`acmgscaler`: An R package and Colab for standardised gene-level variant effect score calibration within the ACMG/AMP framework

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Abstract

Summary

A genome-wide variant effect calibration method was recently developed under the guidelines of the American College of Medical Genetics and Genomics and the Association for Molecular Pathology (ACMG/AMP), following ClinGen recommendations for variant classification. While genome-wide approaches offer clinical utility, emerging evidence highlights the need for gene- and context-specific calibration to improve accuracy. Building on previous work, we have developed an algorithm tailored to converting functional scores from both multiplexed assays of variant effects (MAVEs) and computational variant effect predictors (VEPs) into ACMG/AMP evidence strengths. Our method is designed to deliver consistent performance across different genes and score distributions, with all variables adaptively determined from the input data, preventing selective adjustments or overfitting that could inflate evidence strengths beyond empirical support. To facilitate adoption, we introduce `acmgscaler`, a lightweight R package and a plug-and-play Google Colab notebook for the calibration of custom datasets. This algorithmic framework bridges the gap between MAVEs/VEPs and clinically actionable variant classification.

Availability

The package and the Colab notebook are available on GitHub: https://github.com/badonyi/acmgscaler.

Supplementary data

Supplementary data can be downloaded from the OSF repository https://osf.io/7hjnm.

Background

To establish a unified approach to clinical genetic and genomic testing, the American College of Medical Genetics and Genomics and the Association for Molecular Pathology (ACMG/AMP) outlined guidelines for assessing the pathogenicity and benignity of variants in Mendelian disease genes[1]. These guidelines have since been formalised within a probabilistic framework, demonstrating how ACMG/AMP criteria for combining clinical evidence align with likelihood ratios for pathogenicity[2]. Within this framework, the strength of evidence for each classification (supporting, moderate, strong, and very strong) has been defined to increase exponentially. This model has provided the foundation for systematically validating and calibrating pathogenicity evidence, advancing efforts to refine variant classification and extend the role of predictive tools beyond supporting-level evidence[3].

One such extension applies to computational variant effect predictors (VEPs), where appropriate weighting of evidence is integral to ensuring accurate classification. Recently, Pejaver et al. developed a method to estimate the pathogenic-over-benign density ratio for a variant by considering a narrow sliding window around each score in a sorted and labelled list of predictions, with labels corresponding to a *priori* pathogenic and benign truthsets[4]. The resulting odds of pathogenicity, equivalent to positive likelihood ratios (LR^+; hereafter referred to as LR), can be compared to evidence thresholds established by the ACMG/AMP framework under a predefined prior probability of pathogenicity[1–3]. Using this approach, the authors estimated genome-wide thresholds, *i.e.*, score intervals, for each evidence level across thirteen widely used VEPs. This work has since been extended with the calibration of additional VEPs[5].

Applying genome-wide calibration to VEP scores for variant classification has demonstrated notable benefits. For example, one study used genome-wide thresholds in 300 probands with suspected rare disease and found a 2.6-fold increase in variants reaching strong evidence for pathogenicity compared to when only established disease-associated genes were considered[6]. Importantly, this analysis concluded that genome-wide calibration is unlikely to result in the inappropriate classification of an excessive number of variants as pathogenic or likely pathogenic[6]. However, others have raised concerns about the limitations of genome-wide calibration, particularly in terms of obscuring performance across different genes and modes of inheritance[7–9]. These findings suggest that genome-wide calibration alone may not be sufficient to address these discrepancies and highlight the need for a gene- and context-specific calibration method.

Multiplex assays of variant effect (MAVEs) provide an unbiased source of functional evidence[10–12], offering huge potential to improve the classification of germline genomic variants, particularly rare missense variants frequently classified as uncertain significance[13]. However, similar to the output of VEPs, raw scores from MAVEs vary in range and distribution across genes and do not readily correspond to ACMG/AMP evidence strengths.

Here, building on previous work[8,14,15], we develop a method based on bootstrapped kernel density estimates to compute LRs for any functional score distribution—whether derived from MAVEs or VEPs—using pathogenic and benign truthset labels. The resulting LRs support robust and reproducible integration of functional scores from diverse sources into variant classification under ACMG/AMP guidelines. We have made our method available as an R package for high-throughput calibration studies, alongside a Google Colab notebook providing a simple interface for bench scientists.

Implementation

Likelihood ratio estimation

We follow van Loggerenberg et al. in using Gaussian kernel density estimation to derive LRs for functional scores[14], as the sliding window method developed by Pejaver et al.[4] is not feasible at the gene level due to data sparsity. We set a lower limit on the number of variants in the truthset, requiring at least ten benign and ten pathogenic labels. To avoid extrapolating LRs beyond the observed range, input scores are first clamped to the range of labelled scores, and then rescaled to the [0, 1] interval to ensure scale invariance. Density estimation is performed separately on the pathogenic and benign score distributions, using 1,024 equidistant evaluation points and a bandwidth selected by biased cross-validation. This process is repeated 1,000 times by resampling the reference distributions with replacement, applying kernel density estimation to each resample and projecting the resulting densities onto a common grid of 1,024 points via linear interpolation. A fixed random seed is used to eliminate run-to-run variability.

