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## Scoring Reading Parameters: An Inter-Rater Reliability Study Using The MNREAD Chart

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► **To cite this version:**

Karthikeyan Baskaran, Antonio Filipe Macedo, Yingchen He, Laura Hernandez-Moreno, Tatiana Queirós, et al.. Scoring Reading Parameters: An Inter-Rater Reliability Study Using The MNREAD Chart. 2019. hal-02079375

**HAL Id: hal-02079375**

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Preprint submitted on 26 Mar 2019

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# PLOS ONE

## Scoring Reading Parameters: An Inter-Rater Reliability Study Using The MNREAD Chart

--Manuscript Draft--

<b>Manuscript Number:</b>	
<b>Article Type:</b>	Research Article
<b>Full Title:</b>	Scoring Reading Parameters: An Inter-Rater Reliability Study Using The MNREAD Chart
<b>Short Title:</b>	Inter-Rater Reliability Of The MNREAD Acuity Chart
<b>Corresponding Author:</b>	Aurélie Calabrèse Aix-Marseille Université Marseille, FRANCE
<b>Keywords:</b>	low vision; reading performance; reading test; MNREAD acuity chart; inter-rater reliability; computer-based scoring algorithms
<b>Abstract:</b>	<p><b>Purpose:</b> First, to evaluate inter-rater reliability when human raters estimate the reading performance of visually impaired individuals using the MNREAD acuity chart. Second, to evaluate the agreement between computer-based scoring algorithms and compare them with human rating.</p> <p><b>Methods:</b> Reading performance was measured for 101 individuals with low vision, using the Portuguese version of MNREAD. Seven raters estimated the maximum reading speed (MRS) and critical print size (CPS) of each individual MNREAD curve. MRS and CPS were also calculated automatically for each MNREAD curve using two different algorithms: the original standard deviation method (SDev) and a non-linear mixed effects (NLME) modeling. Intra-class correlation coefficients (ICC) were used to estimate absolute agreement between raters and/or algorithms.</p> <p><b>Results:</b> Absolute agreement between raters was excellent for MRS (ICC = 0.97; 95%CI [0.96, 0.98]) and good for CPS (ICC = 0.77; 95%CI [0.69, 0.83]). For CPS inter-rater reliability was poorer among less experienced raters (ICC = 0.70; 95%CI [0.57, 0.80]) compared to experienced ones (ICC = 0.82; 95%CI [0.57, 0.80]). Absolute agreement between the two algorithms was excellent for MRS (ICC = 0.96; 95%CI [0.91, 0.98]). For CPS, the best possible agreement was good and for CPS defined as the print size sustaining 80% of MRS (ICC = 0.77; 95%CI [0.68, 0.84]).</p> <p><b>Conclusion:</b> For MRS, inter-rater reliability is excellent, even considering the possibility of noisy and/or incomplete data collected in low-vision individuals. For CPS, inter-rater reliability is lower, which may be problematic, for instance in the context of multicenter studies or follow-up examinations. Setting up consensual guidelines to deal with ambiguous datasets may help improve reliability. While the exact definition of CPS should be chosen on a case-by-case basis depending on the clinician or researcher's motivations, evidence suggests that estimating CPS as the smallest print size sustaining about 80% of MRS would increase inter-rater reliability.</p>
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<b>Opposed Reviewers:</b>	
<b>Additional Information:</b>	
<b>Question</b>	<b>Response</b>
<b>Financial Disclosure</b>	AFM and LHM were supported by FCT (COMPETE/QREN) grant reference

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Date: January 31<sup>st</sup> 2019

Dear members of the Editorial Board,

Please find enclosed our manuscript entitled: “**Scoring Reading Parameters: An Inter-Rater Reliability Study Using The MNREAD Chart**”, by Karthikeyan Baskaran, Antonio Filipe Macedo, Yingchen He, Laura Hernandez-Moreno, Tatiana Queirós, J. Stephen Mansfield, and Aurélie Calabre se, which we would like to submit for publication as an research article in PLoS ONE.

