models, we identified 41 genetic etiologies with de novo variants in two or more individuals (Table S6). The most common genetic etiologies in our cohort were SCN1A (n = 16), STXBP1 (MIM: 602926) (n = 14), KCNQ2 (MIM: 602235) (n = 9), SCN2A
Figure 2. Overview of Genetic Etiologies and Associations in the Current Study

Overview of the genetic etiologies with de novo variants in the cohort of 846 individuals included in the current study, sorted by significance of phenotypic similarity (p value phenotype). The number of individuals per sub-cohort (cohort), variant type (variant), and broad phenotypes (phenotypes) is shown. The number reflects the number of individuals with a certain feature, and the size and color of a bubble reflects relative frequency within the specific column. The cohort columns list the number of individuals with de novo variants in the EGRP, EPGP/Epi4K, and RES cohorts. The variant column lists the total number of individuals with missense (miss.) and PTV variants.

| Gene   | Cohort (number of individuals) | Phenotype | P-value | DD | Focal | Gen. | P-value phenotype | Miss. | PTV |
|--------|---------------------------------|-----------|---------|----|-------|------|-------------------|-------|-----|
| SCN1A  | EGRP 8, EP 8, RES 8             | 1.36 x 10^-41 | 10      | 11 | 16    | < 10^-5 | 6                 | 10    |
| STXB1  | EGRP 9, EP 5, RES 0             | 1.31 x 10^-41 | 13      | 1  | 6     | 0.00206 | 8                 | 6     |
| SLC6A1 | EGRP 2, EP 0, RES 0             | 1.85 x 10^-5  | 1       | 0  | 2     | 0.00937 | 1                 | 1     |
| AP2M1  | EGRP 2, EP 0, RES 2             | 4.02 x 10^-11 | 4       | 1  | 3     | 0.01026 | 4                 | 0     |
| KCNB1  | EGRP 3, EP 1, RES 2             | 9.12 x 10^-16 | 4       | 4  | 5     | 0.01904 | 5                 | 1     |
| DNM1   | EGRP 2, EP 2, RES 2             | 9.69 x 10^-13 | 4       | 2  | 6     | 0.01347 | 6                 | 0     |
| GABBR2 | EGRP 0, EP 2, RES 2             | 5.54 x 10^-5  | 2       | 2  | 1     | 0.02969 | 2                 | 0     |
| SCN2A  | EGRP 3, EP 3, RES 2             | 3.41 x 10^-19 | 7       | 3  | 6     | 0.03297 | 6                 | 2     |
| CHD2   | EGRP 0, EP 1, RES 3             | 3.57 x 10^-12 | 3       | 1  | 4     | 0.03697 | 0                 | 4     |
| STXB1  | EGRP 1, EP 1, RES 1             | 7.15 x 10^-9  | 2       | 0  | 2     | 0.04076 | 2                 | 1     |
| SCN8A  | EGRP 1, EP 2, RES 1             | 1.54 x 10^-11 | 4       | 4  | 5     | 0.04754 | 5                 | 0     |
| UNC13A | EGRP 2, EP 0, RES 0             | 1.35 x 10^-4  | 2       | 2  | 0     | 0.05727 | 2                 | 0     |
| NEXM1  | EGRP 1, EP 1, RES 1             | 1.13 x 10^-14 | 4       | 1  | 4     | 0.05954 | 0                 | 4     |
| SYNGAP1| EGRP 0, EP 3, RES 0             | 2.48 x 10^-10 | 2       | 0  | 3     | 0.05628 | 2                 | 1     |
| WRD4S  | EGRP 1, EP 1, RES 1             | 1.63 x 10^-11 | 3       | 2  | 2     | 0.10654 | 0                 | 3     |
