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## Modeling the ACMG/AMP Variant Classification Guidelines as a Bayesian Classification Framework

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## Abstract

**Purpose**—We evaluated the ACMG/AMP variant pathogenicity guidelines for internal consistency and compatibility with Bayesian statistical reasoning.

**Methods**—The ACMG/AMP criteria were translated into a naïve Bayesian classifier, assuming four levels of evidence and exponentially scaled odds of pathogenicity. We tested this framework with a range of prior probabilities and odds of pathogenicity.

**Results**—We modeled the ACMG/AMP guidelines using biologically plausible assumptions. Most ACMG/AMP combining criteria were compatible. One ACMG/AMP likely pathogenic combination was mathematically equivalent to pathogenic and one ACMG/AMP pathogenic combination was actually likely pathogenic. We modeled combinations that include evidence for and against pathogenicity, showing that our approach scored some combinations as pathogenic or likely pathogenic that ACMG/AMP would designate as VUS.

**Conclusion**—By transforming the ACMG/AMP guidelines into a Bayesian framework, we provide a mathematical foundation for what was a qualitative heuristic. Only two of the 18 existing ACMG/AMP evidence combinations were mathematically inconsistent with the overall framework. Mixed combinations of pathogenic and benign evidence could yield a likely pathogenic, likely benign, or VUS result. This quantitative framework validates the approach adopted by the ACMG/AMP, provides opportunities to further refine evidence categories and combining rules, and supports efforts to automate components of variant pathogenicity assessments.

## INTRODUCTION

In 2008, Plon *et al.* published recommendations for sequence variant classification for seven cancer susceptibility genes<sup>1</sup>. They coupled quantitative, probability-based thresholds for variant classification to a Bayesian approach for estimating probabilities of pathogenicity for variants of uncertain significance (VUS).<sup>1,2</sup> Recently, Richards *et al.* (representing the American College of Genetics and Genomics and the Association for Molecular Pathology, ACMG/AMP) published guidelines for evaluating Mendelian disease gene variants.<sup>3</sup> The ACMG/AMP guidelines codified multiple approaches to variant pathogenicity assessments in use by clinical genetic/genomic testing laboratories. The first stage of their process reduced this assessment into qualitatively distinct evidence types (functional, genetic, population, *in silico*, etc.) and stratified the strength of evidence into categories (supporting, moderate, strong, very strong, and stand alone). The second stage tallied evidence for or against pathogenicity using “combining criteria”, where various combinations would lead to semi-quantitative categorical pathogenicity assessments (pathogenic, likely pathogenic, VUS, likely benign, or benign) similar to the five Plon *et al.*<sup>1</sup> categories.

Juxtaposing these two achievements raises two questions. First, whether the ACMG/AMP rules are internally consistent. Second, whether the systematic, qualitative, categorical ACMG/AMP combining criteria represent a Bayesian heuristic similar to that used for hereditary cancer variants. To address these questions, we analyzed the ACMG/AMP approach in a Bayesian framework.

## METHODS

Bayesian reasoning starts with a prior probability (Prior\_P), which is modified using conditional factors, expressed as probabilities, odds, or likelihoods, to raise or lower the Prior\_P. Using Bayes rule to combine these factors results in a posterior probability (Post\_P). We interpreted the evidence categories given in Tables 3 and 4 of Richards *et al.*<sup>3</sup> as categorical conditional probabilities or odds of pathogenicity (OP), which could mathematically favor a pathogenic (odds >1) or benign (odds <1) interpretation. To test Bayesian compatibility of the ACMG/AMP combining criteria, we created an Excel spreadsheet that uses Bayes rule to calculate a Post\_P from a Prior\_P and the OP from four categories of pathogenic and two categories of benign data. Each of the “Rules for combining criteria to classify sequence variants” described in Table 5 of Richards *et al.*<sup>3</sup> was encoded (Table S1). In principle, this approach could transform their qualitative Table 5 “combining criteria”<sup>3</sup> into a formal, quantitative framework, based on several assumptions:

1. Each piece of evidence considered by ACMG/AMP was independent, which allows use of a naïve Bayesian classifier with multiple data types expressed individually as OP, the overall OP being obtained by multiplying the odds from each piece of evidence.
2. In encoding the combining criteria, we accepted all but one type of ACMG/AMP evidence, building a mathematical model that preserves the relative strengths of each type of evidence. We excluded BA1, “benign stand alone” because it is used as absolute evidence that a variant is benign, irrespective of other evidence, which is contrary to Bayesian reasoning. The BA1 filter is useful for excluding a variant from entering a Bayesian framework, and will be addressed separately by the ClinGen Sequence Variant Interpretation (SVI) Working Group.
3. We transformed the adjectival ACMG/AMP descriptors (supporting, moderate, strong, or very strong) into four conditional probabilities; the odds of pathogenicity relationships. The strength of evidence relationships among the categories supporting ( $O_{PSu}$ ), moderate ( $O_{PM}$ ), strong ( $O_{PSl}$ ), and very strong ( $O_{PVSt}$ ) defined by the ACMG/AMP guidelines<sup>3</sup> were scaled exponentially such that  $O_{PSu}^X = O_{PM}$ ,  $O_{PM}^X = O_{PSl}$ , etc. The “evidence of benign impact” categories were assigned reciprocal OP to the corresponding pathogenicity categories. If  $N$  is the number of criteria with a given strength of evidence category in a classification rule (detailed in Richards *et al.*<sup>3</sup> Table 5), with categories named as subscripted above, the OP attributable to each of the pathogenic data combining rules given in Table 5 is expressible as a specific example of equation 1:

