**Variability and bias in optimal cutoffs and accuracy estimates due to data-driven cutoff selection: Simulation study using data from 100 PHQ-9 accuracy studies**

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**KEY POINTS**

**Question:** Does data-driven optimal cutoff selection in Patient Health Questionnaire-9 (PHQ-9) screening accuracy studies generate cutoffs that diverge from population cutoffs and overstate accuracy?

**Findings:** Optimal PHQ-9 cutoffs identified varied from ≥ 2 to ≥ 21 for samples with N = 100 and ≥ 5 to ≥ 11 for N = 1,000. Mean mis-estimation of sensitivity and specificity were 6.4 and -0.8 percentage points for samples of N = 100 and 1.8 and -0.6 percentage points for N = 1,000.

**Meaning:** In this simulation study, we illustrated how data-driven cutoff selection may mis-identify optimal cutoffs and exaggerate PHQ-9 screening accuracy.

**ABSTRACT**

**Importance:** Test accuracy studies often use small datasets to simultaneously select an “optimal” cutoff that maximizes test accuracy and generate accuracy estimates.

**Objective:** To conduct a simulation, or re-sampling, study with real participant data to evaluate the degree that data-driven optimal cutoff selection for screening for major depression with the Patient Health Questionnaire-9 (PHQ-9) may result in selection of optimal cutoffs that diverge from population optimal cutoffs and generate biased accuracy estimates.

**Design, Setting, and Participants:** We used data from an existing individual participant data meta-analysis database on PHQ-9 screening accuracy to represent a hypothetical population. Studies in the database compared participant PHQ-9 scores with major depression classification. From the population, we randomly sampled 1,000 studies each of 100, 200, 500, and 1,000 participants.

**Main outcomes and measures:** For the full population and each simulated study, an optimal cutoff was selected by maximizing Youden’s J. Accuracy estimates for optimal cutoffs in simulated studies were compared to accuracy in the full population.

**Results:** The population included 44,503 participants (4,541 with major depression) from 100 primary studies. The population optimal cutoff was ≥ 8. Optimal cutoffs in simulated studies ranged from 2-21 in samples of 100, 3-14 in samples of 200, 4-13 in samples of 500, and 5-11 in samples of 1,000 participants. The percentage of simulated studies that identified the true optimal cutoff of ≥ 8 was 17% for samples of 100, 22% for samples of 200, 26% for samples of 500, and 33% for samples of 1,000. Compared to estimates for cutoff ≥ 8 in the population, sensitivity was overestimated by 6.4 percentage points, 4.9 percentage points, 2.2 percentage points, and 1.8 percentage points in samples of 100, 200, 500, and 1,000 participants. Specificity was within 1 percentage point across sample sizes.

**Conclusions and relevance:** In this simulation study, optimal cutoffs and accuracy estimates differed substantially from population values when data-driven methods were used to simultaneously identify an optimal cutoff and estimate accuracy. Clinicians should use cutoffs generated from well-conducted meta-analyses and adopt population-specific cutoffs that diverge from general cutoffs only if from large studies or replicated in multiple studies.

**Registration:** PROSPERO (CRD42014010673)

**Keywords:** data-driven analysis, depression, individual participant data meta-analysis, methods, screening, simulation study

**Running Title:** Data-driven cutoff selection with the PHQ-9

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1. **INTRODUCTION**

Studies on depression screening tool accuracy often use data-driven approaches and small samples and numbers of depression cases to simultaneously determine an ‘optimal’ cutoff and estimate accuracy [1-3]. A recent review of 172 studies found that median sample size was 194 and median number of depression cases approximately 20 [1]. Seventy-six percent of included studies identified an ‘optimal’ cutoff that diverged from a standard cutoff, and authors of 40% of those studies recommended that their optimal cutoff, rather than the standard cutoff, be used in their population [1].

