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BASIC RESEARCH ARTICLE

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Beyond one-cutoff-fits-all: determining cutoff values for the PTSD checklist for DSM-5 (PCL-5)

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ABSTRACT

Background: There is no universally optimal cutoff score for identifying probable PTSD, which makes reliable PTSD diagnosis challenging not only across different populations but also in different settings. Reliable outcomes require tailoring cutoff scores to the population, intended use (clinical, research, or prevalence estimation), and appropriate statistical methods to ensure their validity.

Objective: While previously little emphasis has been placed on thorough methodological evaluation and purpose-driven cutoff selection, this work addresses these gaps by evaluating optimal PCL-5 cutoff scores for clinical use, prevalence estimation, and research in a German-speaking clinical sample.

Methods: Previously published data from 443 trauma-exposed individuals in Germany were re-analyzed for this purpose. PTSD was assessed using the PCL-5 and with CAPS-5 clinical interview. Optimal cutoffs were identified using ROC analysis, applying standard estimation methods and prioritising diagnostic utility based on specific objectives.

Results: After evaluating various cutoff points for different purposes, we identified the following as most suitable for this sample: a cutoff of 34 for clinical use (sensitivity: 0.892, specificity: 0.645, PPV: 0.824, NPV: 0.763); 38 for prevalence estimation (sensitivity: 0.840, specificity: 0.703, PPV: 0.840, NPV: 0.703); and 42 or 43 for identifying clear-cut cases in research or resource-limited settings (sensitivity: 0.774–0.760, specificity: 0.742–0.761, PPV: 0.848–0.855, NPV: 0.639–0.631). The originally intended cutoffs of 31–33 yielded acceptable to excellent diagnostic utility parameters but were not identified as optimal for any specific purpose.

Conclusion: This study highlights the variability in optimal PCL-5 cutoffs, linking selection to specific clinical or research aims. It provides validated cutoffs for PTSD prevalence in a German clinical sample, with limitations regarding generalizability to lower-prevalence populations. Future research should refine cutoffs for diverse populations and improve diagnostic precision.

Más allá de un punto de corte único: determinación de los valores de corte para la lista de verificación de TEPT del DSM-5 (PCL-5)

Antecedentes: No existe una puntuación de corte universalmente óptima para identificar un posible TEPT, lo que dificulta un diagnóstico fiable no solo en diferentes poblaciones, sino también en diferentes contextos. Para obtener resultados fiables, es necesario adaptar las puntuaciones de corte a la población, el uso previsto (clínico, de investigación, o estimación de la prevalencia) y utilizar métodos estadísticos adecuados para garantizar su validez.

Objetivo: Si bien anteriormente se ha prestado poca atención a la evaluación metodológica exhaustiva y a la selección de puntos de corte con un propósito definido, este trabajo aborda estas deficiencias mediante la evaluación de las puntuaciones de corte óptimas del PCL-5 (por su sigla en inglés) para uso clínico, estimación de la prevalencia, e investigación en una muestra clínica de habla alemana.

Métodos: Con este propósito se volvieron a analizar datos publicados previamente de 443 personas expuestas a traumas en Alemania. El TEPT se evaluó mediante el PCL-5 y la entrevista clínica CAPS-5 (por su sigla en inglés). Se identificaron los puntos de corte

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PCL-5; PTSD diagnosis; cutoff scores; ROC analysis; prevalence estimation; clinical sample; sensitivity and specificity; psychometric properties

PALABRAS CLAVE

PCL-5; diagnóstico del TEPT; propiedades psicométricas; sensibilidad y especificidad; muestra clínica; puntuaciones de corte; análisis ROC; estimación de la prevalencia

HIGHLIGHTS

- Context matters: PTSD screening requires purpose-specific cutoff scores rather than a universal threshold.
- Validated cutoffs: this study determines optimal PCL-5 scores for clinical screening, prevalence estimation, and research.
- Methodological refinement: this study applies a purpose-driven approach to determining PTSD cutoff scores, emphasising statistical rigour and diagnostic utility.

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óptimos mediante análisis ROC, aplicando métodos de estimación estándar y priorizando la utilidad diagnóstica según objetivos específicos.
Resultados: Tras evaluar diversos puntos de corte para diferentes propósitos, se identificaron los siguientes como los más adecuados para esta muestra: un punto de corte de 34 para uso clínico (sensibilidad: 0.892, especificidad: 0.645, VPP: 0.824, VPN: 0.763); 38 para la estimación de la prevalencia (sensibilidad: 0.840, especificidad: 0.703, VPP: 0.840, VPN: 0.703); y 42 o 43 para la identificación de casos claros en contextos de investigación o con recursos limitados (sensibilidad: 0.774-0.760, especificidad: 0.742-0.761, VPP: 0.848-0.855, VPN: 0.639-0.631). Los puntos de corte inicialmente previstos, de 31 a 33, arrojaron parámetros de utilidad diagnóstica de aceptables a excelentes, pero no se identificaron como óptimos para ningún propósito específico.
Conclusión: Este estudio destaca la variabilidad en los puntos de corte óptimos de PCL-5, vinculando la selección con objetivos clínicos o de investigación específicos. Proporciona puntos de corte validados para la prevalencia del TEPT en una muestra clínica alemana, con limitaciones en cuanto a la generalización a poblaciones de menor prevalencia. Las investigaciones futuras deberían refinar los puntos de corte para diversas poblaciones y mejorar la precisión diagnóstica.