Log-LRs are computed across resamples as the difference between pathogenic and benign log-densities at each index in the common grid, resulting in a 1,000 × 1,024 matrix. To stabilise estimates in sparse regions, we apply adaptive regularisation:

$$\lambda_i = \frac{\mathrm{MAD}_i}{\max_j \mathrm{MAD}_j} \cdot \frac{\sqrt{\sum_j (\mathrm{MAD}_{j+1} - \mathrm{MAD}_j)^2}}{\sum_j \mathrm{MAD}_j}$$

Here, MAD_i is the median absolute deviation of log-LRs at grid index i. The first term scales MAD values to reflect relative variability across the score range. The second term, a root-sum-of-squares of lagged differences, acts as a roughness penalty similar to L2 regularisation. This formulation penalises sharp or erratic fluctuations in the log-LRs while leaving stable regions largely unaffected.

At this stage, the log-LRs may be non-monotonic due to boundary effects or multimodal structures in the score distributions, which could reflect noise, assay or VEP limitations, or inaccuracies in truthset labels. When higher scores indicate a greater likelihood of pathogenicity, a lower score should not yield a higher LR, as this would suggest local overfitting. To correct this, we apply isotonic regression to enforce monotonicity in the log-LR matrix, ensuring a gradual or stepwise increase in evidence across the score range. The direction of monotonicity is determined by the sign of the Spearman correlation between the column-wise mean of log-LRs and the input scores. The final LRs are obtained by computing the median log-LR across resamples, exponentiating to return to linear space, and mapping the estimates to the input scores based on their grid indices. A flowchart illustrating the method is shown in **Figure 1**.

Computing confidence intervals for the likelihood ratios

We compute 95% confidence bounds for the population median of log-LRs across resamples by inverting the sign test, using the exact binomial distribution of order statistics[16]. The choice of a confidence interval for the location of the median log-LR, rather than, *e.g.*, a percentile interval for the distribution of log-LRs, better aligns with our classification goal, as we care most about where the typical (central) log-LR lies. It is important to clarify that these confidence bounds do not represent uncertainty in the posterior probability of pathogenicity as defined in the ACMG/AMP framework. Instead, they reflect variability in the LR itself, estimated from the regularised and monotonic log-LR distribution. A classification based on a variant for

which both the point estimate and the lower (for pathogenic) or upper (for benign) confidence bound exceed a given threshold is less likely to be affected by future truthset updates, *e.g.*, the inclusion of additional pathogenic variants, than one based on the point estimate alone. Accordingly, we classify variants into evidence strengths using the lower bound when the point estimate exceeds one, and the upper bound when it falls below.

Choice of bandwidth selector

The bandwidth parameter controls the smoothness of the estimated density functions and can substantially affect the resulting LRs. We evaluated four automatic bandwidth selectors available in base R: `'nrd0'` (Silverman's rule of thumb), `'bcv'` (biased cross-validation), `'SJ'` (Sheather–Jones), and `'ucv'` (unbiased cross-validation)[17–19]. To select the most suitable method, we compared the average width of the LR confidence interval across seven human disease genes with available MAVE datasets, AlphaMissense[20], and CPT-1[21] scores. These two VEPs were selected for their top performance in a recent benchmarking study[22]. All seven genes include at least ten missense variants classified as benign/likely benign and pathogenic/likely pathogenic in ClinVar[23], with a minimum review status of one star, which served as truthset labels for calibration. For each gene, the score set with the highest area under the receiver operating characteristics curve was selected. The genes, MAVE studies, score set sources, and the number of pathogenic and benign variants are listed in **Table S1**. As shown in **Figure 2A**, `'bcv'` yielded the narrowest confidence intervals on average, suggesting greater stability, and was therefore set as the bandwidth selector in our method.

Determining likelihood points for a given prior

The prior probability of pathogenicity (hereafter 'prior') represents the estimated likelihood that a randomly selected, previously uncharacterised variant is disease-causing in a patient presented with a given phenotype before considering variant-specific evidence. Global estimates, such as 0.1[2] and the more recent 0.0441[4], provide a useful baseline across diverse disease-associated genes, but priors may vary substantially between genes, and even among phenotypes. This variation arises from differences in gene properties, such as biological role, functional constraint, variant inheritance and disease mechanism. To leave room for future advances in gene-specific prior estimation, the default prior of 0.1 can be replaced with a user-specified value.