Previous studies on data-driven selection of test cutoffs have reported that these methods produce overly optimistic accuracy estimates, especially in small samples [4-8]. However, most of these studies used simulated datasets based on hypothetical test score distributions rather than real participant data. We previously analyzed Edinburgh Postnatal Depression Scale (EPDS) data from 13,255 participants and found that in 1,000 simulated or “re-sampled” studies, the cutoff maximizing Youden’s J (sensitivity + specificity – 1) [9] ranged from ≥ 5 to ≥ 17 with re-sampled studies of N = 100 and ≥ 8 to ≥ 13 with N = 1,000. Mean sensitivity overestimation was 7 percentage points (pp) for N = 100 versus 1pp for N = 1,000, while specificity was underestimated by 1pp across sample sizes [8].

The standard cutoff traditionally used to screen for major depression with the Patient Health Questionnaire-9 (PHQ-9) is ≥ 10 [10-14]. An individual participant data meta-analysis (IPDMA) of 100 primary studies (44,503 participants, 4,541 major depression cases) confirmed that a cutoff of ≥ 10 maximized combined sensitivity and specificity in studies that used a “gold standard” semi-structured interview reference standard, although the optimal cutoff was ≥ 8 when fully structured interviews, designed for lay administration, were used [15, 16].

Many primary studies of PHQ-9 accuracy emphasize results from data-driven optimal cutoffs. [1].The degree that accuracy is overestimated when data-driven cutoffs are used for the PHQ-9, however, is not known. The objective of the present study was to determine the degree that using data-driven methods to simultaneously select an optimal PHQ-9 cutoff and estimate accuracy may bias estimates. We estimated, across different sample sizes, the degree that data-driven cutoff selection results in (1) sample-specific optimal cutoffs that differ from the population-level optimal cutoff and (2) biased accuracy estimates. In addition, for comparison, we (3) estimated accuracy using the population-level optimal cutoff in individual re-sampled studies and compared to population accuracy.

1. **MATERIALS & METHODS**

We used data from an IPDMA of PHQ-9 diagnostic accuracy to represent a hypothetical “population” from which studies of different sizes could be re-sampled [16]. The main IPDMA was registered in PROSPERO (CRD42014010673), and a protocol was published [19]. A protocol for the present study was published in the Open Science Framework repository prior to initiation [20]. Details on the methodology used to identify, obtain, and synthesize the data included in the present study are provided in eMethods1 and eMethods2. We used a similar methodological approach as our EPDS simulation study [8]. Because of the overlap of methods in the present study and previous studies, we described the methods similarly and followed reporting guidance from the Text Recycling Research Project [21].

**2.1 Data analysis**

For the purposes of the present study, we used our IPDMA dataset to represent a hypothetical population and defined population sensitivity and specificity values for PHQ-9 cutoffs to be those estimated in the hypothetical population. In our main IPDMA on PHQ-9 accuracy, we accounted for clustering of observations within each study, and we applied sampling weights to account for imbalances in participant samples when, for instance, all participants with positive screens but only a random portion of those with negative screens were administered a diagnostic interview. In the present study, we ignored clustering and sampling weights to have a defined population from which we could draw samples that represented simulated primary studies and to be able to analyze the population data and simulated primary study data with the same analytical approach. In addition, in the main IPDMA, we stratified included studies by reference standard type because previous studies have shown that different types of diagnostic interviews classify major depression differently [22-23]. However, in main analyses of the present study, we did not stratify studies by reference standard because we were not evaluating the true screening accuracy of the PHQ-9, and combining included studies that used different reference standards allowed us to have a single hypothetical population for simulation. As a result, this procedure produced accuracy estimates that differed from those reported in the published IPDMA [16]. In the present study, we calculated the population optimal cutoff that maximized Youden’s J in the full IPDMA dataset, which was ≥ 8.

First, we described the individual primary studies included in the IPDMA dataset in terms of sample size, number of major depression cases, and optimal cutoff (based on maximizing Youden’s J). If there was a tie in maximum Youden’s J between multiple cutoffs, we randomly selected one of the cutoffs. We chose to use Youden’s J because it is by far the most commonly used method for selecting optimal cutoffs in depression screening accuracy studies, and our re-sampling study aimed to reflect current research practices [1].