The primary goal of this work is to evaluate inter-rater reliability when human raters estimate reading performance using the MNREAD acuity chart. Our motivation for this study was the lack of evidence that different extraction methods used by different raters would lead to comparable estimates of reading performance, which is especially relevant in the context of multicenter studies, or when looking at follow-up data. Our results demonstrate excellent inter-rater reliability for the Maximum Reading Speed (i.e. the fastest that one can read when print size is not limiting) and good inter-rater reliability for the Critical Print Size (i.e. the print size for which reading speed is maximum). Our work also provides further tips and instructions on how to score noisy and/or incomplete MNREAD data. These tips may serve as a starting point to help clinicians and researchers reduce variability.

We confirm that this manuscript has not been published elsewhere and is not under consideration by another journal. All Authors have approved the manuscript and agree with submission to PLoS ONE.

Authors report no conflict of interest, except for JSM who receives royalties from the sales of MNREAD Acuity Charts.

We appreciate your consideration of publication of this paper.

Sincerely,

Aur lie Calabre se, PhD





1 **Full title: Scoring Reading Parameters: An Inter-Rater Reliability Study**  
2 **Using The MNREAD Chart.**

3

4 **Short title: Inter-Rater Reliability Of The MNREAD Acuity Chart.**

5

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26 **Word count:**

27 Abstract = 300 words

28 Text = 3740 words

29 Intro = 1025; Methods = 1010; Results = 580; Discussion = 1011; Conclusion = 114

30 References = 30; Figures = 5; Tables = 4

31

32 **Funding:**

33 This work was partially supported by FCT (COMPETE/QREN).

34

35 **Declarations of interest:**

36 Author JSM receives royalties from the sales of MNREAD Acuity Charts.

37

38 **Abstract**

39 Purpose: First, to evaluate inter-rater reliability when human raters estimate the reading  
40 performance of visually impaired individuals using the MNREAD acuity chart. Second, to  
41 evaluate the agreement between computer-based scoring algorithms and compare them with  
42 human rating.

43 Methods: Reading performance was measured for 101 individuals with low vision, using the  
44 Portuguese version of MNREAD. Seven raters estimated the maximum reading speed (MRS) and  
45 critical print size (CPS) of each individual MNREAD curve. MRS and CPS were also calculated  
46 automatically for each MNREAD curve using two different algorithms: the original standard  
47 deviation method (SDev) and a non-linear mixed effects (NLME) modeling. Intra-class  
48 correlation coefficients (ICC) were used to estimate absolute agreement between raters and/or  
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50 Results: Absolute agreement between raters was excellent for MRS (ICC = 0.97; 95%CI [0.96,  
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55 good and for CPS defined as the print size sustaining 80% of MRS (ICC = 0.77; 95%CI [0.68,  
56 0.84]).

57 Conclusion: For MRS, inter-rater reliability is excellent, even considering the possibility of noisy  
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60 examinations. Setting up consensual guidelines to deal with ambiguous datasets may help  
61 improve reliability. While the exact definition of CPS should be chosen on a case-by-case basis  
62 depending on the clinician or researcher's motivations, evidence suggests that estimating CPS as  
63 the smallest print size sustaining about 80% of MRS would increase inter-rater reliability.

## 64 **Introduction**

65 Reading difficulty is a major concern for patients referred to low-vision centers [1]. Therefore,  
66 most Quality-of-Life questionnaires assessing the severity of vision disability contain one or  
67 more items on subjective reading difficulty [2-5]. However, substantial discrepancy has been  
68 observed between self-reported reading difficulty and measured reading speed [6]. For this  
69 reason, reading performance should be evaluated objectively to serve as a reliable outcome  
70 measure in clinical trials, multisite investigations or longitudinal studies. To assess, for instance,  
71 the success of vision rehabilitation techniques, surgical procedures or ophthalmic treatments,  
72 measures of reading ability should be obtained using standardized tests with demonstrated high  
73 repeatability.