$$OP = O_{PVSt} \left( \frac{N_{PSu}}{X^3} + \frac{N_{PM}}{X^2} + \frac{N_{PSl}}{X} + \frac{N_{PVSt}}{1} \right)$$

The corresponding equation for the benign data combining rules is expressible as a specific example of equation 2:

$$OP = O_{PVS_t} \left( \frac{N_{BSu}}{X^3} - \frac{N_{BSl}}{X} \right)$$

4. The ACMG/AMP defined the term ‘likely pathogenic’ to mean >90% certainty of a variant being disease-causing, but below a higher “pathogenic” threshold. In Bayesian terms, these translate to a Post\_P of >0.90 for likely pathogenic and, if compatible with the Plon *et al.*<sup>1</sup> definitions, a higher pathogenic threshold at Post\_P >99% certainty of pathogenicity. These probability thresholds, plus the extent to which different combining rules do (or don’t) arrive at equivalent Post\_P’s, provide criteria for judging the internal consistency of the qualitative rules and their compatibility with a Bayesian framework.
5. Obtaining numeric results for purposes of illustration requires that we either select a Prior\_P or test a range of Prior\_P’s. For simplicity, we have provided a set of calculations using a Prior\_P of 0.10. This Prior\_P is reasonable for a panel testing scenario where it is likely that the laboratory would encounter on the order of ten variants in a panel of biologically relevant susceptibility genes and perhaps one of them is the actual pathogenic variant. It is also the approximate empirically measured Prior\_P for the combination of missense substitutions, in-frame indels, and proximal splice junction variants in *BRCA1* and *BRCA2*.<sup>2,4,5</sup> Finally, the structure of the ACMG/AMP criteria include an implicit lower constraint of 0.10 for a Prior\_P, as they specify that if none of the criteria are met, the variant is a VUS, thus the prior must be between 0.10 and 0.90, which is the Post\_P range for a VUS. There are many other potential Prior\_P’s for different scenarios if the underlying assumptions of the ACMG/AMP framework were discarded. For the present analysis, as described above, we chose to accept the ACMG/AMP assumptions, but future work should be undertaken to explore whether other approaches that violate those assumptions may yield improved results.

We then tested the ACMG/AMP guidelines in this quantitative framework, under the hypothesis that we could identify an algorithmically plausible value of the exponent  $X$  and then biologically plausible combinations of numerical values of: 1) the strength of the very strong evidence ( $O_{PVS_t}$ ) (which, combined with the exponent  $X$ , determines the strength of the strong, moderate, and supporting evidence) and 2) the Prior\_P that would yield similar Post\_Ps as those defined by the ACMG/AMP. Specifically, (i) the Post\_Ps of the likely pathogenic combinations would be between 0.90 and 0.99, (ii) the Post\_Ps of the likely benign combinations would be between 0.001 and <0.10, (iii) the pathogenic combinations would have Post\_Ps >0.99, and (iv) the one benign category has Post\_P <0.001. In fact, there was a uniquely optimal value for the exponent  $X$ , under which many combinations of  $O_{PVS_t}$  and Prior\_P meet these criteria for a large majority of the combining rules. In Table 1 we calculate several Post\_P’s using  $X=2.0$ , a Prior\_P of 0.10, and  $O_{PVS_t} = 350$  (other combinations were calculated, data not shown).

### Code availability

Exploration of the Bayesian compatibility of the ACMG/AMP combining criteria that we describe here can be entirely replicated using the supplementary file Table S1.

## RESULTS

The classical formulation of Bayes rule is specified as follows (equation 3):

$$P(A | B) = \frac{P(B | A) * P(A)}{P(B)}$$

For the purposes of this analysis, we defined P(A) as the probability of pathogenicity (or prior probability (Prior\_P), P(B) as the probability of the evidence for pathogenicity, P(A|B) the probability of pathogenicity given the evidence (or posterior probability Post\_P), and P(B|A) as the probability of the evidence, given that the variant is pathogenic. This equation can be rearranged to accommodate odds instead of probabilities, and simplified as follows (equation 4):

$$Post\_P = \frac{OddsPath * Prior\_P}{((OddsPath - 1) * Prior\_P + 1)}$$

The spreadsheet that we created to explore Bayesian compatibility of the ACMG/AMP combining criteria was programmed to enable a simple grid search, or parameter sweep, that could be used to either optimize or find plausible values of key variables. In this spreadsheet, the Prior\_P and Odds\_Path for the “very strong” category ( $OP_{VSD}$ ) were independently searchable variables. The four categories of pathogenic data included in the spreadsheet were used to model the ACMG/AMP pathogenic evidence categories “supporting”, “moderate”, “strong”, and “very strong”. Each of the ACMG/AMP combining rules was modeled in the spreadsheet.