Likelihood points corresponding to ACMG/AMP evidence strengths under a predefined prior can be determined using the framework introduced by Tavtigian et al[2]. Here, we approximate this by considering that the P_{ii} and LP_i combining rules yield internally inconsistent likelihood points: P_{ii} produces a posterior probability below the expected 0.99 threshold, whereas LP_i exceeds it. To determine the very strong pathogenicity threshold, we identify the smallest LR that satisfies at least 13 of 14 posterior probability criteria across the LP and P combining rules. Although the original ACMG/AMP framework imposes additional conditions—requiring the LB combining rules to have a posterior probability between 0.05 and 0.001, and the B combining rule to be below 0.001—we find that enforcing the criteria for P and LP implicitly maintains a similar relationship between the prior and the LR threshold for the very strong pathogenicity evidence (P_{VSt}). As shown in **Figure 2B**, for priors below 0.2, our method closely aligns with the proposed combining rules, yielding slightly more conservative values above 0.2. Notably, for the prior of 0.1 used by Tavtigian et al., which gives a P_{VSt} threshold of 350, our approach yields the same value. For the prior of 0.0441 suggested by Pejaver et al., which corresponds to a P_{VSt} threshold of 1124, our estimate is 1131. A

difference of seven LR points is negligible in practice, as it represents only 0.64% of the range between the strong and very strong evidence thresholds under this prior.

Deriving score thresholds for evidence levels

To compute score intervals for the evidence levels, we first determine P_{VSt} under the specified prior and derive the corresponding LR thresholds for the remaining levels. For each evidence level, the corresponding score threshold is obtained by linearly interpolating the score at which the lower confidence bound of the LR crosses the evidence threshold if the point estimate exceeds one, and the upper bound otherwise. Since MAVE assays often achieve high variant coverage, and VEPs typically assign scores to all possible missense variants, an alternative is to include these variants in the calibration even without truthset labels. The advantage is that, for unlabelled variants whose scores fall within the range of labelled scores, LRs can still be estimated directly via the density approach.

Calibration examples

Full calibration profiles for the seven genes, using a global prior of 0.1, are shown separately for MAVE assays, AlphaMissense, and CPT-1 scores in **Figure 3**. Despite substantial differences in distribution shape, modality, and scale across score sets, the LR estimates generally track well with the empirical density distributions of pathogenic and benign variants. This alignment suggests that the method is robust to underlying functional score characteristics and captures consistent evidence strengths across both experimental and computational predictors. While the confidence intervals may appear narrow, this reflects the robustness of the central tendency of the LR estimates. As a complementary visualisation, we show percentile-based confidence intervals in **Figure S1**, which better reflect the overall variance of the resampled log-LR distribution but are less aligned with our classification objective, which depends on the location and uncertainty of the central estimate. Calibrated datasets are available on OSF (https://osf.io/7hjnm).

Colab notebook

We have created a Google Colab interface for `acmgscaler`, allowing calibration of custom datasets without the need to install R. The input form, along with an example calibration output, is shown in **Figure 4**. The available settings are simplified to a numeric score column and a class column containing the truthset labels. The class column should include at least ten instances of 'P' (pathogenic/positive class) and 'B' (benign/negative class) labels each. For any other or missing labels, LRs will also be computed. A custom prior can be set, influencing the evidence strength-based classification results. Upon running the cell, an upload button appears to provide data in CSV format. Once calibration is complete, the Colab automatically downloads the results, while the interactive table allows data export in different formats or filtering through a simple graphical interface. A separate cell enables visualisation of the input score *vs* LR curve, with the corresponding ACMG/AMP evidence thresholds highlighted under the predefined prior.

R package

Installation. The development version of `acmgscaler` can be installed using `devtools`:

```r
# install devtools if not installed yet
install.packages('devtools')

# install the package from the GitHub repository
devtools::install_github('badonyi/acmgscaler')
```

Computing LRs. The main function `add_likelihood_ratios()` adds LRs as new columns to an existing dataframe containing the variant scores (`value`) and the truthset labels (`class`). For convenience, LRs are computed for all numeric columns if `value` is set to NULL. The example data included in the package contains MAVE scores for BRCA1 and TP53 variants and their class labels from this study.

```r
library(acmgscaler)

# load the example data provided with the package
data(variant_data, package = 'acmgscaler')

variant_data_lr <- add_likelihood_ratios(
  df = variant_data,
  # the column containing the variant scores (optional)
  value = 'score',
  # a grouping variable (optional)
  group = 'gene',
  # prior probability of pathogenicity for classification (default 0.1)
  prior = 0.1
)

head(variant_data_lr, n = 10)
```

gene	variant	class	score	score_lr	score_lr_lower	score_lr_upper	score_evidence
BRCA1	L3F	B	-0.4736396	0.0241031	0.0229618	0.0255996	b_strong
BRCA1	R7L	B	-0.0164586	0.0091660	0.0079297	0.0102897	b_strong
BRCA1	V11I	B	-0.3134249	0.0164570	0.0155806	0.0174208	b_strong
BRCA1	N13K	B	-0.1704730	0.0133267	0.0129186	0.0136497	b_strong
BRCA1	M18K	P	-2.3904807	422.8674679	397.6330407	451.8949642	p_very_strong
BRCA1	M18L	B	-0.0592874	0.0105485	0.0083266	0.0111978	b_strong
BRCA1	M18R	P	-2.4459881	422.8674679	397.6330407	451.8949642	p_very_strong
BRCA1	M18T	P	-1.8874302	94.6533741	68.0684660	105.3566590	p_strong
BRCA1	I21L	B	0.2446975	0.0076655	0.0073734	0.0080617	b_strong
BRCA1	L22S	P	-2.1066758	220.0195214	216.4036623	222.5691474	p_strong