Second, from the IPDMA dataset, we sampled with replacement to generate 1,000 randomly sampled studies each of 100, 200, 500, and 1,000 participants to mimic what would occur in primary studies that use samples of these sizes. For each study, we defined the sample-specific optimal cutoff as the cutoff that maximized Youden’s J with random selection in case of ties. For each sample size, across the 1,000 samples, we (1) graphically illustrated the variability in sample-specific optimal cutoffs and their accuracy estimates; and (2) estimated the mean difference in sensitivity and specificity estimates at the sample-specific optimal cutoffs and at a cutoff of ≥ 8, compared to sensitivity and specificity estimates for a cutoff of ≥ 8 in the population. In additional analyses, we stratified results by optimal cutoff value.

Random selection of participants in simulated samples and averaging sensitivity and specificity across 1,000 samples for each sample size was done to balance other possible sources of divergent accuracy, such as reference standards or individual participant characteristics. Nonetheless, in sensitivity analyses, we repeated the simulation process including only studies that used the semi-structured Structured Clinical Interview for DSM (SCID) as the reference standard.

For all analyses, sensitivity and specificity were estimated using 2 x 2 table counts. Analyses were done using R version 4.2.2.

**2.2 Ethical Approval**

The Research Ethics Committee of the Jewish General Hospital (Montreal, Quebec) determined that research ethics approval was not required, since the study involved IPDMA of anonymized previously collected data. For each included dataset, we confirmed that the original study received ethics approval and that participants provided informed consent.

**3. RESULTS**

**3.1 Description of the 100 included primary studies**

The full IPDMA database included 100 primary studies with 44,503 participants (4,541 major depression cases, 10%), which constituted the “population” for the present study. See eTable1 for primary study characteristics. In the 100 included primary studies, mean sample size was 445 participants (median = 194) and mean number of major depression cases was 45 (median = 29). Study-specific optimal cutoffs ranged from ≥ 3 to ≥ 18 (median = ≥ 10). Frequencies of PHQ-9 scores for cases and non-cases are shown in eTable2 with histograms in eFigure1. PHQ-9 scores were normally distributed (mean and median = 13) among cases and right-skewed among non-cases (mean = 4, median = 3). In the full database population, unweighted sensitivity and specificity for PHQ-9 ≥ 8 were 80.4% and 82.0%.

**3.2 Variability of sample-specific optimal cutoffs in simulated samples**

Figure 1 shows the variability of sample-specific optimal cutoffs from 1,000 re-sampled studies of 100, 200, 500 and 1,000 participants. As sample size increased, the variability in sample-specific optimal cutoffs decreased. In studies of 100 participants, study-specific optimal cutoffs ranged from ≥ 2 to ≥ 21; 17% of studies had an optimal cutoff of ≥ 8 and 45% had an optimal cutoff between ≥ 7 and ≥ 9. When sample size increased to 1,000 participants, the range of optimal cutoffs was ≥ 5 to ≥ 11; 33% of samples had an optimal cutoff of ≥ 8, and 79% had an optimal cutoff between ≥ 7 and ≥ 9.

**3.3 Bias analyses in simulated samples**

As shown in Figure 2, overestimation of sensitivity estimates for sample-specific optimal cutoffs decreased with increasing sample size, whereas specificity estimates remained within 1pp across sample sizes. Precision of both sensitivity and specificity estimates increased with sample size. As shown in Table 1, compared to accuracy estimates for a cutoff of ≥ 8 in the full database, study-specific optimal cutoffs in samples of 100 participants overestimated sensitivity by a mean of 6.4pp (95% confidence interval [CI] 5.7 to 7.1) and overestimated specificity by 0.6pp (95% CI 0.0 to 1.2). When sample size increased to 1,000, study-specific optimal cutoffs overestimated sensitivity by 1.8pp (95% CI 1.5 to 2.1) and underestimated specificity by 0.6pp (95% CI -1.0 to -0.3).