74 Among the standardized tests available, the MNREAD acuity chart can be used to evaluate  
75 reading performance for people with normal vision or low vision in clinical and research  
76 environments [7]. In brief, the MNREAD chart measures four parameters that characterize how  
77 reading performance changes when print size decreases: the maximum reading speed (MRS), the  
78 critical print size (CPS), the reading acuity (RA) and the reading accessibility index (ACC) [8].  
79 The reading acuity and reading accessibility index are clearly defined by the number of reading  
80 errors made at small print sizes and the reading speeds for a range of larger sizes. In the original  
81 MNREAD manual, provided with the chart, MRS and CPS are defined as follows: “The critical  
82 print size is the smallest print size at which patients can read with their maximum reading speed.  
83 [...] Typically, reading time remains fairly constant for large print sizes. But as the acuity limit is  
84 approached there comes a print size where reading starts to slow down. This is the critical print  
85 size. The maximum reading speed with print larger than the critical print size is the maximum  
86 reading speed (MRS).” In short, values for MRS and CPS depend on the location of the flexion

87 point in the curve of reading speed versus print size (Fig 1). In normally sighted individuals, for  
88 whom the MNREAD curve usually exhibits a standard shape (Fig 1-A), the above definitions  
89 may be sufficient to extract MRS and CPS confidently by inspecting the curve. However, they  
90 can be difficult to determine, especially for readers with visual impairments, who may experience  
91 visual field defects (e.g. ring scotoma; Fig 1-B) or the use of multiple fixation sites (i.e. PRL; Fig  
92 1-C) [9]. In such cases, the noisy and/or incomplete dataset resulting from atypical visual  
93 function may be inconsistent with the assumption that people will read at a fairly constant speed  
94 until font size compromises their ability to identify words and MNREAD curves may take an  
95 unusual shape (Fig 1-D). If so, subjective decisions (e.g. ignoring outliers) must be made by the  
96 individual analysing the data (referred to as the “rater” in the present work, as opposed to the  
97 “experimenter” who recorded the data). For this reason, MRS and CPS estimates may be  
98 considered highly sensitive to inter-rater variability.

99

100 **Fig 1: MNREAD curve examples.**

101

102 In an attempt to reduce variability and unify the process of curve information extraction,  
103 alternative scoring methods have been proposed. According to these “simpler” scoring rules,  
104 MRS equals either the single largest reading speed [10] or the mean of the three largest reading  
105 speeds [11]. Nonetheless, a criterion must be chosen for the CPS (smallest print size supporting  
106 reading speed at either: 90% of MRS, 85%, 80%, etc.) but there is no general agreement on the  
107 appropriate criterion to use. Overall, open discussions on how to score MNREAD parameters  
108 optimally still persist in the literature [12] and the choice of scoring method constitutes an  
109 additional factor contributing to inter-rater variability.

110 Another approach to reduce variability is to fit the MNREAD curve and estimate its parameters  
111 using automated algorithms [13]. In the present work, we will focus on two of these methods.  
112 The first one has been described by the MNREAD creators [14,15] and is used in the MNREAD  
113 iPad app [16]. It is also the most widely used in the literature [11,17,18]. In short, it determines  
114 the CPS as the smallest print size that supports reading speeds that are not significantly different  
115 from the reader's maximum reading speed; we will refer to it as the standard deviation method  
116 (SDev). The second method, especially recommended with large but incomplete datasets,  
117 estimates the critical print size from smooth curve-fit to the MNREAD data using non-linear  
118 mixed effects (NLME) modeling [19]; we will refer to it as the NLME method. Both methods are  
119 described in the Methods section. Despite the advantage of these algorithms in operationalizing  
120 the estimation of the MNREAD parameters, they present two major drawbacks: (1) they may not  
121 be easily accessible in clinical environments, (2) they may fail to provide satisfactory measures  
122 with noisy or small and incomplete datasets, necessitating further human inspection of the curves  
123 for validation.