An obvious constraint on the relative strength of the pathogenic evidence categories is that their OP had to ascend from supporting to very strong. In a naïve Bayesian calculation, the OPs from all of the observational evidence are multiplied together to get an overall OP. Here, this multiplication process implies that if an ACMG/AMP combining rule included two evidence criteria from the same category, then the OP from that category would equal the OP of a single evidence squared. That element of Bayesian reasoning led to the hypothesis that, if the ACMG/AMP combining criteria are Bayes-compatible, then the most natural way to model the relative strength of the evidence categories would be to treat the ordered series of categories as an exponential series with a uniform exponential step from one category to the next. Hence, the relative strength of the ordered evidence categories “supporting”, “moderate” and “strong” were linked to “very strong” through a single exponent,  $X$ , which was a third variable that could be optimized by a grid search.

An initial observation from the grid search was that when the exponent  $X$  was set to exactly 2.0, seven pairs of pathogenic combining rules had identical overall OP and identical Post\_Ps, as did ten pairs of likely pathogenic combining rules; no other value we tested

resulted in more than one pair of rules with identical Post\_Ps. This result was independent to Prior\_P and the  $O_{PVSt}$ . Summing across the exponents of the odds path equations presented in Table 1 (or Table S1) from the ACMG/AMP guidelines shows that the matching pairs of combined OP and Post\_Ps is a feature that emerges from the repeating structure of the ACMG/AMP combining rules and the arithmetic used to encode them in the exponent of the OP equation

With the value of the exponent  $X$  set at 2.0, we were left with two critical variables to explore, the prior probability (Prior\_P) and the combined odds of pathogenicity (hereafter, OP), which is the totality of the various types of evidence from Table 3 of ACMG/AMP. We tested a range of OP for the  $x$  category, as all other levels of evidence strength can be derived from this value via assumption 3. We explored a range of values for  $O_{PVSt}$  and Prior\_P to test whether the ACMG/AMP heuristic could be modeled as a Bayesian formulation. We judged these trials by determining if the calculations could yield a value for Post\_P that was internally consistent with the ACMG/AMP rules. We first set out to find a minimum  $O_{PVSt}$ . The  $O_{PVSt}$  of 81 was a unique minimum bound that could simultaneously meet the likely pathogenic and likely benign Post\_P thresholds, but only if the Prior\_P = 0.25 (Figure 1). This is because OP of 81 are the exact odds required to convert a Prior\_P of 0.10 to a Post\_P of 0.90 using Bayes' rule, and the ratio of OP between the likely pathogenic rules (ii, iii, iv, v, and vi) and the likely benign rule (ii) was exactly  $O_{PVSt}^{1.00}$ .

Equations representing each of the ACMG/AMP combining rules are presented in Table 1 and combinations of Prior\_P and  $O_{PVSt}$  that simultaneously satisfy the six rules likely pathogenic (ii, iii, iv, v, and vi) and likely benign (ii) are graphically summarized in Figure 1. Higher values of  $O_{PVSt}$  expand the range of Prior\_P under which a Bayesian interpretation is viable. For example, if  $O_{PVSt} = 350$ , this re-interpretation is compatible with Prior\_P's of 0.10–0.32. At each of the (Prior\_P,  $O_{PVSt}$ ) combinations specified above, broad consistency within the combining rules was evident. Five of the six likely pathogenic rules had Post\_Ps of exactly 0.90 and multiple pairs of pathogenic rules had identical Post\_Ps that were  $>0.99$  with  $O_{PVSt} = 350$  and Prior\_P = 0.10. We noted that there were two problematic ACMG/AMP combining rules; Pathogenic (ii) and Likely Pathogenic (i) (bolded entries, Table I). We could identify no combination of Prior\_P and  $O_{PVSt}$  that would make all 18 rules internally consistent and conclude that the ACMG/AMP framework has a degree of internal inconsistency.