| GABRB3 | EGRP 1, EP 4, RES 0             | 2.16 x 10^-14 | 4       | 1  | 4     | 0.12113 | 5                 | 0     |
| DHDDS  | EGRP 0, EP 1, RES 0             | 7.25 x 10^-9  | 1       | 0  | 2     | 0.16456 | 2                 | 0     |
| PPP3CA | EGRP 1, EP 1, RES 0             | 1.29 x 10^-5  | 1       | 0  | 2     | 0.18136 | 1                 | 1     |
| CACNA1A| EGRP 1, EP 1, RES 1             | 3.21 x 10^-5  | 2       | 1  | 1     | 0.18190 | 9                 | 0     |
| PCDH19 | EGRP 2, EP 0, RES 0             | 1.03 x 10^-4  | 3       | 2  | 3     | 0.19477 | 2                 | 1     |
| KCNA2  | EGRP 1, EP 0, RES 1             | 9.73 x 10^-6  | 2       | 1  | 2     | 0.22159 | 1                 | 1     |
| GRN1   | EGRP 1, EP 1, RES 1             | 3.17 x 10^-7  | 1       | 1  | 2     | 0.27431 | 0                 | 2     |
| NBEA   | EGRP 2, EP 0, RES 0             | 3.75 x 10^-8  | 3       | 1  | 2     | 0.27532 | 0                 | 3     |
| ANKRD11| EGRP 0, EP 2, RES 3             | 4.91 x 10^-4  | 1       | 0  | 2     | 0.32006 | 1                 | 1     |
| CDKL5  | EGRP 0, EP 3, RES 0             | 3.28 x 10^-10 | 1       | 1  | 3     | 0.37592 | 2                 | 2     |
| GNAO1  | EGRP 0, EP 1, RES 0             | 8.88 x 10^-8  | 1       | 1  | 1     | 0.38395 | 2                 | 0     |
| SPTAN1 | EGRP 2, EP 0, RES 0             | 3.90 x 10^-4  | 1       | 0  | 1     | 0.39697 | 2                 | 0     |
| PURA   | EGRP 1, EP 1, RES 1             | 8.92 x 10^-6  | 2       | 1  | 1     | 0.41165 | 2                 | 0     |
| ANKRD17| EGRP 2, EP 0, RES 0             | 2.43 x 10^-4  | 2       | 0  | 2     | 0.41616 | 3                 | 0     |
| KCNT1  | EGRP 1, EP 2, RES 1             | 2.77 x 10^-9  | 3       | 3  | 1     | 0.47874 | 4                 | 0     |
| IQSEC2 | EGRP 2, EP 0, RES 1             | 1.47 x 10^-7  | 3       | 0  | 1     | 0.53261 | 1                 | 2     |
| GABRA1 | EGRP 0, EP 1, RES 0             | 1.01 x 10^-5  | 0       | 1  | 2     | 0.54006 | 2                 | 0     |
| SLC3A2 | EGRP 0, EP 2, RES 0             | 2.56 x 10^-8  | 0       | 0  | 2     | 0.56045 | 0                 | 2     |
| RANAP1 | EGRP 0, EP 0, RES 2             | 1.54 x 10^-6  | 1       | 1  | 2     | 0.57080 | 2                 | 0     |
| KCNQ2  | EGRP 6, EP 2, RES 1             | 4.34 x 10^-24 | 1       | 1  | 2     | 0.63963 | 9                 | 0     |
| COL3A1 | EGRP 1, EP 0, RES 0             | 1.38 x 10^-5  | 0       | 0  | 2     | 0.64324 | 0                 | 2     |
| CASKIN | EGRP 2, EP 0, RES 2             | 9.9 x 10^-5   | 2       | 1  | 1     | 0.65942 | 2                 | 0     |
| CACNA1E| EGRP 1, EP 1, RES 0             | 3.5 x 10^-4   | 2       | 1  | 2     | 0.77109 | 0                 | 2     |
| INO80  | EGRP 1, EP 1, RES 1             | 1.14 x 10^-4  | 1       | 0  | 1     | 0.82967 | 2                 | 0     |
| SPTBN1 | EGRP 2, EP 1, RES 0             | 3.31 x 10^-4  | 2       | 0  | 3     | 0.86884 | 3                 | 0     |
| CACNB4 | EGRP 1, EP 2, RES 1             | 1.56 x 10^-6  | 1       | 0  | 1     | 0.98534 | 2                 | 0     |