1. Introduction

In an ideal world, every mental health diagnosis would be based on a thorough clinical interview with a trained expert – the gold standard for accurately assessing true diagnostic status. Yet, clinical interviews are resource-intensive, making them impractical for large-scale studies or routine clinical settings. Instead, cutoff values on self-report instruments offer an efficient workaround, allowing for the efficient identification of probable cases of disorders like PTSD. This simplicity has made cutoff values especially popular in clinical two-step diagnostic processes, where initial screenings flag high-risk individuals for further assessment, as well as in large-scale scientific studies, where self-report screenings often replace clinical interviews to accommodate practical and economic constraints.

However, relying solely on cutoff values requires careful consideration, as the choice of assessment method – self-report versus structured clinical interviews – can significantly influence outcomes. Self-report tools are prone to biases such as acquiescence, social desirability, and exaggeration (Burchett et al., 2023; Paykel & Norton, 1986; Steenkamp et al., 2010). They are especially vulnerable to upward bias when assessing negative experiences (Anvari et al., 2023) and often reflect complex, context-dependent responses, with individuals favouring moderate answers to avoid negative perceptions (Kuncel & Tellegen, 2009). Additionally, reference biases based on social group standards can cause discrepancies in self-report surveys (Lira et al., 2022). Structured clinical interviews – such as the Clinician-Administered PTSD Scale for DSM-5 (CAPS-5; Weathers et al., 2018) – are generally considered the gold standard in PTSD diagnosis (American Psychiatric Association, 2021; U.S. Department of Veterans Affairs, 2023), although they may also be subject to interviewer biases, such as the halo effect (Merten et al., 2017; Paykel & Norton, 1986). According to Kramer et al. (2023), clinical interviews like the CAPS-5 provide a more nuanced and accurate PTSD evaluation and are a more reliable diagnostic tool. Their study found that the PTSD Checklist for DSM-5 (PCL-5, self-report) often overestimated PTSD symptoms, with higher scores and greater discrepancies in intensity and severity compared to the CAPS-5. The self-report tool was also prone to false alarms (over-reporting) and misses (under-reporting). Further evidence that self-report tools often overestimate PTSD symptoms is demonstrated by Stevens et al. (2013) who found that 53% of people claiming to have PTSD in a forensic setting exhibited symptom exaggeration, with only 3.4% meeting the full DSM-IV-TR PTSD criteria in clinical interviews. Similarly, a meta-analysis revealed that pooled prevalence estimates for PTSD based on self-report surveys are significantly higher (20.4%) than those derived from structured clinical interviews (4.5%) (Siqveland et al., 2017). This highlights the need for carefully calibrated cutoff values that align more closely with clinical interview standards.

Methodologically, there is no single way to determine the ideal cutoff value for diagnostic tools. Instead, multiple criteria and combinations thereof are available. Cutoff values are often established using receiver operating characteristic (ROC) analysis, which integrates diagnostic metrics such as sensitivity (true positive rate), specificity (true negative rate), positive predictive value (PPV; proportion of positive results that are true positives), and negative predictive value (NPV; proportion of negative results that are true negatives). Within the ROC framework, several established statistical methods exist for determining an optimal cutoff value, including the Youden Index (Fluss et al., 2005), the point where sensitivity equals specificity (Greiner et al., 1995; Hosmer & Lemeshow, 2000), and the shortest distance between the ROC curve and the upper-left corner (Metz, 1978; Vermont

et al., 1991). However, these methods can yield markedly different cutoff values, reflecting the complexity of the decision-making process. Moreover, the selection of an appropriate cutoff value should be informed by the specific objectives of the categorical decision (Trevethan, 2017). Depending on the intended application, the prioritisation of metrics such as sensitivity, specificity, PPV, or NPV may vary. For example, in a primary healthcare setting screening for PTSD symptoms six months after a disaster, the focus should be on high sensitivity to identify as many potential cases as possible, with lower specificity acceptable since false positives can be ruled out during follow-up evaluations. In contrast, when estimating PTSD prevalence in the population, the diagnostic tool must balance sensitivity and specificity to ensure the test results accurately reflect the true prevalence. In a research context, where the goal is to compare the individuals with PTSD to those without, two cutoffs may be necessary. One should prioritise a high PPV to ensure accurate identification of true PTSD cases, while the other should focus on a high NPV to reliably exclude non-cases.

The PCL-5 is a widely recognised and validated tool for assessing PTSD in accordance with DSM-5 criteria (Weathers, Blake, et al., 2013; Weathers, Litz, et al., 2013). While its recommended cutoff scores are 31-33, a meta-analysis (Forkus et al., 2022) summarising validation studies across diverse samples revealed that reported cutoffs range from 22 to 49. This variability showcases that cutoff scores are highly context-dependent, influenced by population characteristics such as PTSD prevalence, symptom severity, and demographic factors – a phenomenon known as the spectrum effect (Ransohoff & Feinstein, 1978; Usher-Smith et al., 2016). Diagnostic metrics like sensitivity and specificity fluctuate accordingly, meaning a cutoff that performs well in a clinical sample with high PTSD prevalence may lead to misclassification when applied to a general population sample. This issue is further complicated by methodological inconsistencies in cutoff determination. Studies often vary in their choice of methods for identifying cutoff values, rarely specifying the intended purpose or application of these values, nor addressing how the choice of method influences the outcome. Some studies focus on replicating previously suggested optimal cutoff scores (Krüger-Gottschalk et al., 2017; Moodliar et al., 2020; Rosendahl et al., 2019) or aligning cut scores with those of the PCL-5's predecessor (Blevins et al., 2015; Zuromski et al., 2019). However, most studies rely on a single statistical cutoff determination method within the ROC framework, such as prevalence matching (Ashbaugh et al., 2016), balancing sensitivity and specificity (Fung et al., 2019), Youden's index (Geier et al., 2019; Jiang et al., 2023; Levitt et al., 2021), maximising overall efficiency (Verhey et al., 2018), evaluating the kappa coefficient (Bovin et al., 2016; Hall et al., 2019; Wortmann et al., 2016) or others (Ibrahim et al., 2018; Murphy et al., 2017; Price et al., 2016; van der Meer et al., 2017). Only a few studies compare multiple statistical methods to identify a single cutoff (Jenkins-Guarnieri et al., 2023; Pereira-Lima et al., 2019), and even fewer derive multiple cutoffs from multiple statistical methods tailored to different target groups (Boysan et al., 2017) or applications (Hendrikx et al., 2024; Hoeboer et al., 2024).