Determining score thresholds. Score intervals corresponding to ACMG/AMP evidence levels can be computed with `get_thresholds()`. If a grouping variable is provided, a named list of dataframes is returned, where names correspond to group levels. The first column in the output is `evidence`, which holds the value for evidence strengths, such as 'p_supporting|p_moderate' (where '|' marks the threshold).

```
get_thresholds(
  df = variant_data_lr,
  # a grouping variable (optional)
  group = 'gene',
  # the prior used to compute the LRs
  prior = 0.1
)

print(variant_data_thresholds$BRCA1)
```

evidence	score
b_very_strong|b_strong	NA
b_strong|b_moderate	-0.5924075
b_moderate|b_supporting	-0.7248363
b_supporting|indeterminate	-0.8394503
indeterminate|p_supporting	-1.0178941
p_supporting|p_moderate	-1.0277315
p_moderate|p_strong	-1.0903978
p_strong|p_very_strong	-2.1425087

Conversion to posterior probability of pathogenicity. The helper function `lr_to_posterior()` converts LRs into posterior probabilities.

```
variant_data_lr$score_post <- lr_to_posterior(
  # LR values
  lr = variant_data_lr$score_lr,
  # the prior used to compute the LRs
  prior = 0.1
)

head(variant_data_lr[c('gene', 'variant', 'class', 'score', 'score_post')], n = 10)
```

gene	variant	class	score	score_post
BRCA1	L3F	B	-0.4736396	0.0026710
BRCA1	R7L	B	-0.0164586	0.0010174
BRCA1	V11I	B	-0.3134249	0.0018252
BRCA1	N13K	B	-0.1704730	0.0014786
BRCA1	M18K	P	-2.3904807	0.9791603
BRCA1	M18L	B	-0.0592874	0.0011707
BRCA1	M18R	P	-2.4459881	0.9791603
BRCA1	M18T	P	-1.8874302	0.9131721
BRCA1	I21L	B	0.2446975	0.0008510
BRCA1	L22S	P	-2.1066758	0.9607020

Discussion

We developed a functional score calibration method within the ACMG/AMP framework. This approach is entirely data-driven, eliminating arbitrary thresholds and manual tuning, and yields stable LRs across diverse assay types and computational predictors, regardless of distribution shape or scale.

Our methodology builds on the core idea behind `maveLLR`, a kernel density estimation method developed to assign ACMG/AMP evidence strengths for MAVE assays[14,15]. We extend this framework with resampling, which permits the use of a variance-based penalty to shrink unstable estimates towards one and to compute confidence bounds. Monotonicity constraints on the LRs are enforced via isotonic regression, introducing only modest, local adjustments to the curve and preserving its empirically supported structure. The combination of adaptive shrinkage and a simplified thresholding procedure ensures that the assigned evidence strengths remain robust and conservative. These steps are implemented entirely in base R using highly optimised core functions, maintaining long-term backwards and forwards compatibility. Moreover, we provide a Google Colab wrapper, bypassing the need to install R for single custom datasets.

Zeiberg et al. recently introduced an alternative calibration framework for MAVE assays based on a skew-normal mixture model[24]. This method fits score distributions using parametric components, with monotonicity enforced via an expectation-maximisation algorithm. By jointly estimating parameters across the entire score distribution, this approach is particularly effective at stabilising sparse or extreme score regions. The authors also propose a strategy for estimating the prior (the probability that a variant in a patient with a given phenotype is causal for the disease, before incorporating evidence) by modelling gnomAD[25] scores as a mixture of pathogenic and benign components. In contrast, our framework computes LRs directly from empirical distributions of labelled variants, without relying on parametric assumptions, making it readily generalisable to any continuous score set, including those of VEPs.

The sole parameter in our method is the prior. While genome-wide priors have been estimated before[2,4], deriving reliable context-specific priors remains challenging. This is because Mendelian disease genes frequently have multiple phenotypes, which may differ in their mutational spectra[26] and molecular mechanisms[27]. Even in genes associated with a single phenotype, estimating priors from population data, such as gnomAD, can be problematic. For example, genes with recessive conditions typically have a limited number of alleles that have been observed in the homozygous state, which represent a more suitable proxy for benign variants in these genes than heterozygous alleles[28]. We anticipate that with increasing population sequencing data and advances in statistical genetics methods, reliable estimation of context-specific priors suitable for practical application will be feasible in the near future. Until then, we recommend using a constant prior, *e.g.* 0.1, to avoid the risk of inflating evidence strengths as a result of overestimating the prior.