Sequence variants will sometimes present with a mix of evidence for and against pathogenicity. One weakness of the ACMG/AMP combining criteria was that VUS rule (ii) given in the ACMG/AMP guidelines Table 5 was “the criteria for benign and pathogenic are contradictory”<sup>3</sup>, without defining the relative strengths of “contradictory” evidence. Although the ACMG/AMP guidelines noted that “expert judgment must be applied when evaluating the full body of evidence to account for differences in the strength of variant evidence”, more guidance on how to address conflicting evidence would reduce variation in the application of expert judgment. Indeed, with the exponent  $X$  set to 2.0, equations 1 and 2 can be combined into a single equation 5:



$$OP = O_{PVS1} \left( \frac{N_{PSu}}{8} + \frac{N_{PM}}{4} + \frac{N_{PSI}}{2} + \frac{N_{PVS1}}{1} - \frac{N_{BSu}}{8} - \frac{N_{BSI}}{2} \right)$$

which allows such combinations of evidence types to be combined and calculated. We evaluated four plausible situations where several moderate or strong pathogenic criteria coexist with a supporting benign criterion (e.g., *in silico*). For example, the combination of one very strong pathogenic criterion (PVS1, null variant), plus two moderate pathogenic criteria (PM2, absent from controls & PM6, assumed *de novo*) is designated as pathogenic (combination ib from Richards et al Table 5). If one were to add one supporting benign criterion to these (e.g., adding a benign evidence BP5 “variant found in a case with an alternate molecular basis for disease” to pathogenic rule ib), this would yield a Post\_P of 0.997, which remains in the pathogenic range. In contrast, the combination of two strong pathogenic criteria (ACMG/AMP pathogenic combination (ii)), plus one strong benign (adding BS1 “allele frequency is greater than expected for disorder”), yields a posterior probability of 0.675, which is VUS. Indeed, a variety of combinations led to either pathogenic, likely pathogenic, or VUS; these and additional examples are explored in Table 2.

## DISCUSSION

While there was no *a priori* reason for a consistent Bayesian interpretation to emerge from the ACMG/AMP guidelines, it did. Interestingly, the ACMG/AMP committee did not consider Bayes rule when they were formulating their guidelines (personal communications, H. Rehm and E. Lyon). Our analysis showed that the ACMG/AMP guidelines<sup>3</sup> delineated a heuristic system for variant classification that is compatible with a formal, quantitative, naïve Bayesian classifier. This is an important observation because it provides a mathematical foundation to what could be considered to be (or dismissed as) simply a pragmatic description of existing clinical laboratory practice. Our most important conclusion is that the ACMG/AMP framework is Bayesian in character and fundamentally sound.

We set out to understand the repeating structure within the ACMG/AMP combining criteria and to learn why it was compatible with scaling the relative strength of the ordered evidence categories to the power of 2.0. On close inspection, we noted that multiple pairs of the ACMG/AMP pathogenic combining criteria were related to each other through the rubric of “one criterion from a given strength of evidence category can be replaced with two criteria from the next weaker category”. Indeed, each pair of combining criteria that have the same OP and Post\_P feature either an instance of this rubric or else its higher order version “one criterion from a given strength of evidence category can be replaced with four criteria from the two steps weaker category”. Because in a naïve Bayesian calculation the OPs from all of the observational evidence are multiplied together to get an overall OP, this rubric is equivalent to the quantitative assertion that “OP attributed to a given strength of evidence category is equal to the square of OP attributed to the next weaker category”. Hence, the repeated use of this structural rubric is deeply compatible with the exponential scaling to the

power 2 that we found through a grid search and used in our subsequent analyses of the Prior\_P and  $O_{PVSt}$ .

Having established that the ACMG/AMP guidelines were Bayesian in character and deriving an equation to formalize that rubric, we next set out to determine if the combining criteria were internally consistent. While our analysis supported most of the “rules for combining criteria” from the ACMG/AMP recommendations<sup>3</sup>, two inconsistencies were observed, using a Prior\_P of 0.10 and  $O_{PVSt} = 350$ . First, likely pathogenic rule (i) (one very strong plus one moderate evidence of pathogenicity) was equivalent in strength to pathogenic rules (iiia, iiib, and iiic) – all of these yielded a Post\_P of 0.994. Second, and of greater concern, pathogenic rule (ii) (minimally, two strong criteria supporting pathogenicity) was weaker than the other pathogenic rules, yielding a Post\_P of 0.975. This was intermediate in strength between the five internally consistent likely pathogenic rules (ii to vi, which yield a Post\_P of 0.900) and the next tier of pathogenic rules (iiia, iiib, and iiic). Indeed, likely pathogenic rules (ii and iv) supplemented with one additional moderate criterion in favor of pathogenicity yielded Post\_Ps of 0.975; nonetheless, these combinations would be likely pathogenic under the ACMG/AMP guidelines. We could identify no combination of Prior\_P and  $O_{PVSt}$  that would allow all 18 of the specified evidence combinations (Richards et al, Table 5) to be internally consistent. The two internal inconsistencies we identified could lead to over- or underestimating variant pathogenicity probability, leading to variant misclassification. Laboratories may choose to exercise their expert judgement by requiring that pathogenic rule ii (two strong criteria), which our analysis suggests yields a Post\_P of 0.975, may need to be buttressed by the addition of two supporting or one moderate criterion that support pathogenicity to raise it above the threshold of 0.990. Alternatively, the addition of a single supporting criterion of pathogenicity would raise it from 0.975 to 0.988, which can arguably be considered sufficiently close to the 0.99 threshold to warrant a designation as pathogenic.