There is no universally optimal cutoff score for identifying probable PTSD, which makes reliable PTSD diagnosis challenging not only across different populations but also in different settings. In practice, a single cutoff value is often derived from a specific study and applied universally without sufficient critical evaluation. This over-reliance, particularly when applied to populations outside the original norm sample, can lead to inaccurate conclusions. Screening results should therefore be seen as indicators of probable, not definitive, PTSD diagnoses, especially where clinical interviews are not the standard (Bovin & Marx, 2023). Reliable outcomes require tailoring cutoffs to the population's characteristics (Forkus et al., 2022) and, as we argue, the intended use – whether clinical, research, or prevalence estimation – along with a careful selection of statistical methods to ensure the cutoff aligns with its specific purpose. While the initially suggested cutoff scores for the German PCL-5 (31–33) have been validated in a clinical sample with high PTSD prevalence (Krüger-Gottschalk et al., 2017), no systematic evaluation has been conducted for determining optimal cutoffs specifically for prevalence estimation or research purposes, such as identifying clear-cut cases. To address this gap, we re-analyzed an expanded version of this dataset. We evaluated and compared several well-established methods for determining cutoff scores within the ROC framework, incorporating a purpose driven prioritisation of sensitivity, specificity, PPV, and NPV, as needed for the objective. This study revisits the existing clinical cutoff and proposes an empirically derived cutoff score tailored to prevalence estimation and research purposes in German-speaking clinical populations.

2. Method

2.1. Procedure and participants

The inclusion criteria for the analysis sample required participants to be individuals seeking treatment in trauma-focused treatment centres across Germany, with exposure to at least one traumatic event and a minimum of one month elapsed since the trauma, as assessed via self-report on the Life Events Checklist

(LEC). Recruitment was conducted within several trauma treatment centres across Germany and through newspaper advertisements. Recruitment involved informed consent, questionnaire completion and typically on the same day or within a few days clinical interviews. Licensed or trained psychologists with at least a bachelor's degree, following a two-day training and ongoing supervision, conducted interviews. The study was approved by the Ethics Committee of Dresden University (Approval Numbers: EK-No. 45022015 and EK-No. 467122017). All participants provided written informed consent in accordance with the Declaration of Helsinki.

The study integrated two distinct datasets. The first dataset, derived from Krüger-Gottschalk et al. (2017), included 345 individuals with trauma exposure recruited from five trauma-focused treatment centres across Germany (Münster, Berlin, Dresden, Mannheim, Hamburg) between March 2014 and December 2015. This publication provides a detailed validation of the PCL-5 and an initial examination of the psychometric properties of the cutoff values proposed by Weathers, Blake, et al. (2013) and Weathers, Litz, et al. (2013). A subset of 32 participants from this dataset was recruited through newspaper advertisements, hence non-treatment seeking. The second dataset consisted of 107 participants assessed during routine intake procedures at the outpatient trauma ward of the Department of Psychotherapy and Psychosomatic Medicine at the Technical University Dresden, Germany between April 2018 and November 2022. The combined study sample initially comprised 452 participants. After excluding nine individuals who provided no responses on the PCL-5, the final sample consisted of 443 participants. The sample was predominantly female, with 280 females (63.2%), 162 males (36.6%), and one participant (0.2%) with unreported gender. Participants' ages ranged from 18 to 69 years ($M = 38.49$, $SD = 12.06$). Importantly, none of the participants had received any trauma-related interventions at the time of assessment, ensuring that the findings reflect the effects of trauma without the confounding influence of prior treatment. Although minor differences exist between the subsamples (e.g. gender distribution, age), both datasets were methodologically and contextually aligned, justifying their integration for the purposes of cutoff estimation. Descriptive statistics and inferential comparisons across subsamples are reported in Supplementary Table 2.

2.2. Instruments

The Life Events Checklist 5 (LEC-5; Weathers, Blake, et al., 2013; Weathers, Litz, et al., 2013) is a self-report instrument designed to assess lifetime exposure to traumatic events. It includes 16 predefined types of trauma and an additional item for describing any other significant stressful experiences. Participants indicate their exposure to these events with the options 'Happened to me,' 'Witnessed it,' 'Learned about it,' or 'Part of my job.' Responses of 'Not sure' or 'Doesn't apply' are classified as not exposed to that particular event.