We developed our method with missense variants in mind, as most VEPs are limited to them. However, the approach can in principle be applied to any variant type, provided the scores are derived from the same assay or VEP and reflect quantitatively comparable functional consequences. Particular care is needed when including nonsense variants from MAVEs. For the majority of MAVE approaches that rely on exogeneous constructs, a premature stop codon will result in a truncated protein product, which may not mimic the biological effects within cells where nonsense-mediated decay is often involved. Still, users should evaluate whether the assay setup captures the relevant biology for each variant type when performing calibration.

Another important consideration is the potential for circularity in the calibration dataset. We used ClinVar-labelled pathogenic and benign variants as the truthset to calibrate MAVE and VEP scores across seven

human genes. However, many of the MAVE assays may have already contributed functional evidence towards these clinical classifications[29,30], raising the possibility of inflating the calibrated evidence strength. VEPs are similarly susceptible to this form of bias[31]. For example, AlphaMissense was trained in part on population allele frequencies, which inform benignity assessments under ACMG/AMP guidelines[32], although the resulting bias appears modest[22,33]. CPT-1 was partially trained on MAVE data, including the assay for the MTHFR gene, yet showed no strong evidence of bias in our calibration. To mitigate circularity, truthsets ideally should exclude variants whose classification relied on the predictive features being evaluated. As MAVEs and VEPs are increasingly incorporated into clinical variant interpretation, such circularity is likely to become more pervasive. It will therefore be essential to track the provenance of supporting evidence to ensure robust calibration and reliable downstream use. Sources of potential circularity warrant careful consideration in calibration projects intended to inform clinical decision-making.

Truthset composition remains a key determinant of attainable evidence strength in the ACMG/AMP framework[34]. For simplicity, we used ClinVar-labelled pathogenic and benign variants without stratifying by disease phenotype or inheritance mode. However, such context-specific considerations are critical for accurate clinical calibration and are already being implemented by variant curation expert panels. We emphasise that future efforts to refine calibration approaches should continue to incorporate these dimensions, along with advances in estimating prior probabilities of pathogenicity. We hope that our method will serve as a basis for further methods development in this field.

Notes on system requirement

The package has no external dependencies and has been tested on R versions >=3.5.0. Memory usage is approximately constant owing to the fixed size of the log-LR matrix. Calibrating the datasets in this study required a peak RAM of 121 MB on an Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz with 1 GB of RAM.

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Figures

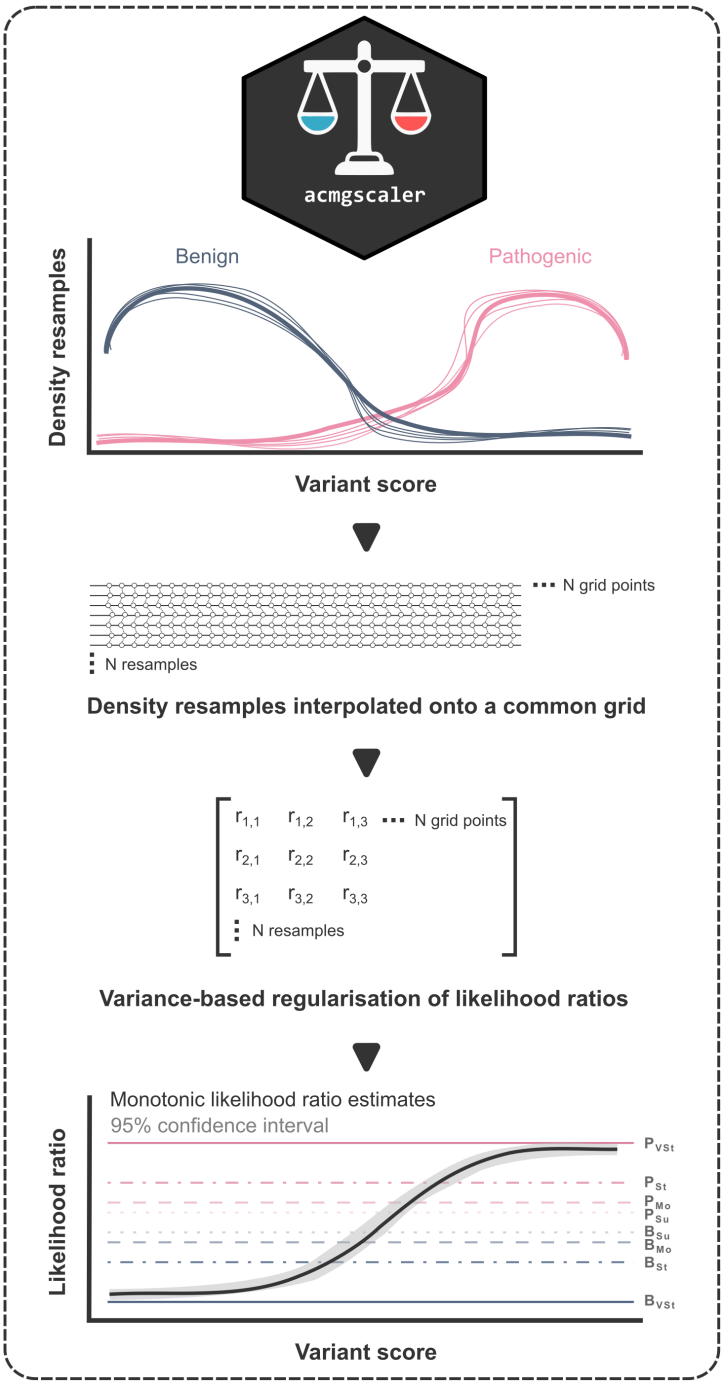

Figure 1. Method flowchart.