The clinical consequences of the potential errors that might result from these two inconsistencies are not necessarily symmetric or equivalent and adjustment or revision of these criteria should be considered. As noted above, the asymmetry of potential errors in classification lead us to have greater concern that combining rule pathogenic (ii) overestimates pathogenicity (relative to a somewhat lesser concern that likely pathogenic rule (i) underestimate pathogenicity). In general, we hold the view that incorrectly downgrading a variant from pathogenic to likely pathogenic is less likely to cause a serious clinical error than incorrectly overestimating the pathogenicity of a likely pathogenic variant to be pathogenic. That being said, it is important to remember that the ACMG/AMP criteria were guidelines, not practice standards and they included the caveat that “expert judgment must be applied when evaluating the full body of evidence”. We encourage laboratories to take our analyses into consideration as a part of their expert judgment when they evaluate variants that fall into one of the two categories that we have identified as being inconsistent. Looking forward, this and other analyses should be taken into account as a part of the deliberative processes of the ClinGen consortium Genomic Variant Working Group and Sequence Variant Working Group as well as future revisions of the ACMG/AMP guidelines.



The second major implication of our work is that there are a number of scenarios where there is a mix of evidence, some supporting and some weighing against pathogenicity. The ACMG/AMP VUS criterion (ii) was defined as “the criteria for benign and pathogenic are contradictory”. This has been widely discussed and it is likely that most laboratories interpret this to apply to situations where the evidence for and against pathogenicity are relatively balanced in their strength. It does not seem reasonable that a single supporting criterion for benign (e.g., BP4, *in silico* or BP6, reputable source) would sufficiently contravene very strong evidence for pathogenicity, resulting in a determination of VUS. Our approach demonstrates that this is not the case and that supporting evidence against pathogenicity, in combination with strong evidence for pathogenicity, can lead to posterior probabilities in the range of likely pathogenic or even pathogenic. We have provided a single, unified equation that can yield an estimate of pathogenicity for any potential combination of criteria. We have included as a supplemental file, a simple spreadsheet calculator that uses this equation such that inputting any set of criteria leads to a calculated Post\_P (Table S1). As in the discussion above, expert judgment is always necessary and we do not intend this calculator to be a substitute for that.

The transition from the ACMG/AMP categorical heuristic to a formal, quantitative Bayesian framework provides a number of potential opportunities to refine and evolve these criteria. For example, we accepted the implicit assumption of the ACMG/AMP guidelines that each categorical type of evidence of the ACMG/AMP framework at the same evidence strength level had the same mathematical support. That is to say, e.g., PS1 (same amino acid change), PS2 (*de novo*), PS3 (functional data), and PS4 (case vs. control) all had identical OP. This was a reasonable simplifying assumption for the ACMG/AMP heuristic, but it may be incorrect. Should it be determined that one of these criteria had somewhat more or less strength of evidence than the others, it would be trivial to adapt equation 5 to include any number of terms in the exponent section of the equation, adjusting the denominator of that term to reflect a more precise weighting of a particular piece of evidence. This is not practical in the current ACMG/AMP categorical heuristic because the number of combining criteria rules (Richards et al table 5) would rise exponentially with respect to the number of distinct evidence weights and the resulting combining criteria would be unwieldy.

A second example of an opportunity to improve the system is based on the recognition that some data types included in the ACMG/AMP guidelines are continuous variables (e.g., segregation), rather than categorical yes/no attributes of variants. Indeed, an inherently unsatisfying attribute of categorical systems is that they tend to misrepresent reality near the category threshold(s). A quantitative system allows continuous evidence types to be integrated into the system as continuous, rather than categorical criteria. A straightforward extension of our work would be to replace the six exponential terms in equation 5 with a term for each evidence type, such that it expressed  $P(B|A)$ , or odds of that evidence being observed if the variant were pathogenic. Examples of such approaches have been developed for several evidence types in both breast<sup>2,5-7</sup> and colorectal<sup>8-10</sup> cancer genetic analyses. Our Bayesian re-interpretation of ACMG/AMP could provide robust mathematical guidelines, e.g., how much segregation corresponds to each category of evidence in favor of pathogenicity. This could be extended to data types not yet quantitatively integrated, e.g., computational predictors and functional assays. In this way, the field of variant classification

could transition from a primarily subjective endeavor to a primarily quantitative and objective endeavor.