The PTSD Checklist for DSM-5 (Weathers, Blake, et al., 2013; Weathers, Litz, et al., 2013) comprises 20 items that reflect the symptoms of PTSD as outlined in the DSM-5. The severity of these symptoms over the past month is assessed using a 5-point Likert scale, ranging from 0 ('Not at all') to 4 ('Extremely'). This tool offers two options for a preliminary PTSD diagnosis: the diagnostic algorithm based on DSM-5 criteria (given that at least one B item, one C item, two D items, and two E items at a rating of 2 (moderately) or above are endorsed) and another based on a symptom severity score cutoff of 31-33. The German versions of the PCL-5 and the LEC-5 were translated, backtranslated and validated to ensure accuracy (Krüger-Gottschalk et al., 2017). In the validation study, the suggested cutoff scores by Weathers, Blake, et al. (2013) and Weathers, Litz, et al. (2013) demonstrated acceptable psychometric properties. No alternative optimal cutoff scores were identified based solely on overall efficiency, other statistical approaches for cutoff determination have not been deployed at this time.

To confirm PTSD diagnoses, the German version of the Clinician-Administered PTSD Scale for DSM-5 (CAPS-5; Müller-Engelmann et al., 2023; Weathers et al., 2018) was administered. The CAPS-5 is a structured clinical interview that evaluates the presence and severity of DSM-5 PTSD symptoms, with clinicians rating symptom frequency and intensity on a scale from 0 ('Absent') to 4 ('Extreme/incapacitating').

2.3. Statistical analysis

All analyses were conducted in R (R Core Team, 2021) with the *optimalcutpoints* package (López-Ratón et al., 2014) for cutoff determination applying its predefined methods as referenced in the package documentation. The *mice* package has been used for missing data treatment (Buuren & Groothuis-Oudshoorn, 2011). Missing data analysis using Little's MCAR test indicated that data were likely missing completely at random ($\chi^2(317) = 348.54$, $p = .108$). To ensure robust analyses, preserve statistical power and the original distribution of the complete dataset and given the small proportion of missingness (4.7%), we proceeded with multiple imputation using the predictive mean matching method, which is appropriate under MCAR assumptions.

The diagnostic performance of the test was evaluated using the area under the curve (AUC) from ROC analyses. The AUC quantifies a test's ability to

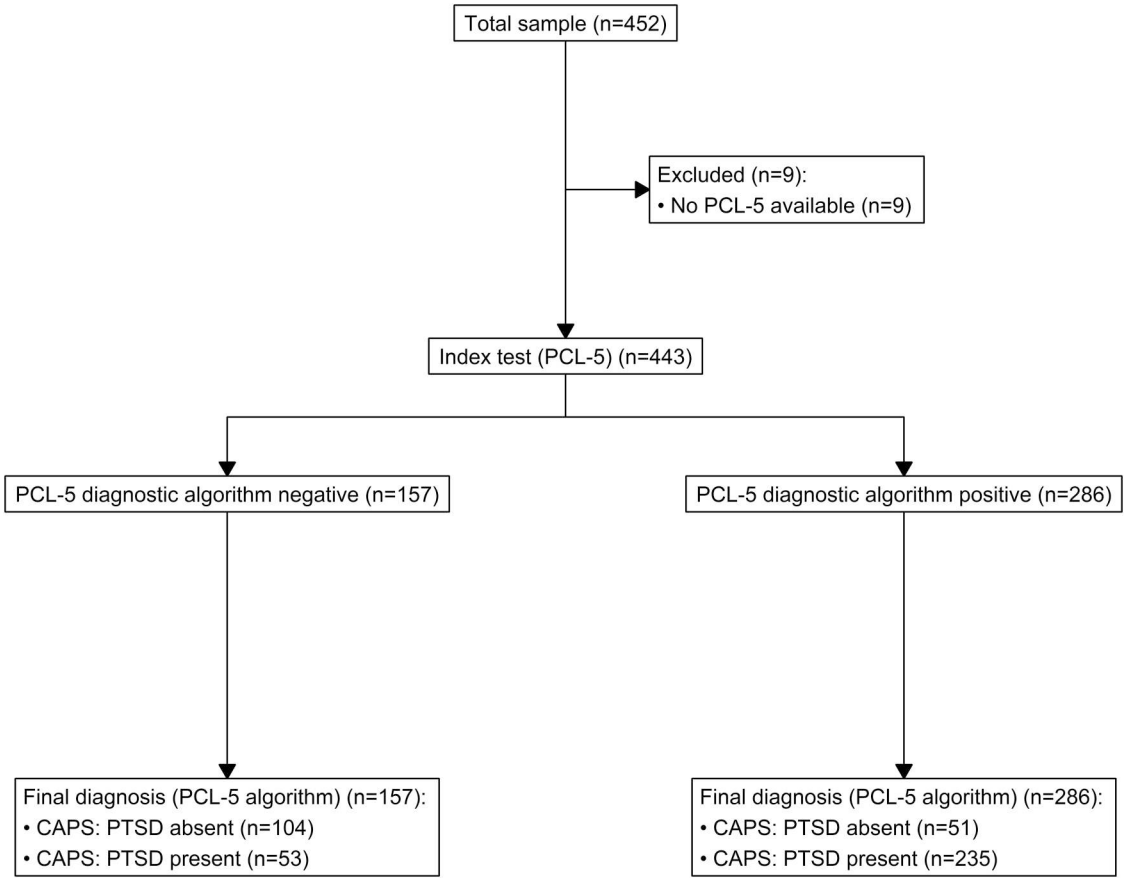

Figure 1. Flowchart of Participants through the study.

distinguish between cases and non-cases, with values ranging from 0.5 (no better than chance) to 1.0 (perfect discrimination) (Faraggi & Reiser, 2002).