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Genetic Etiologies Implicated in DEE Have Distinct HPO Signatures

To determine the specific HPO terms driving phenotypic similarity for distinct genetic etiologies, we determined the relative contribution of specific HPO terms to each gene-specific similarity, comparing the observed and expected contribution of each HPO term (Figures 3 and 4). In summary, we identified 882 nominally significant gene-HPO associations (Table S3), and the comparison of observed and expected HPO terms resulted in gene-specific patterns (Figures 3, 4, and S7). The significant HPO terms reflect known phenotypic features associated with each genetic etiology, such as “febrile seizures” (HP: 0002373; \( p = 2.0 \times 10^{-10} \)) and “hemiclonic seizures” (HP: 0006813; \( p = 3.4 \times 10^{-5} \)) with SCN1A, “abnormality of central motor function” (HP: 0011442; \( p = 0.0015 \)) with STXBP1, and “developmental regression” (HP: 0002376; \( p = 0.019 \)) with SLC6A1 (MIM: 137165).

Phenotypic Similarity Analysis Provides Statistical Evidence in 11 Genetic Etiologies

We next assessed whether genetic etiologies shared by two or more individuals have phenotypic similarities that were higher than expected by chance (Figures 2 and 5). We determined the median phenotypic similarity between individuals with each of the 41 genetic etiologies with two or more de novo variants had a nominal p value of »0.05, suggesting that the observed number of de novo variants in these genes was higher than expected by chance (Figure 2).

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Phenotypic Similarity Analysis Provides Statistical Evidence in 11 Genetic Etiologies

We next assessed whether genetic etiologies shared by two or more individuals have phenotypic similarities that were higher than expected by chance (Figures 2 and 5). We determined the median phenotypic similarity between individuals with each of the 41 genetic etiologies with two or more de novo variants and compared the observed median similarity score to the expected similarity score derived through 100,000 permutations. We identified 11 genetic etiologies with nominally significant phenotypic similarities (Figure 2). The significance for each of these genetic etiologies emerges consistently when adding individuals to the overall cohort and is not dependent on a single sub-cohort in this study (Figure 6). Comparing the statistical evidence for disease causation based on phenotypic evidence (phenotypic similarity) to genetic evidence (frequency of de novo variants) shows that the statistical evidence from the frequency of de novo variants is typically higher than the evidence derived from phenotypic similarity. However, both lines of evidence are independent. Some genetic etiologies with strong evidence based on the frequency of de novo variants are not significant based on phenotypic similarity, such as IQSEC2 (MIM: 300522) and PCDH19 (MIM: 300460). Other genetic etiologies, including DNM1 (MIM: 602377), SCN8A (MIM: 600702), and AP2M1 (MIM: 601024), have a relatively high phenotypic similarity compared to the frequency of de novo variants. In addition, SCN1A and STXBP1 demonstrate a high degree of phenotypic similarity and statistical significance based on the frequency of de novo variants. The \( \text{sim}_{cm} \) and \( \text{sim}_{max} \) algorithms showed some degree of variation between the statistical evidence for distinct genetic etiologies, but results from both algorithms were highly correlated (Figure S1).

The correlation between both algorithms is intriguing because both techniques emphasize slightly different aspects of the assigned phenotypes: the \( \text{sim}_{max} \) generates a higher degree of similarity when multiple related phenotypes were assigned, e.g., “focal clonic seizures” (HP: 0002266) in addition to “focal aware seizure” (HP: 0002349), whereas the \( \text{sim}_{cm} \) algorithm would only assign similarity on the basis of the shared ancestral terms. In summary, the \( \text{sim}_{max} \) algorithm is affected by the density of the assigned HPO terms within a specific sub-branch, whereas the \( \text{sim}_{cm} \) algorithm is dependent on the granularity of the HPO framework (Supplemental Notes).