A third opportunity is that by translating the ACMG/AMP system into a quantitative framework, we can begin to objectively evaluate if the various forms of evidence indeed have the relative weights that the system posits. As noted above, it is straightforward to ask the question of whether the four strong pathogenic criteria are equally strong. Our approach allows the various levels to be compared. Based on our assumptions,  $O_{PVSt}$  has an odds of pathogenicity of 350,  $O_{PSI}$  of 18.7 (i.e.,  $\sqrt{350}$ ),  $O_{PM}$  4.3 (i.e.,  $\sqrt{18.7}$ ), and  $O_{PSu}$  2.08 (i.e.,  $\sqrt{4.3}$ ),  $O_{BSI}$  0.053 (i.e.,  $1/\sqrt{350}$ ), and  $O_{BSu}$  0.48 (i.e.,  $1/\sqrt{4.3}$ ). These various forms of evidence can then be tested against experimental data, such as functional assays or population constraint, that either support or argue against pathogenicity to determine if their relative weighting is valid. As well, it would be useful to determine whether real Prior\_Ps fall within the range over which the classifiers are valid. With  $O_{vst}=350$  and other constraints of the ACMG/AMP structure, this range was 0.10 to 0.32. It is worth noting that the valid range of Prior\_Ps is directly dependent on the strength of OP (Figure 1).

Re-interpretation of the ACMG/AMP guidelines in a quantitative Bayesian framework shows that the existing classification system is fundamentally sound, albeit with minor weaknesses. The analysis also identifies important developmental opportunities. Concerns about the relative weakness of the pathogenic rule (ii), and evidence that the stronger pathogenic rules could accommodate one or two supporting criteria for benign, yet still result in a likely pathogenic classification, underline the need for clinical judgment during variant classification using the existing system. Looking forward, transformation of the ACMG/AMP system into a quantitative Bayesian calculator – coupled to refined and more accurately quantitated evidence – could integrate additional data types, increase overall flexibility, and provide a pathway towards automation of the classification process.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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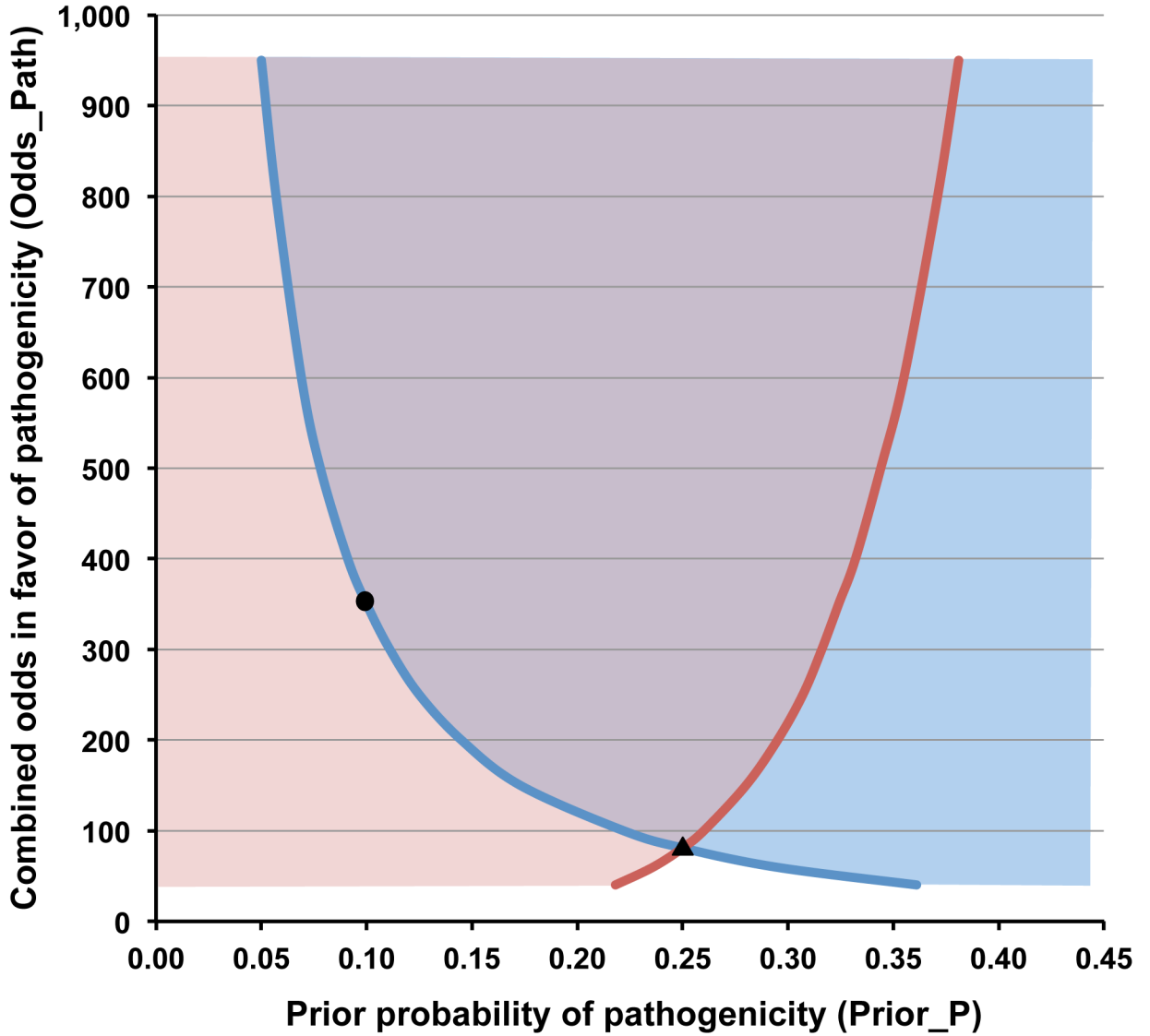
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**Figure 1.** Permissible solutions to Likely Pathogenic (LP) and Likely Benign (LB) equations. X–Y Combinations of Prior probability of pathogenicity (Prior\_P) and Odds very strong ( $O_{Vst}$ ) lying to the right of the blue curve satisfy combining rules Likely Pathogenic (ii–vi). X–Y combinations of Prior\_P and  $O_{Vst}$  lying to the left of the red curve satisfy the Likely Benign combining rule (ii). Values between the two curves and above their intersection at (Prior\_P=0.25,  $O_{Vst}$ =81) simultaneously meet LP and LB criteria. Values outside of the two curves and below their intersection at (Prior\_P=0.25,  $O_{Vst}$ =81) meet neither LP nor LB criteria. The black triangle marks the minimum simultaneous solution of LP and LB at Prior\_P=0.25,  $O_{Vst}$ =81. The black circle marks the solution of LP and LB at Prior\_P=0.10,  $O_{Vst}$ =350 illustrated in Table 1.