We sought to identify the optimal cutoff points for the PCL-5 by evaluating and comparing various cutoffs using established approaches that balance sensitivity, specificity, and predictive values. We first applied commonly used approaches to optimise sensitivity and specificity. The Youden's Index is defined as maximising the sum of sensitivity and specificity. Another typical approach is to minimise the absolute difference between sensitivity and specificity, where both are treated as equal (SpEqualSe). Additionally, we selected the point on the ROC curve closest to the top-left corner (ROC01). We took the cutoff resulting from maximising the product of sensitivity and specificity (MaxProdSpSe). Lastly, we determined the cutoff that simultaneously maximises both sensitivity and specificity as independent metrics (MaxSpSe). Second, predictive values are crucial for evaluating screening test results (Trevethan, 2017). We applied several methods to optimise predictive values. One approach involved selecting the cutoff where the probability of having the condition, given a positive result, exceeds 0.85 (ValuePPV). Similarly, we identified the cutoff where the probability of not having the condition, given a negative result, exceeds 0.85 (ValueNPV). Another method minimised the absolute difference between PPV and NPV (NPVEqualPPV). Additionally, we explored criteria that maximise either the sum (MaxSumNPVPPV) or the product (MaxProdNPVPPV) of PPV and NPV. Third, we selected cutoff estimation methods that refine the analysis by accounting for prevalence estimation and misclassification costs. The Prevalence Matching criterion ensures that the sample prevalence matches the predicted prevalence using the formula $p \times Sensitivity + (1-p) \times (1 - Specificity)$, where p is the estimated prevalence from the sample. In all cost analyses, the cost/benefit of false negatives and false positives was set equally to 1. The Misclassification Cost Term (MCT) criterion minimises the expression.

$$\frac{Cost\ of\ False\ Negatives}{Cost\ of\ False\ Positives} \times p \times (1 - Sensitivity) + (1-p) \times (1 - Specificity)$$

The Cost–Benefit (CB) methodology identifies the optimal cutoff by maximising net benefit, calculated as:

$$Net\ Benefit = (Benefit\ from\ TP \times TP) - [(Cost\ ofFP \times FP) + (Cost\ of\ FN \times FN)]$$

The optimal cutoff is selected based on the highest net benefit or lowest total cost, often analyzed through the

slope of the ROC curve. Lastly, we used a criterion that maximises the Kappa Index (MaxKappa), assessing improvement over chance prediction with the confusion matrix.

3. Results

The base rate of PTSD in the sample as identified through the CAPS diagnostic status was high (n = 288, 65.02%). Equally, the DSM-5 diagnostic algorithm on the PCL-5 screened 286 individuals (64.56%) positive for probable PTSD (see Figure 1).

The distribution of PCL-5 sum scores in the total sample had a mean of 42.01 (SD = 19.47), a median of 46, and a range from 0 to 80, reflecting generally high PTSD severity. Figure 2 shows distinct score distributions between individuals with and without PTSD according to the CAPS-5, with moderate overlap. A Welch Two-Sample t-test confirmed a significant difference in mean PCL-5 scores between individuals with PTSD (M = 50.24, SD = 19.47) and those without (M = 26.73, SD = 19.47), $t(247.69) = -13.59$, $p < .001$, 95%CI[−26.92,−20.10]. The area under the ROC curve (AUC) was 0.829 (95% CI [0.786, 0.871]), indicating good diagnostic accuracy. These results support the use of cutoff scores to distinguish between groups.

The methods for determining cutoffs produced a wide range of values from 7 to 43 (see Table 1 and Figure 3), with most methods recommending cutoffs of 34 or higher. Surprisingly, the commonly cited cutoffs of 31–33 were not identified as optimal by any method, despite their good to excellent metrics for sensitivity and PPV and satisfactory metrics of specificity and NPV.

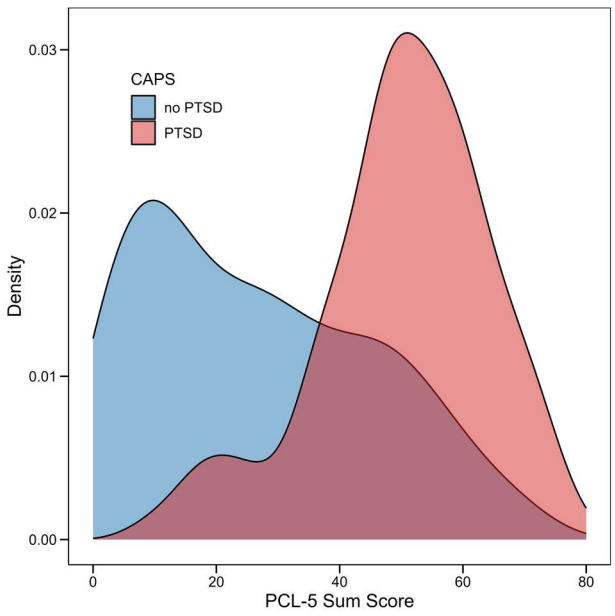

Figure 2. Score Distributions of Individuals With and Without PTSD According to the CAPS-5.

Table 1. Optimal cutoff points and diagnostic utility parameters.