In our study, we used a uniform bioinformatic pipeline for variant filtration. Because our pipeline processed heterogeneous exome data with varying quality, we decided to implement conservative thresholds for variant filtration, requiring at least 10 reads of the alternate allele to be present for the de novo analysis. We compared our results with the previously reported data from the Epi4K study and found that the threshold used in our study reliably identified all previously reported de novo variants. addition, several individuals from the Epi4K cohort and EuroEPINOMICS-RES cohort had been found to carry de novo copy number variants, including known disease genes such as SCN1A, SCN2A, and GABRB3 (MIM: 137192). We subsequently repeated the phenotypic similarity analysis including the previously reported copy number variants (Tables S1 and S2). Neither analysis resulted in significant changes to the phenotypic similarities generated for each genetic etiology.

HPO Term Combinations Result in Unique Phenotype Profiles

In order to assess whether HPO terms can yield unique profiles that are predictive of the presence of a genetic etiology, we assessed the positive predictive value (PPV) of the combination of HPO terms that showed the strongest associations with genetic etiologies. As expected, we found that PPV increases with the addition of more HPO terms (Figure S3) but that the predicted frequency of individuals with the combination of HPO terms decreased. We then
assessed the number of HPO terms per genetic etiology required to yield a PPV of 0.8 (Table 1). These term combinations, although only estimated to be present in a subset of individuals, have a probability of at least 80% for a de novo variant in the gene to be present. For some genetic etiologies, the combination of HPO terms required for a PPV of 0.8 is expected to be present in a significant number of individuals. For example, for DNM1, the combination of four HPO terms, including “brain atrophy” (HP: 0000707) “atrophy/degeneration affecting the central nervous system” (HP: 0007367), “aplasia/hypoplasia involving the central nervous system” (HP: 0002977), and “EEG with spike-wave complexes (<2.5 Hz)” (HP: 0010847), is expected in 41% of individuals with de novo variants in the gene, compared to 0.06% of individuals in the remainder of the cohort, resulting in a PPV of 0.8 for this combination of terms.

Phenotypic Similarity Increases with the Inclusion of Unaffected Population Controls

In our current cohort of 846 individuals, the genetic evidence based on the probability of de novo variants in identified genetic etiologies was stronger than the statistical evidence derived from phenotypic similarity associated with that etiology. We reason that both parameters are driven by different factors in the overall cohort. The statistical significance of the frequency of de novo variants is greatest when the study cohort consists of a large number of affected individuals with a single underlying genetic etiology. Accordingly, inclusion of additional individuals with heterogeneous or unselected phenotypes will reduce the frequency of de novo variants for a specific genetic etiology in the larger cohort. In contrast, the phenotypic similarity associated with a given etiology is artificially diminished in cohorts of individuals with homogeneous
phenotypes because the information content of terms depends upon its frequency in the cohort and, consequently, variation in phenotypic features is necessary for phenotypic similarity analysis to distinguish individuals who share a particular genetic etiology from those who do not. This is exemplified by the relatively low IC of “seizures” (HP: 0001250, IC = 0.075). In contrast to the diluting effect on the frequency of de novo variants, inclusion of individuals with heterogeneous phenotypes is likely to increase the phenotypic similarity of individuals.
with the same underlying genetic etiology because gene-related phenotypic features would become less frequent and therefore more informative. We tested this hypothesis by expanding our cohort to include 1,548 population controls that were sequenced for de novo variants and not assigned HPO terms (Figure 6). We observed the expected reduction in statistical significance for de novo variants, whereas the statistical evidence for phenotypic similarity increased. The trend continued when we subsequently added simulated population controls without de novo variants or phenotypic features. These results indicate that methods assessing phenotypic similarity may have an advantage in cohorts with heterogeneous phenotypes where genetic evidence based on the frequency of de novo variants may be insufficient to identify gene-disease associations. In these cohorts, the statistical evidence derived from phenotypic similarity may exceed the genetic evidence, particularly if future studies can exploit deeper phenotype data.