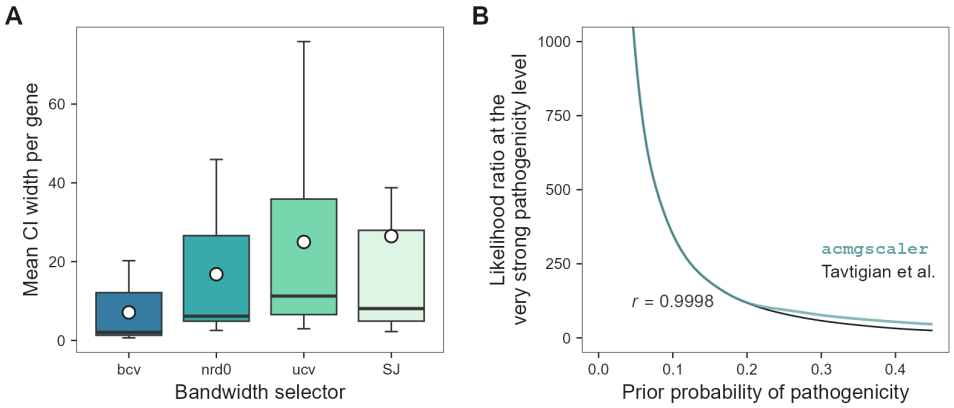

Figure 2. **A**: Comparison of bandwidth selection methods for computing LRs. The y axis shows the gene-averaged width of the LR confidence interval across calibrated MAVE, AlphaMissense and CPT-1 scores. **B**: Likelihood points for the very strong pathogenicity level as implemented in the `acmgscaler` package. The Pearson correlation (r) with the reference method by Tavtigian et al. is shown.