Cutoff	Sensitivity	Specificity	PPV	NPV	OE	Method	Prevalence (%)
7	1	0.161	0.689	1	0.707	MaxSumNPVPPV, MaxProdNPVPPV	94.36
20	0.958	0.439	0.76	0.85	0.777	ValueNPV	81.94
26	0.924	0.51	0.778	0.782	0.779	NPVEqualPPV	77.2
31	0.906	0.6	0.808	0.775	0.799	-	72.91
32	0.903	0.613	0.812	0.772	0.801	-	72.23
33	0.896	0.632	0.819	0.766	0.804	-	71.11
34	0.892	0.645	0.824	0.763	0.806	MCT, CB	70.43
35	0.889	0.652	0.826	0.759	0.806	MaxKappa, MCT, CB	69.98
37	0.854	0.69	0.837	0.718	0.797	Youden	66.37
38	0.84	0.703	0.84	0.703	0.792	MaxProdSpSe, PrevalenceMatching	65.01
39	0.823	0.716	0.843	0.685	0.786	ROC01	63.43
42	0.774	0.742	0.848	0.639	0.763	ValuePPV	59.37
43	0.76	0.761	0.855	0.631	0.761	SpEqualSe, MaxSpSe	57.79
-	0.816	0.671	0.822	0.662	0.765	DSM-5 diagnostic algorithm	64.56

Note. Abbreviations used in the table are defined as follows: PPV = Positive Predictive Value; NPV = Negative Predictive Value; OE = Overall Efficiency; CB = Cost-Benefit; MaxKappa = Maximum Kappa Index; MaxProdNPVPPV = Maximum Product of NPV and PPV; MaxProdSpSe = Maximum Product of Sensitivity and Specificity; MaxSpSe = Maximum Sensitivity and Specificity; MaxSumNPVPPV = Maximum Sum of NPV and PPV; MCT = Misclassification Cost Term; NPVEqualPPV = Equal NPV and PPV; PrevalenceMatching = Matching sample and predicted prevalence; ROC01 = Point closest to (0,1) on the ROC curve; SpEqualSe = Sensitivity equal to Specificity; ValueNPV = NPV with a threshold; ValuePPV = PPV with a threshold.

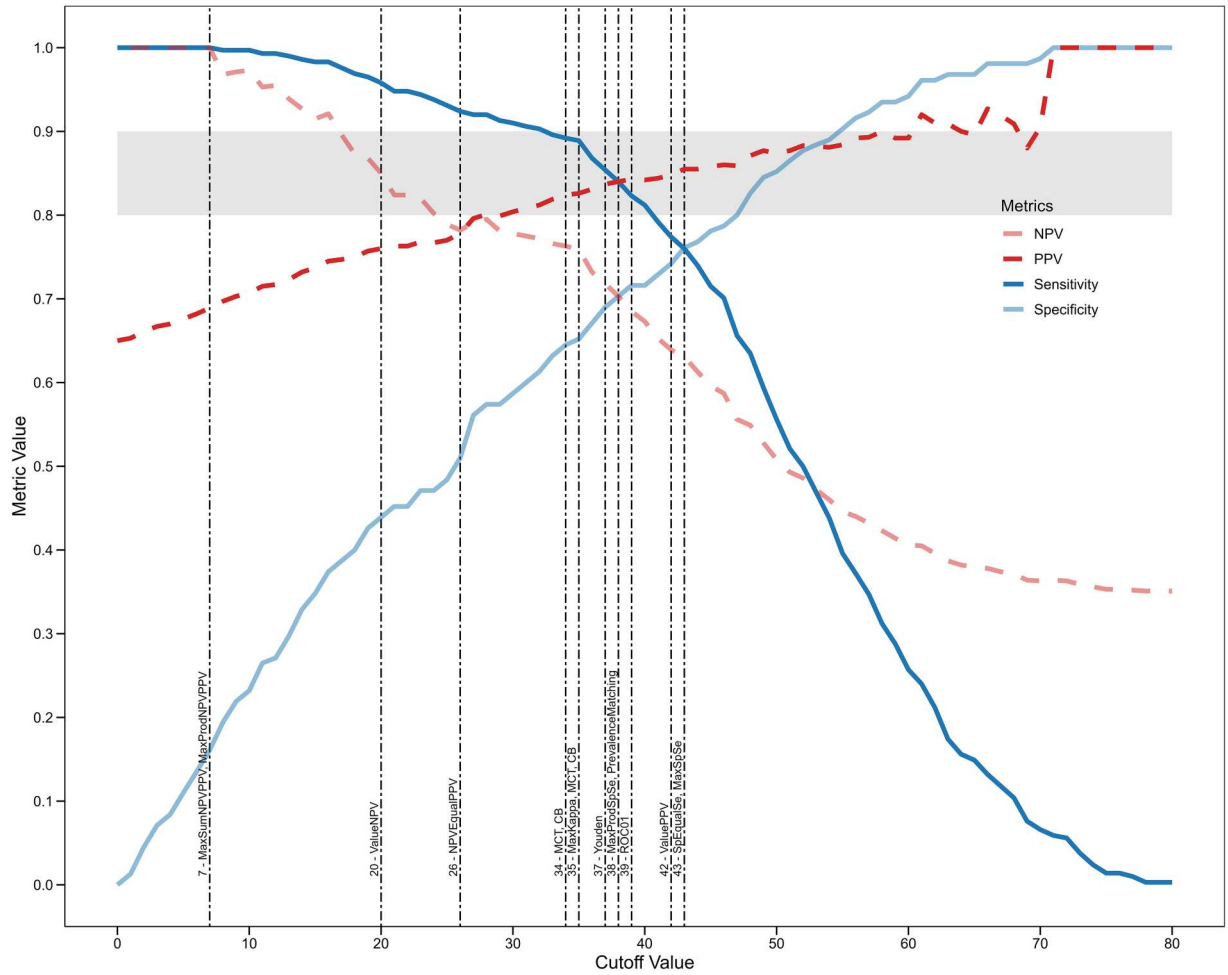

Figure 3. Diagnostic utility parameters (Sensitivity, Specificity, NPV, PPV) for each possible cutoff value.