Discussion

In our study we assessed whether harmonization of sparse and heterogeneous phenotypic data via the HPO is capable of capturing associated clinical features and phenotypic similarities. Our aim was to model the cognitive process of recognizing gene-disease relationships through computational algorithms, providing a scalable method for phenotype analysis in large datasets. We reasoned that clinical features associated with distinct genetic etiologies may be prominent enough to stand out from the phenotypes in the larger cohort. We identified gene-specific phenotypic signatures and found that, for 11 genetic etiologies with de novo variants, the associated phenotypic similarities were greater than expected by chance. Because of a lack of consistent frameworks and techniques, correlating clinical and genetic findings at scale remains a major hurdle in biomedical research and, despite attempts at standardization, phenotypic terminology
remains heterogeneous. Concepts to harmonize clinical phenotypic descriptions and to provide defined relationships between individual terms attempt to address this issue, and the HPO is one of the most frequently used frameworks. We demonstrate that the structure of the HPO can be used to harmonize phenotypic data across cohorts, including all major studies in the field of epilepsy research where trio exome data has been generated and where phenotypic features have been systematically captured. We further demonstrate that this conceptual framework can be used to operationalize previously vague concepts, such as phenotypic depth. For example, we find that the EPGP/Epi4K cohort only has a median of nine assigned phenotypic terms compared to the manually phenotyped EGRP cohort, which has a median of 13.5 phenotypic terms, translating into a median difference in IC of 131.9 (Figure 1, inset). Such concepts may help advance the understanding on how quality and quantity of phenotypic data associated with large genomic datasets can be measured and evaluated.

We find that the gene-phenotype associations identified in the harmonized clinical data correspond to the known phenotypic features in many of the genetic etiologies that are included in our study. For example, we find that the EPGP/Epi4K cohort only has a median of nine assigned phenotypic terms compared to the manually phenotyped EGRP cohort, which has a median of 13.5 phenotypic terms, translating into a median difference in IC of 131.9 (Figure 1, inset). Such concepts may help advance the understanding on how quality and quantity of phenotypic data associated with large genomic datasets can be measured and evaluated.

We next evaluated whether the phenotypic terms linked to specific genetic etiologies were sufficiently strong for a gene-specific phenotypic signature to emerge. We applied two algorithms based on the MICA concept, assessing pairwise phenotypic similarities between individuals through the combination of the most specific terms shared by both individuals.29 Although both our algorithms are based on slightly different strategies, we find convergence for both concepts—both our simmax and simcm measures identify at least ten distinct genes associated with phenotype features more similar than expected by chance. Given that all individuals included in our study had epilepsy or neurodevelopmental disorders, we conclude that phenotypic features associated with genetic etiologies, including SCN1A, STXBP1, SLC6A1, AP2M1, and KCNB1, are not only similar per se, but they are also sufficiently similar to be identified within a cohort of individuals with related phenotypes.
Given that we used the example of Rett Syndrome as an introduction to the conceptual framework of phenotypic similarity, we performed a simulation to test whether the phenotypic similarity between six individuals with Rett Syndrome would appear significant if they were added to our existing dataset (Figure S3 and Supplemental Notes). In our simulation, although these four individuals with hypothetical MECP2 de novo variants would not be significantly similar if only a single term is added (“stereotypical hand wringing” [HP: 001217]), these individuals will have significant phenotypic similarity when two phenotypic terms are assigned (“stereotypical hand wringing” [HP: 001217] and “developmental regression” [HP: 0002376], p = 0.05) or when four phenotypic terms are assigned (“stereotypical hand wringing” [HP: 001217], “developmental regression” [HP: 0002376], “absent speech” [HP:0001344], and “apraxia” [HP:0002186], p = 0.002). This hypothetical example highlights that our approach