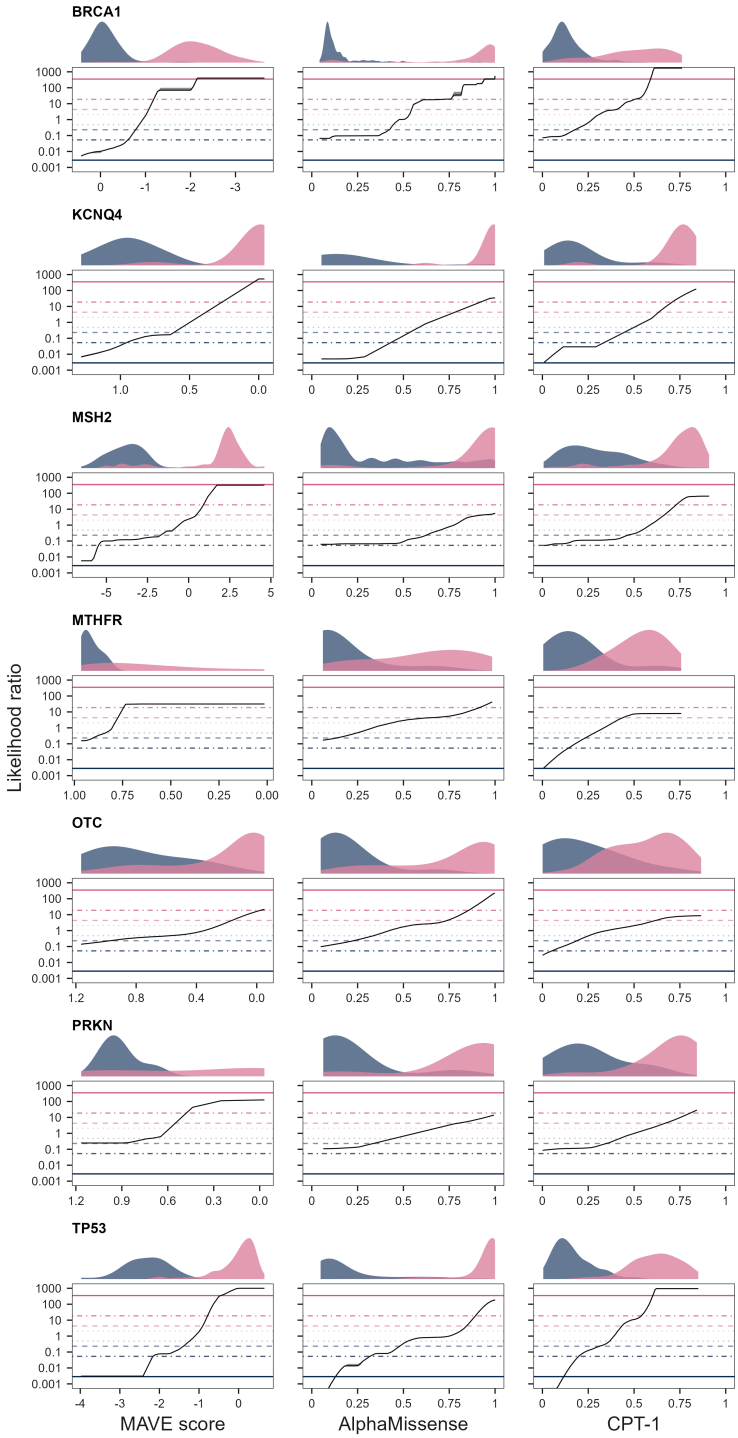

Figure 3. Calibrated MAVE assay, AlphaMissense and CPT-1 scores for missense variants in human genes using `acmgscaler`. Density plots show the distribution of pathogenic (pink) and benign (blue) scores. In MAVE assays, the x axis is inverted for BRCA1, KCNQ4, MTHFR, OTC, PRKN, and TP53 for consistent directionality. Where visible, shaded areas represent 95% confidence intervals. Horizontal bars correspond to evidence strengths under a prior of 0.1 (from top to bottom: pathogenic very strong, pathogenic strong, pathogenic moderate, pathogenic supportive, benign supportive, benign moderate, benign strong, benign very strong).

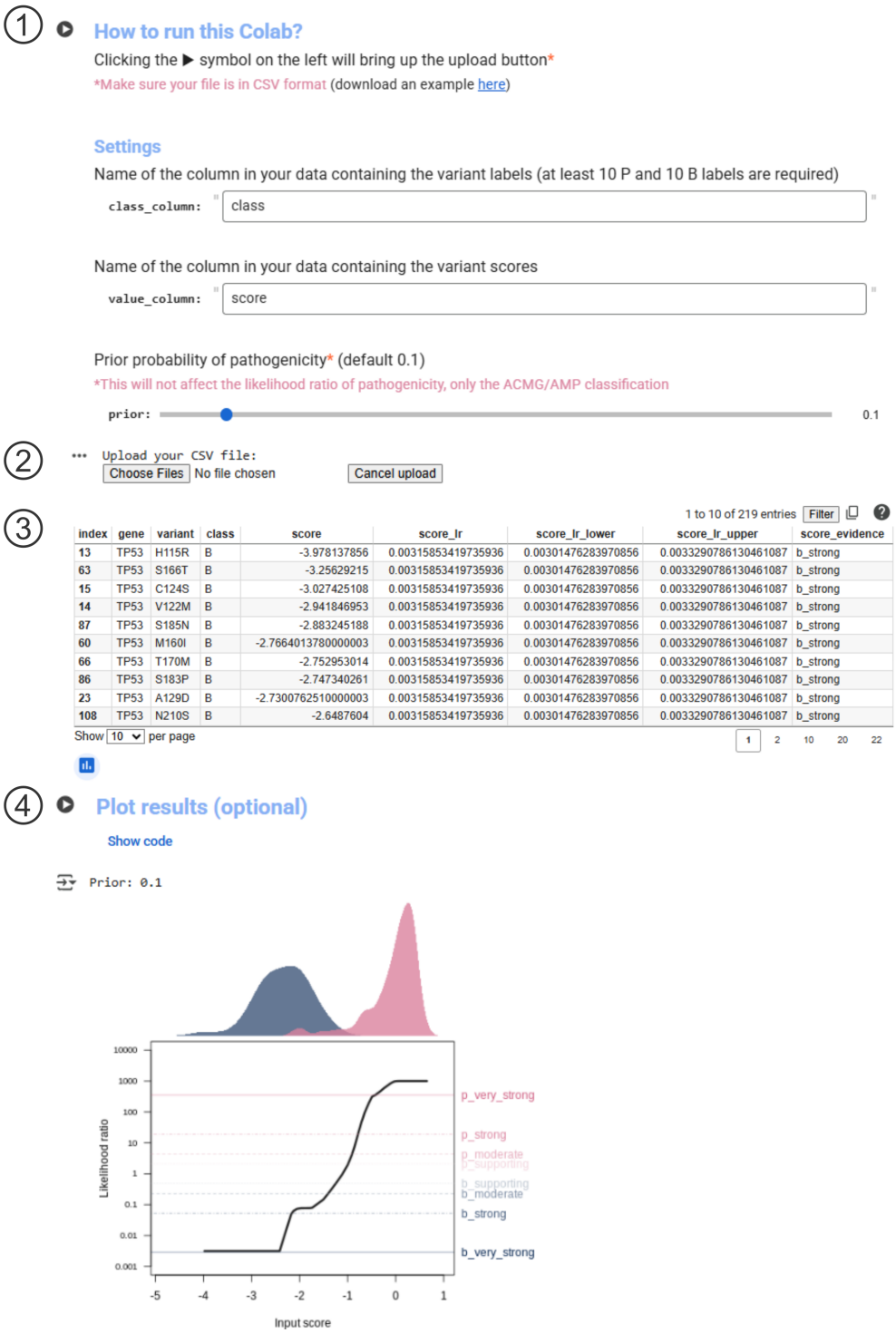

Figure 4. Colab notebook for variant classification. **1)** Input fields. **2)** Upload button. **3)** Interactive results table. **4)** Visualisation of the input score *vs* LR curve.