Traditional methods that balance sensitivity and specificity simultaneously suggest relatively high cutoff scores for the PCL-5. Specifically, Youden's Index identifies a cutoff of 37, yielding excellent sensitivity (0.854) but mediocre specificity (0.69). The MaxProdSpSe method (which corresponds to the maximum AUC) recommends a cutoff of 38, resulting in good sensitivity (0.84) and slightly improved specificity (0.703). The ROC01 method (shortest distance to the top-left corner of the ROC curve) suggests a cutoff of 39, maintaining good sensitivity (0.823) with further improvement in specificity (0.716). Methods that aim to equalise (SpEqualSe) or maximise both sensitivity and specificity (MaxSpSe) yield a higher cutoff of 43, where both sensitivity and specificity decline to moderate levels at 76%. This trend of higher cutoff points appears to be driven by the gradual improvement in specificity, which only achieves an acceptable level at a cutoff of 47 (PPV: 0.859, NPV: 0.556). At this point, sensitivity drops to 0.656, while specificity increases to a respectable 0.8, reflecting a trade-off between the two indicators.

While sensitivity and specificity are commonly prioritised in cutoff determination, focusing on predictive values offers another lens to ensure accurate diagnostic outcomes. Methods that focus on predictive values propose two distinct cutoff strategies. One approach suggests a very high cutoff (42, ValuePPV) to ensure accurate positive predictions, meaning that individuals identified as positive by the test have an 85% or higher probability of having PTSD. Alternatively, a very low cutoff (20, ValueNPV) is recommended for reliable negative predictions, indicating that individuals identified as negative by the test have a similarly high probability of not having PTSD. A midpoint cutoff of 26 (derived from NPVEqualPPV) balances these values, providing an approximate probability of 78% that the test result corresponds to the true diagnostic status. However, some methods, such as MaxSumNPVPPV and MaxProdNPVPPV, did not provide viable cutoff points, suggesting a cutoff of 7, which was not practical for diagnostic purposes.

Methods that incorporate prevalence estimation and misclassification costs suggest mid-range cutoffs as optimal. Both the Misclassification Cost Term (MCT) and Cost–Benefit (CB) methods indicate a cutoff of 34, while Prevalence Matching suggests a cutoff of 38. In addition to favourable sensitivity and specificity, the latter yields a high PPV of 0.84 and closely approximates the sample

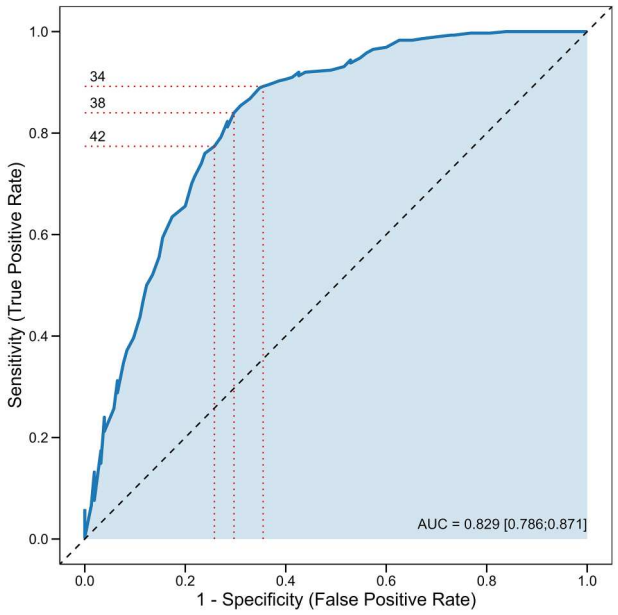

Figure 4. Receiver Operating Characteristic (ROC) Curve for Selected PCL-5 Cutoff Values (34, 38, and 42).

prevalence at 65.02%, with minimal deviation. Notably, the MaxKappa method supports a cutoff of 35, further reinforcing these mid-range thresholds. Figure 4 displays a selection of cutoff points on a ROC curve.

4. Discussion

Given the widespread use of cutoff values in research and clinical practice, our analysis identified a range of cutoff points for the PCL-5 in a trauma-exposed clinical sample. Using different methods within the ROC framework, these cutoffs were tested against a clinical interview, emphasising that cutoff selection should be tailored to specific clinical or research goals, rather than relying on a single value for all contexts. For clinicians, a cutoff of 34 seems particularly effective, as it prioritises sensitivity and reduces the likelihood of missing cases requiring treatment. This threshold strikes a good balance between sensitivity and specificity, ensuring both a strong PPV and a high NPV. In practical terms, this enables clinicians to identify most PTSD cases while minimising the risk of misclassifying individuals without the disorder. Notably, the originally proposed cutoffs of 31–33 by Weathers, Blake, et al. (2013) and Weathers, Litz, et al. (2013) also demonstrate clinical utility, a finding corroborated by Krüger-Gottschalk et al. (2017), who highlighted their effectiveness in a previous publication. For researchers conducting population-level screenings without additional clinical interviews, a cutoff of 38 seems to be most suitable. This cutoff is well aligned with population prevalence and reflecting the true distribution of PTSD cases. Higher cutoffs, such as 42 or 43, are useful in contexts where high specificity and PPV are crucial. These cutoffs reduce false positives, which is advantageous for research focused on the most clear-cut PTSD cases, ensuring that the participants identified have a strong likelihood of having the disorder. This leads to a more precise subgroup of participants who meet stringent PTSD criteria, resulting in more accurate and reliable findings. In resource-limited settings, higher cutoffs help allocate limited resources more effectively by prioritising those with the highest likelihood of PTSD, thus optimising the use of available support and focusing interventions where they are most needed.