As shown in Table 1 and Figure 3, when each re-sampled study used a pre-specified cutoff of ≥ 8, mean sample-specific sensitivity and specificity values were similar to those in the population for all sample sizes.

As shown in eTable3, across sample sizes, bias in estimates increased as the sample-specific optimal cutoff diverged from ≥ 8. When the sample-specific optimal cutoff was lower than ≥ 8, specificity was underestimated, whereas when the sample-specific optimal cutoff was higher than ≥ 8, specificity was overestimated. The opposite pattern was seen for sensitivity, although there was a shift in values, given that even when the sample-specific cutoff was exactly ≥ 8, sensitivity was, on average, overestimated.

**3.4 Sensitivity Analyses**

As shown in eTable4 and eTable5, variability in sample-specific optimal cutoffs and bias in sensitivity and specificity were similar to the main results when only studies that used the SCID reference standard were included.

1. **DISCUSSION**

**4.1 Principal Findings**

This was the first study to assess bias in PHQ-9 accuracy estimates due to data-driven optimal cutoff selection. Strengths included the use of a large sample and real participant data.

The main finding of this simulation, or re-sampling, study was that data-driven optimal PHQ-9 cutoffs often differed from the population optimal cutoff, sometimes substantially, and produced biased accuracy estimates. As sample size increased from 100 to 1,000 participants, variability in optimal cutoffs decreased from a range of ≥ 2 to ≥ 21 to a range of ≥ 5 to ≥ 11 and overestimation in sensitivity compared to the population value decreased from 6.4pp to 1.8pp, while specificity remained within 1pp. The magnitude and direction of bias differed depending on how far the sample-specific optimal cutoff was from the population optimal cutoff of ≥ 8. When a pre-defined cutoff of ≥ 8 was used in re-sampled studies, mean accuracy estimates were consistent with overall population estimates.

**4.2 Comparison with Other Studies**

Previous distribution-based simulation studies have found that data-driven cutoff selection in small samples results in exaggerated accuracy estimates [4-7]. Most studies on depression screening tool accuracy have small sample sizes and numbers of depression cases. Individual studies often report results from one, several, or many cutoffs, with the result being a wide range of optimal cutoffs and accuracy estimates across studies [1-3]. Many authors conclude that sample characteristics influence accuracy and that different optimal cutoffs are needed for particular population subgroups. Results from the present study and the previous simulation study on the EPDS [8] suggest that variability in optimal cutoffs and accuracy estimates often occurs due to chance and imprecision in small samples even when all samples are drawn from the same population. The findings that data-driven methods and small samples may explain divergent results across studies are consistent with the results of several large IPDMAs [15,16,24,25],which found that there were no substantive differences in depression screening tool accuracy based on participant characteristics. Additionally, the finding in the present study that accuracy estimates were similar between the full population and re-sampled studies when the same cutoff was used underlines that divergences can be attributed to data-driven methods and sample size rather than characteristics of participants in each sample.

Our finding that there were larger biases in sensitivity compared to specificity is not surprising, given that most studies have many fewer participants with depression than without. In addition, PHQ-9 scores among cases were normally distributed, whereas scores among non-cases were heavily right-skewed. Similar results were seen in the simulation study of EPDS data, which found that overestimation of sensitivity reduced from 7pp in samples of 100 participants to 1pp in samples of 1,000 participants, while specificity was underestimated by 1pp across sample sizes [8].These findings suggest that data-driven methods for cutoff selection can allow for substantial sensitivity gains with only minor costs to specificity, although at the individual study level, sensitivity can be either over- or underestimated.