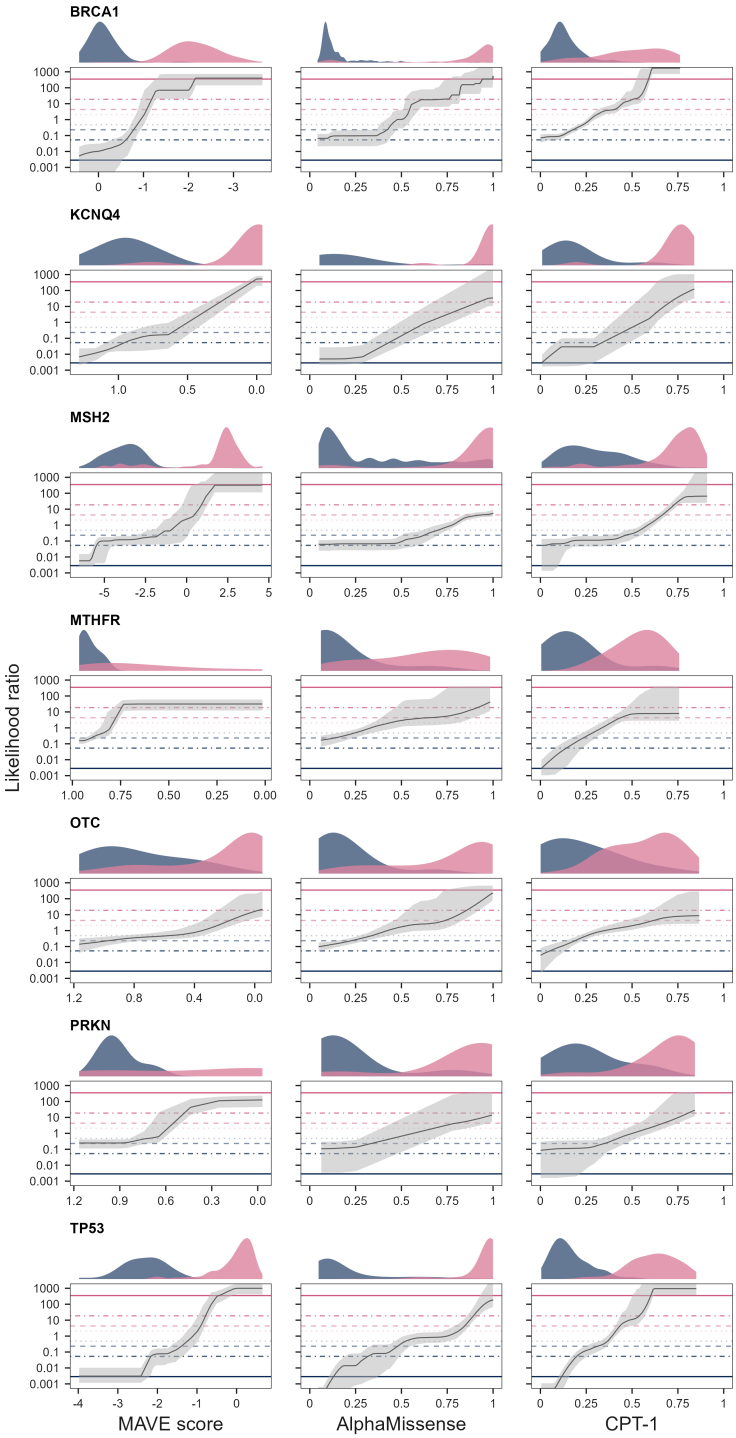

Figure S1. Calibration results as shown in **Figure 3**, with shaded areas representing the 2.5th and 97.5th percentiles of the bootstrap distribution of LR estimates.

Gene	Reference	Score name	MaveDB ID	N_b	N_p
BRCA1	[35]	function.score.mean		82	158
KCNQ4	[36]		00000094-a-2	10	13
MSH2	[37]		00000050-a-1	242	127
MTHFR	[38]		00000049-a-1	11	32
OTC	[39]		00000112-a-1	10	94
PRKN	[40]		00000114-a-1	16	15
TP53	[41]	RFS_H1299		37	182

Table S1. Sources of MAVE datasets. Either the MaveDB ID or the score name from the original publication is given. N_b and N_p are the number of benign and pathogenic missense mutations in the datasets, respectively. Note that AlphaMissense and CPT-1 have full coverage in these genes with equal or greater labelled variant counts.