Our study extends previous work in two significant ways. First, we systematically compared a range of well-established statistical methods for estimating cutoffs, including the Youden Index, equalising sensitivity and specificity, prevalence matching, and others. Unlike earlier studies that often relied on a single method, our approach revealed considerable variability in the optimal cutoffs identified even within the same dataset. Second, we explicitly linked cutoff selection to the intended purpose of the instrument, whether for clinical diagnosis, population-level prevalence estimation or other research purposes. By focusing on the context and objectives of the assessment, our findings provide a useful framework for optimising diagnostic accuracy while reducing reliance on a single threshold. Additionally, our results expand on the findings of Forkus et al. (2022), who reported a wide range of optimal cutoffs across different samples (22–49) in their meta-analysis. Our observation of similar variability within a single sample highlights that this phenomenon is not merely a result of population differences but also reflects the influence of methodological choices and objectives. Despite the complex and context-dependent nature of cutoff determination, our findings reaffirm its value as an important tool for clinical and research purposes. While some critics might argue for relying solely on diagnostic algorithms to bypass the challenges of selecting optimal cutoffs, our results suggest otherwise. We found that a well-determined cutoff score not only achieves superior psychometric properties but also provides greater flexibility for specific applications. This aligns with recent work by Pettrich et al. (2024), which demonstrated that carefully calibrated cutoffs outperform the diagnostic algorithm in reflecting the construct validity of PTSD.

Our study offers several key strengths in determining optimal cutoffs for the PCL-5. First, we adopted a comprehensive approach by considering statistical methods and practical implications, ensuring that our cutoff values are both robust and contextually relevant. To our knowledge, we are one of the first to propose multiple cutoff values for the same instrument,

each tailored to specific research or clinical objectives. This nuanced approach allows for more accurate and adaptable use of the PCL-5 in different contexts. Our study contributes to the field by introducing a validated cutoff score for PTSD prevalence estimation in a German clinical sample. This facilitates low-effort, low-resource screening, enabling large-scale prevalence studies without the need for resource-intensive clinical interviews. This approach is particularly relevant given recent meta-analyses (Grekin & O'Hara, 2014; Oakley et al., 2021; Rezayat et al., 2020), which highlight that most studies estimating PTSD prevalence rely exclusively on screening tools rather than clinical interviews. By addressing this gap, our findings open new possibilities for efficiently estimating PTSD prevalence, especially in settings where clinical interviews may not be feasible.

Despite its strengths, this study has several limitations. The findings are based on the German version of the PCL-5 and CAPS-5 in a German clinical sample and therefore contextualised in the clinical German linguistic and cultural context – this may limit generalizability of found cutoff values to other settings. First, for other language versions and cultural groups, different cutoff values may emerge – as highlighted by the wide variability reported in the meta-analysis of PCL-5 validation studies across diverse samples by Forkus et al. (2022). Second, because the sample included only trauma-exposed individuals from German clinical settings, the cutoffs may not fully apply to lower-prevalence populations. In such contexts, the positive predictive value may decline (Usher-Smith et al., 2016), and higher thresholds may be needed to maintain specificity – potentially reducing sensitivity. Thus, while the findings are well-suited for clinical use, caution is advised when applying them to general or non-clinical populations. Third, our findings are based on a general trauma-exposed clinical sample and may not extend to specific clinical subgroups. Finally, our analyses were conducted solely within the ROC framework. While this approach provides useful insights, further validation using alternative statistical methods could yield a more comprehensive understanding of cutoff performance across different contexts. Selecting an appropriate cutoff value for the intended use is critical when using the PCL-5 or any other screening instrument. The observed variability in optimal cutoff values across populations, settings, and language versions underscores the need for a context-sensitive approach in both research and clinical practice. While a flexible, sample-specific approach to cutoff selection enhances diagnostic precision, it also risks reducing comparability across studies if cutoff choices are inconsistent or poorly justified. Therefore, we do not recommend re-validating cutoffs for every new sample as a universal requirement; rather, researchers should adopt validated cutoffs from comparable populations whenever possible. In cases where the population deviates substantially from the original validation context – such as non-treatment-seeking or culturally distinct groups – cutoff re-evaluation or adjustment may be necessary, particularly if prevalence estimation or diagnostic classification is a primary aim. To balance flexibility with comparability, researchers should provide a clear rationale for selected cutoffs and where feasible report corresponding diagnostic utility parameters to improve transparency and replicability. If only one validated cutoff is available for the population of interest, results should be interpreted with caution – as preliminary diagnoses rather than definitive conclusions – especially in the absence of a structured clinical interview. Additionally, continuous PCL-5 scores should be reported alongside binary classifications to facilitate meta-analytic integration. For clinicians, it is important to recognise that cutoffs optimised for high-prevalence, treatment-seeking populations may not transfer well to general or non-clinical samples. In such cases, cutoff scores should be interpreted cautiously and supplemented by clinical judgment. Future research should prioritise validating and refining multiple cutoff values tailored to diverse populations and purposes, including those with varying PTSD prevalence rates. Replicating this work in general population samples would address current limitations in generalizability and yield more robust, context-sensitive cutoffs. Moreover, methodological advancements – such as Bayesian frameworks that incorporate population-specific base rates, prior probabilities, and symptom severity distributions – offer promising avenues for improving diagnostic precision and enhancing the clinical and scientific utility of the PCL-5 across diverse contexts.

Disclosure statement

During the revision of this work, the author used ChatGPT v2 in order to refine language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication. No potential conflict of interest was reported by the authors.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to the informed consent given by the participants.

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