| Gene  | PPV  | Number of Terms | Cumulative Frequency | Individuals with Etiology | HPO ID                  | HPO Term                      | Frequency |
|-------|------|-----------------|----------------------|---------------------------|--------------------------|--------------------------------|-----------|
| DNMI  | 0.80 | 4               | 0.41                 | 5                         | HP: 0012444              | brain atrophy                    | 0.80      |
|       |      |                 |                      |                           | HP: 0007367              | atrophy/degeneration affecting the CNS | 0.80      |
|       |      |                 |                      |                           | HP: 0002977              | aplasia/hypoplasia involving the CNS | 0.80      |
|       |      |                 |                      |                           | HP: 0010847              | EEG with spike-wave complexes (<2.5 Hz) | 0.80      |
| KCNB1 | 0.81 | 5               | 0.070                | 6                         | HP: 0011442              | abnormality of central motor function | 0.83      |
|       |      |                 |                      |                           | HP: 0011443              | abnormality of coordination        | 0.50      |
|       |      |                 |                      |                           | HP: 0000729              | autistic behavior                  | 0.50      |
|       |      |                 |                      |                           | HP: 0000708              | behavioral abnormality             | 0.67      |
|       |      |                 |                      |                           | HP: 0000234              | abnormality of the head            | 0.50      |
| SCN1A | 0.90 | 5               | 0.23                 | 16                        | HP: 0002373              | febrile seizures                   | 0.81      |
|       |      |                 |                      |                           | HP: 0002069              | generalized tonic-clonic seizures  | 0.94      |
|       |      |                 |                      |                           | HP: 0003593              | infantile onset                    | 0.81      |
|       |      |                 |                      |                           | HP: 0010850              | EEG with spike-wave complexes      | 0.75      |
|       |      |                 |                      |                           | HP: 0011153              | focal motor seizure                | 0.50      |
| STXBPI | 0.87 | 5               | 0.63                 | 14                        | HP: 0002167              | neurological speech impairment     | 0.86      |
|       |      |                 |                      |                           | HP: 0000750              | delayed speech and language development | 0.86      |
|       |      |                 |                      |                           | HP: 0001263              | global developmental delay         | 1.00      |
|       |      |                 |                      |                           | HP: 0011446              | abnormality of higher mental function | 0.86     |
|       |      |                 |                      |                           | HP: 0012758              | neurodevelopmental delay           | 1.00      |
| AP2M1 | 0.86 | 6               | 0.18                 | 4                         | HP: 0001252              | muscular hypotonia                 | 0.75      |
|       |      |                 |                      |                           | HP: 0000750              | delayed speech and language development | 0.75      |
|       |      |                 |                      |                           | HP: 0011463              | childhood onset                    | 0.75      |
|       |      |                 |                      |                           | HP: 0010819              | atonic seizures                    | 0.75      |
|       |      |                 |                      |                           | HP: 0000708              | behavioral abnormality             | 0.75      |
|       |      |                 |                      |                           | HP: 0003808              | abnormal muscle tone               | 0.75      |
| CHD2  | 0.84 | 6               | 0.12                 | 4                         | HP: 0002133              | status epilepticus                 | 0.75      |
|       |      |                 |                      |                           | HP: 0011463              | childhood onset                    | 0.75      |
|       |      |                 |                      |                           | HP: 0000708              | behavioral abnormality             | 0.75      |
|       |      |                 |                      |                           | HP: 0001249              | intellectual disability           | 0.75      |
|       |      |                 |                      |                           | HP: 0002373              | febrile seizures                   | 0.50      |
|       |      |                 |                      |                           | HP: 0002123              | generalized myoclonic seizures     | 0.75      |

For each genetic etiology in the cohort, the number of terms needed to reach a positive predictive value (PPV) of at least 80% was calculated. Displayed are all etiologies that required 6 terms or less to reach this threshold. HPO terms and their frequency within each genetic etiology are displayed.
can recapitulate the clinical recognition of specific phenotypes, such as Rett Syndrome.

To demonstrate the role of phenotypic homogeneity on the results of our study, we assessed how the inclusion of actual and simulated control individuals would affect the results of our study. We find that the phenotypic distinctiveness of all genetic etiologies increases with the inclusion of controls, whereas the probability of de novo variants decreases. We further demonstrate that, with sufficient numbers of controls, the significance derived from our phenotypic similarity analysis will surpass the significance derived on the basis of the probability of de novo variants, even when using sparse phenotypic features. This emphasizes the utility of methods based on phenotypic similarity when assessing the causative role of rare genetic changes in large cohorts. Such methods may be useful for identifying individuals with extremely rare monogenic causes when analyzing population-based studies or entire healthcare systems.