**Table 1**

Calculations to Test the Internal Consistency of Current ACMG/AMP Guidelines

Combining Rules <sup>a</sup>	Odds Path Equation <sup>b</sup>	Prior P <sup>c</sup>	Combined Odds Path <sup>d</sup>	Posterior P <sup>e</sup>
Path (ia)	$= 350 \left( \frac{0_{PSu}}{8} + \frac{0_{PM}}{4} + \frac{1_{PSl}}{2} + \frac{1_{PVsl}}{1} \right)$	0.10	6,548	0.999
Path (ib)	$= 350 \left( \frac{0_{PSu}}{8} + \frac{2_{PM}}{4} + \frac{0_{PSl}}{2} + \frac{1_{PVsl}}{1} \right)$	0.10	6,548	0.999
Path (ic)	$= 350 \left( \frac{1_{PSu}}{8} + \frac{1_{PM}}{4} + \frac{0_{PSl}}{2} + \frac{1_{PVsl}}{1} \right)$	0.10	3,148	0.997
Path (id)	$= 350 \left( \frac{2_{PSu}}{8} + \frac{0_{PM}}{4} + \frac{0_{PSl}}{2} + \frac{1_{PVsl}}{1} \right)$	0.10	1,514	0.994
<b>Path (ii)</b>	$= \mathbf{350} \left( \frac{\mathbf{0}_{PSu}}{\mathbf{8}} + \frac{\mathbf{0}_{PM}}{\mathbf{4}} + \frac{\mathbf{2}_{PSl}}{\mathbf{2}} + \frac{\mathbf{0}_{PVsl}}{\mathbf{1}} \right)$	<b>0.10</b>	<b>350</b>	<b>0.975</b>
Path (iiia)	$= 350 \left( \frac{0_{PSu}}{8} + \frac{3_{PM}}{4} + \frac{1_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	1,514	0.994
Path (iiib)	$= 350 \left( \frac{2_{PSu}}{8} + \frac{2_{PM}}{4} + \frac{1_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	1,514	0.994
Path (iiic)	$= 350 \left( \frac{4_{PSu}}{8} + \frac{1_{PM}}{4} + \frac{1_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	1,514	0.994
<b>Likely Path (i)</b>	$= \mathbf{350} \left( \frac{\mathbf{0}_{PSu}}{\mathbf{8}} + \frac{\mathbf{1}_{PM}}{\mathbf{4}} + \frac{\mathbf{0}_{PSl}}{\mathbf{2}} + \frac{\mathbf{1}_{PVsl}}{\mathbf{1}} \right)$	<b>0.10</b>	<b>1,514</b>	<b>0.994</b>
Likely Path (ii)	$= 350 \left( \frac{0_{PSu}}{8} + \frac{1_{PM}}{4} + \frac{1_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	81	0.900
Likely Path (iii)	$= 350 \left( \frac{2_{PSu}}{8} + \frac{0_{PM}}{4} + \frac{1_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	81	0.900
Likely Path (iv)	$= 350 \left( \frac{0_{PSu}}{8} + \frac{3_{PM}}{4} + \frac{0_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	81	0.900
Likely Path (v)	$= 350 \left( \frac{2_{PSu}}{8} + \frac{2_{PM}}{4} + \frac{0_{PSl}}{2} + \frac{0_{PVsl}}{1} \right)$	0.10	81	0.900