**4.3 Implications**

Clinicians and policy makers who make decisions regarding depression screening should be aware that optimal cutoffs for the PHQ-9 and other depression screening tools identified in small single studies should be interpreted cautiously. Decisions regarding what cutoffs to use should ideally be based on large, well-conducted meta-analyses, or based on multiple validations in studies with adequate sample size for desired precision levels. In addition, clinicians may want to prioritize either sensitivity or specificity in different clinical settings, rather than consider them equally as is the case when selecting cutoffs based on Youden’s J, and select higher or lower cutoffs, depending on health and resource priorities [26]. The optimal cutoff of ≥ 8, which was identified in our hypothetical population was not derived using methods that account for clustering and sample weights and may reflect that participants from studies that used different reference standards were combined. Cutoffs and accuracy estimates from the main PHQ-9 IPDMA should be used clinically [16]. Depression screening questionnaires are not intended to establish clinical diagnoses but can be used for screening followed by clinical evaluation of those who screen positive. Whether screening should occur in practice requires evidence from clinical trials of benefit, which has not been established [27].

Although the Standards for Reporting of Diagnostic Accuracy Studies (STARD) reporting guideline recommends a priori sample size calculations [28], most depression screening tool accuracy studies do not conduct such calculations [2,3]. Researchers conducting primary studies on accuracy should conduct sample size calculations prior to recruitment to ensure the inclusion of sufficient numbers of both cases and non-cases for desired precision levels in accuracy estimates [29]. In addition, selective cutoff reporting bias occurs when researchers select which cutoffs to report accuracy results for in their individual studies based on the relative accuracy at those cutoffs in their sample (e.g., reporting accuracy estimates for cutoffs that maximize Youden’s J, but not for other cutoffs) [17,18]. Selective cutoff reporting bias has been found to underestimate sensitivity for cutoffs below a clearly defined standard cutoff and overestimate sensitivity for cutoffs above the standard [17,18]. Since summary accuracy estimates for a pre-defined cutoff do not tend to be biased, researchers should report accuracy estimates for all possible cutoffs rather than just those that are optimal in a given study or cutoffs close to the optimal cutoff [17,18]. Additionally, statistical methods for estimating cutoffs and “out-of-sample” performance, such as smoothing based on kernel estimation and bootstrapping, should be considered [30].

Beyond variability in accuracy estimates, researchers should also consider variability in the optimal cutoff that may be identified in individual studies. It is possible that authors of primary studies could use statistical methods to estimate uncertainty around optimal cutoffs in their individual studies, for instance via confidence intervals [31,32], and use internal validation methods (e.g., bootstrapping) to adjust for bias due to optimism [30,33]. Further work to test and demonstrate such methods for the purpose of mental health screening is needed.

**4.4 Limitations**

A limitation to consider is that we did not include datasets from recently published studies on PHQ-9 accuracy; however, we do not expect that the inclusion of more recent studies would alter results, given that newer studies would likely be of similar sample sizes and heterogeneity. We included data from 100 primary studies, and we believe that the dataset used for this study adequately represents a hypothetical population for simulation purposes. A second possible limitation is that we used only Youden's J to select optimal cutoffs. It is by far the most common method in depression screening accuracy studies [1] and performs similarly to other indices (e.g., the Euclidean distance) [34], but it is known to be unreliable and prone to overestimation. It is possible that results could differ slightly for an alternative method.

1. **CONCLUSIONS**

In summary, using samples with small numbers of participants and cases to simultaneously identify an optimal cutoff and estimate its accuracy results in optimal cutoffs that vary widely from study to study and exaggerated accuracy estimates. Variability in optimal cutoffs and the extent of sensitivity exaggeration reduces as sample size increases. Researchers should conduct a priori sample size calculations to ensure the inclusion of sufficient numbers of both cases and non-cases in diagnostic accuracy studies, report accuracy estimates for all cutoffs rather than just study-specific optimal cutoffs, and avoid making recommendations about optimal cutoffs and accuracy based on small single studies. They should consider using statistical methods that improve optimal cutoff identification and estimation of accuracy outside of the study sample. Users of diagnostic accuracy evidence, including researchers, clinicians, and policy makers, should evaluate studies of PHQ-9 accuracy with caution and ensure that recommendations regarding cutoffs are based on adequately powered and analyzed research studies or well-conducted meta-analyses.