Our phenotypic similarity analysis also showed several unexpected findings. Several genetic etiologies with relatively homogeneous phenotypes did not demonstrate the degree of phenotypic similarity that would have been expected. Most prominently, individuals carrying de novo variants in KCNQ2 did not show more phenotypic similarity than expected by chance. This finding is surprising given that clinical features in individuals with KCNQ2-related disorders are strikingly similar given the almost universal seizure onset in the neonatal period. A total of 45 HPO terms, including “neonatal onset” (HP: 0003623), “EEG with burst suppression” (HP: 0010851), “epileptic encephalopathy” (HP: 0200134), “encephalopathy” (HP: 0001298), and “gastroesophageal reflux” (HP: 0002020), were nominally associated with KCNQ2. We reviewed the phenotypic terms contributing to the nine individuals with KCNQ2-related disorders and found that the ten most strongly associated phenotypic terms were absent in three individuals (EIEE49, EPGP011188, and EPGP015469). In two of these individuals, we observed a very low depth of phenotyping. Individuals EIEE49 and EPGP015469 only had four and six phenotypic terms assigned, respectively, whereas the seven other individuals with de novo variants in KCNQ2 had a median of 11 assigned HPO terms. This observation suggests that the lack of similarity in individuals with KCNQ2 may be due to incomplete phenotyping rather than true phenotypic variation. As expected, when we added missing phenotypic terms to the three individuals, the overall phenotypic similarity became significant. The phenotypic similarity for all nine individuals reached $p = 0.008$ when adding the top three terms and $p = 5.0 \times 10^{-5}$ when adding the top ten terms associated with KCNQ2 missing in individuals EIEE49, EPGP011188, and EPGP015469.

The ability to pinpoint the lack of phenotypic similarity to individual factors, such as incomplete phenotyping, may highlight a strength of our approach—by harmonizing phenotypic information into a common format, it becomes possible to dissect phenotypes in individual genetic etiologies and identify sets of clinical features that drive the observed phenotypic similarity. However, the KCNQ2 example also highlights the need for methods that ensure that phenotypes are encoded uniformly and in an exhaustive manner. Although the overall framework of the HPO allows for both detailed and shallow datasets to be merged and analyzed jointly, it is a conceptual weakness of the HPO that phenotype quality and certainty cannot be encoded. Because it will remain conceptually challenging to distinguish incomplete phenotyping from truly absent phenotypes, quality measures and standard operation procedures for phenotypes will be required to ensure that the already heterogeneous phenotype data is not confounded as a result of low-quality phenotyping data.

Our study had several limitations. We observed a range of phenotypic terms assigned to the individuals and a significant difference among the different cohorts included: the EGRP cohort was significantly more deeply phenotyped compared to the EPGP/Epi4K or EuroEPINOMICS cohorts. Given the difference in phenotyping depth within and between cohorts, key aspects of the clinical presentation in some individuals may be incomplete, thus limiting the capacity of the similarity algorithms to identify individuals with shared features. Furthermore, the phenotypic features captured for an individual may only capture those manifesting by the age at last data collection. For example, individuals with loss-of-function variants in SCN2A typically present with developmental delay and autism, and seizures are frequently observed only after the age of two. Consequently, for younger individuals, seizures may not be recorded. In the EGRP sub-cohort in which age of recruitment was systematically recorded in 151/192 individuals, 30/151 individuals were recruited and phenotyped before the age of two. Accordingly, phenotypic similarities due to clinical features with later onset would not be able to be detected in this cohort. However, this limitation in recruitment strategy and data collection applies to traditional phenotypic analyses. We expect that more thorough longitudinal phenotypic details will be made available in the future through improved methods of extracting clinical information from electronic medical records, including advanced natural language processing and corrections for age-dependent phenotypic features.