Combining Rules <sup>a</sup>	Odds Path Equation <sup>b</sup>	Prior P <sup>c</sup>	Combined Odds Path <sup>d</sup>	Posterior P <sup>e</sup>
Likely Path (vi)	$= 350 \left( \frac{4_{PSu}}{8} + \frac{1_{PM}}{4} + \frac{0_{PSl}}{2} + \frac{0_{PVSl}}{1} \right)$	0.10	81	0.900
Likely Benign (i)	$= 350 \left( -\frac{1_{BSu}}{8} - \frac{1_{BSl}}{2} \right)$	0.10	0.03	0.0028
Likely Benign (ii)	$= 350 \left( -\frac{2_{BSu}}{8} - \frac{0_{BSl}}{2} \right)$	0.10	0.23	0.025
Benign (ii)	$= 350 \left( -\frac{0_{BSu}}{8} - \frac{2_{BSl}}{2} \right)$	0.10	0.0028	0.00032

Notes.

<sup>a</sup>Combining criteria from Richards et al<sup>3</sup> ACMG/AMP guidelines Table 5.

<sup>b</sup>This column includes the specific use of either equation 1 or equation 2 from the main text, with the exponent N's filled in for that specific combining criteria.

<sup>c</sup>See text for discussion of the setting of the prior probability for these calculations.

<sup>d</sup>This value represents the combined odds of pathogenicity, which is the product of the odds of pathogenicity equation (1 or 2) multiplied by the prior probability.

<sup>e</sup>The posterior probability is calculated by the equation (OddsPathogenicity\*Prior P)/((OddsPathogenicity-1)\*Prior\_P+1). The two combining criteria from the ACMG/AMP guidelines - (pathogenic (ii) and likely pathogenic (i) are bolded as they are the two combinations we identified as internally inconsistent (see text).



**Table 2**  
Calculations to Evaluate Combinations of Evidence for and Against Pathogenicity

Novel combining criteria <sup>a</sup>	Odds Path Equation <sup>b</sup>	Prior P <sup>c</sup>	Combined Odds Path <sup>d</sup>	Posterior P <sup>e</sup>
One VS Path (PVS1), two Mod Path (PM2 & PM6), one Supp Benign (e.g., adding criterion BPS to pathogenic combining rule ii)	$\left( \frac{0_{PSu}}{8} + \frac{2_{PM}}{4} + \frac{0_{PSt}}{2} + \frac{1_{PVSt}}{1} + \frac{1_{BSu}}{8} - \frac{0_{BSy}}{2} \right) = 350$	0.10	3,148	0.997
Two Str Path, one Supp Benign (e.g., adding criterion BP4 to pathogenic combining rule ii)	$\left( \frac{0_{PSu}}{8} + \frac{0_{PM}}{4} + \frac{2_{PSt}}{2} + \frac{0_{PVSt}}{1} + \frac{1_{BSu}}{8} - \frac{0_{BSy}}{2} \right) = 350$	0.10	168	0.949
Two Str Path, two Supp Benign (e.g., adding BP4 & BP5 to pathogenic combining rule ii)	$\left( \frac{0_{PSu}}{8} + \frac{0_{PM}}{4} + \frac{2_{PSt}}{2} + \frac{0_{PVSt}}{1} + \frac{2_{BSu}}{8} - \frac{0_{BSy}}{2} \right) = 350$	0.10	81	0.900
Two Str Path, one Str Benign (e.g., adding BS1 to pathogenic combining rule ii)	$\left( \frac{0_{PSu}}{8} + \frac{0_{PM}}{4} + \frac{2_{PSt}}{2} + \frac{0_{PVSt}}{1} + \frac{0_{BSu}}{8} - \frac{1_{BSy}}{2} \right) = 350$	0.10	18.7	0.675

Notes:

<sup>a</sup> Novel combinations of pathogenic and benign criteria not specifically considered by the ACMG/AMP guidelines.<sup>3</sup>

<sup>b</sup> This column includes the specific use of either equation 1 or equation 2 from the main text, with the exponent N's filled in for that specific combining criteria.

<sup>c</sup> See text for discussion of the setting of the prior probability for these calculations.

<sup>d</sup> This value represents the combined odds of pathogenicity, which is the product of the odds of pathogenicity equation (1 or 2) multiplied by the prior probability.

<sup>e</sup> The posterior probability is calculated by the equation  $(\text{OddsPathogenicity}^{\text{Prior P}})/((\text{OddsPathogenicity}-1)^{\text{Prior P}+1})$ .

Abbreviations: VS Path; very strong pathogenic criterion, Mod Path; moderate pathogenic criterion; Other abbreviations from Richards et al.<sup>3</sup> Note that equation 1 from the manuscript was modified to add two negative exponents, which allow the addition of evidence types benign strong and benign supporting. Note that the ACMG/AMP guidelines<sup>3</sup> did not include any very strong or moderate strength benign criteria. See text for the discussion of stand alone criterion BAI, which is not included in this equation.