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Members of the DEPRESSD PHQ Group contributed:

To data extraction, coding, and synthesis: CH, YW, AK, ZN, MImran, DBR, KER, MA, AWL. Via the design and conduct of database searches: JB, LAK. As members of the DEPRESSD Steering Committee, including conception and oversight of collaboration: PC, SG, JPAI, SBP, RCZ, YT. As a knowledge user consultant: SM. By contributing included datasets: SBP, SHA, DA, BA, LA, HRB, ABeraldi, CNB, ABhana, CHB, RIB, PB, GC, MHC, JCNC, LFC, DC, KC, AC, YC, FMD, JMdMvG, JRF, FHF, SField, JRWF, DF, BG, LJG, FGS, EPG, CGG, BJH, LHantsoo, MH, LHides, SEH, SH, TH, MInagaki, MIG, HJJ, NJ, MEK, KMK, BAK, YK, MLara, HFLA, SIL, MLotrakul, SRL, BLöwe, NPL, CL, RAM, LM, PBM, AM, SMS, TNM, KM, JEMN, LN, FLO, BWP, PP, IP, AP, SLP, TJQ, ER, SDR, KR, AGR, ISS, MTS, JS, EHS, ASidebottom, ASimning, LSpangenberg, LStafford, SCS, KS, PLLT, MTR, TDT, AT, CMvdFC, TvH, PAV, LIW, JLW, DW, JW MAW, KWinkley, KWynter, MY, QZZ, YZ.

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**Figure 1. Variability of data-driven optimal cutoffs in 1,000 samples of size 100, 200, 500, and 1,000**

**Figure 2. Variability in accuracy estimates of the optimal cutoffs in 1,000 samples of size 100, 200, 500, and 1,000, compared to accuracy estimates from a cutoff of ≥ 8 in the population**

Edges of boxes represent the 25th and 75th percentiles; mid-lines represent the medians

Dotted horizontal line represents the accuracy of the *true population optimal cutoff* in the full PHQ-9 IPDMA dataset (cutoff of ≥ 8; sensitivity = 80.4%, specificity = 82.0%)

**Figure 3. Variability in accuracy estimates of a cutoff of ≥ 8 in 1,000 samples of size 100, 200, 500, and 1,000, compared to accuracy estimates from a cutoff of ≥ 8 in the population**

Edges of boxes represent the 25th and 75th percentiles; mid-lines represent the medians

Dotted horizontal line represents the accuracy of the *true population optimal cutoff* in the full PHQ-9 IPDMA dataset (cutoff of ≥ 8; sensitivity = 80.4%, specificity = 82.0%)

**Table 1. Mean bias of accuracy estimates (with 95% confidence intervals) for 1,000 samples of size 100, 200, 500, and 1,000**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Sample size = 100 | | Sample size = 200 | | Sample size = 500 | | Sample size = 1,000 | |
| **Sensitivity** | **Specificity** | **Sensitivity** | **Specificity** | **Sensitivity** | **Specificity** | **Sensitivity** | **Specificity** |
| Sample-specific optimal cutoffa – Population optimal cutoff of ≥ 8b | 6.4 (5.7, 7.1) | 0.6 (0.0, 1.2) | 4.9 (4.3, 5.5) | -0.3 (-0.8, 0.2) | 2.2 (1.8, 2.6) | 0.0 (-0.4, 0.3) | 1.8 (1.5, 2.1) | -0.6 (-1.0, -0.3) |
| Sample-specific cutoff of ≥ 8 – Population optimal cutoff of ≥ 8 | -0.8 (-1.7, 0.0) | 0.1 (-0.1, 0.4) | 0.2 (-0.3, 0.8) | -0.1 (-0.2, 0.1) | 0.1 (-0.2, 0.4) | 0.0 (-0.1, 0.1) | -0.1 (-0.4, 0.1) | 0.0 (-0.1, 0.1) |

Differences are presented as mean difference (95% confidence interval)

a Sample-specific optimal cutoff refers to the cutoff maximizing Youden’s J in each simulated sample

b the optimal cutoff in the full PHQ-9 IPDMA dataset is ≥ 8 (sensitivity = 80.4%, specificity = 82.0%)