A further limitation of our study was our reliance on retrospective data and that there may have been bias on how clinicians assigned HPO terms on the basis of their knowledge or assumption of the underlying genetic cause. Although we cannot exclude such an effect in the EGRP cohort, both the EPGP and RES cohorts were phenotyped prior to sequencing and HPO term assignment was not performed knowing the individuals’ genotypes. Despite this blinding, we cannot exclude that clinicians may have been biased toward an assumed underlying genetic diagnosis.

In summary, we demonstrate that an HPO-based framework is capable of bridging and harmonizing phenotypic data across various clinical datasets that were captured...
alongside large sequencing projects in the epilepsies. Although clinical data is heterogeneous and sparse, the mapping of features to a common ontology allows for the detection of frequently associated clinical features. The subsequent use of phenotypic similarity algorithms enables the detection of significant clinical similarities between individuals with shared genetic etiologies. These methods provide independent statistical evidence for disease causation and can be viewed as an extension of the clinical-genetic approach of defining disease entities through phenotypic resemblance. Given the increasing amounts of deep phenotypic data available for systematic analysis, methods that use computational phenotypes have the potential to identify novel genetic etiologies, particularly in situations when individuals have distinct phenotypic features and when the causative genetic etiology is rare.

Data and Code Availability

The code generated during this study are available through GitHub (https://github.com/galerp/helbig_lab_hpo_sim). The data from EuroEPINOMICS-RES (EGA), accession numbers EGAS00001000190, EGAS00001000386, and EGAS00001000048, and Ep4kar (dbgap), accession number phs000653.v2.p1, are publicly available. A subset of the data from EuroEPINOMICS-RES (EGA), accession number EGAS00001000190, EGAS00001000386, and Epi4k (dbgap), accession number EGAS00001000048, are publicly available. A subset of the datasets supporting the current study have not been deposited in a public repository because of local consent and IRB restrictions but are available from the corresponding author on request.

Supplemental Data

Supplemental Data can be found online at https://doi.org/10.1016/j.ajhg.2020.08.003.

Consortia

The members of the Non-Classical Epileptic Encephalopathy (NCEE) Study Group are Ralf Berkenfeld, Ingo Berggräfe, Andrea Dieckmann, Mildred Endziniene, Andreas Faber, Andre Franke, Helge Gallwitz, Markus Gschwind, Christian M. Korff, Gerd Kurlemann, Sebastien Lebon, Johannes R. Lemke, Frank Maier, Thomas Mayer, Rikke Möller, Susanne Schubert-Bast, Niklas Schwarz, Simone Seifert, Bernhard J. Steinhoff, Inga Talvik, Shan Tang, and Holger Thiele.

The EPGP Investigators are Bassel Abou-Khalil, Brian Aldredge, Dina Amrom, Eva Andermann, Jocelyn Bautista, Sam Berkovic, Judith Bluvstein, Alex Boro, Gregory Cescino, Damian Consalvo, Sabrina Cristofaro, Patricia Crumrine, Orrin Devinsky, Dennis Dlugos, Michael Epstein, Robyn Falhstrom, Miguel Fiol, Nathan Fountain, Kristen Fox, Jacqueline French, Catharine Freyer, Daniel Friedman, Eric Geller, Tracy Glauser, Simon Glynn, Kevin Haas, Sheryl Haut, Jean Hayward, Sucheta Joshi, Andres Kanner, Heidi Kirsch, Robert Knowlton, Eric Kossoff, Rachel Kuperman, Ruben Kuzniecky, Daniel Lowenstein, Shannon McGuire, Paul Motika, Gerard Nesbitt, Edward Novotny, Ruth Ottman, Juliann Paolicchi, Jack Parent, Kristen Park, Annapurna Poduri, Neil Risch, Lynette Sadleir, Ingrid Scheffer, Renee Shellhaas, Elliott Sherr, Jerry J. Shih, Shlomo Shinnar, Rani Singh, Joseph Sirven, Michael Smith, Michael R. Sperling, Joe Sullivan, Liu Lin Thio, Anu Venkat, Eileen Vining, Gretchen Von Allmen, Judith Weisenberg, Peter Widdess-Walsh, and Melodie Winawer.

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Declaration of Interests

The authors declare no competing interests.
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