124 The Repeatability of the MNREAD chart measures has been assessed before in low vision  
125 populations. Overall, studies have reported good intra and inter-session reliability [11,17,18,20],  
126 as well as good repeatability across multiple testing sites and experimenters [21]. But to our  
127 knowledge, variability of the MNREAD estimates scored by different raters from the same  
128 dataset has not been evaluated. This question of inter-rater variability is especially relevant (1) in  
129 the context of multicenter studies, where data are scored by different raters with different levels  
130 of expertise, (2) when comparing results from different studies performed by different groups, or  
131 (3) when looking at follow-up data involving different raters.

132 We have investigated the reliability of CPS and MRS estimates for MNREAD data collected  
133 from participants with visual impairments. First, we evaluated the inter-rater reliability among  
134 raters (Analysis 1). Second, we evaluate agreement between the NLME and SDev algorithms  
135 (Analysis 2). Third, we evaluated agreement between raters and the two algorithms (Analysis 3).

136

## 137 **Methods**

### 138 **Participants**

139 Data from 101 participants with visual impairment were selected from a larger dataset, originally  
140 collected to study the prevalence and costs of visual impairment in Portugal (PCVIP-study)  
141 [22,23]. Only participants whose visual acuity in the better eye was 0.5 decimal (0.3 logMAR) or  
142 worse and/or whose visual field was less than 20 degrees were selected for the present study.  
143 Among them, only the participants who read at least five sentences on the MNREAD chart with  
144 their “presenting reading glasses” were included. The study protocol was reviewed by the ethics  
145 committee for Life Sciences and Health of the University of Minho (REF: SECVS-084/2013) and  
146 was conducted in accordance with the principles of the Declaration of Helsinki. Written informed  
147 consent was obtained from all participants. The study was registered with the Portuguese data  
148 protection authority with the reference 9936/2013 and received approval number 5982/2014.

### 149 **MNREAD Data**

150 Reading performance was measured for each participant using the Portuguese version of the  
151 MNREAD acuity chart [24]. Reading distance was adjusted for each participant and chosen  
152 according to his/her near visual acuity. Participants were asked to read the chart aloud as fast and



153 accurately as possible, one sentence at a time, starting from the largest print size. For each  
154 sentence, reading time and number of misread words were recorded and reported on a score sheet  
155 by the experimenter. Data were then transferred into a digital file and further processed in R [25].  
156 For each individual test, a corresponding MNREAD curve was plotted using the mnreadR  
157 package [26] to display log reading speed as a function of print size (see S1 Appendix for all 101  
158 curves). Because the shape of the curve can influence visual estimation of the reading parameters,  
159 reading speed was plotted using a logarithmic scale so that reading speed variability (which is  
160 proportional to the overall measure of reading speed) was constant at all speeds [14].

### 161 **Raters' visual scoring**

162 Seven raters were recruited to estimate the MRS and CPS of each individual MNREAD curve.  
163 Since inter-rater reliability may be influenced by raters' prior experience with the MNREAD  
164 chart, we included raters with different levels of expertise in MNREAD parameters estimation.  
165 Each rater gave a self-rated score of expertise (on a 5 point scale from 0 = 'no previous to  
166 experience' to 4 = 'top expertise'), both before and after rating all the MNREAD curves, to  
167 account for the amount of practice gained during the study. Each rater was provided with S1  
168 Appendix, containing the 101 MNREAD curves to score. Raters were instructed to follow the  
169 standard guidelines provided with the MNREAD chart instructions (see Introduction). However,  
170 coming from patients with impaired vision, many of the curves had noisy or incomplete data,  
171 which potentially made it difficult to estimate the MRS and CPS. In such cases, we provided  
172 more detailed instructions to the raters. These detailed instructions are available in S2 Appendix.

### 173 **Algorithms' automated scoring**

174 MRS and CPS were also calculated automatically for each 101 datasets using two algorithm-  
175 based estimations: the 'standard deviation' method and non-linear mixed effects modeling. The

176 standard deviation method (SDev) uses the original algorithm described in [14] and [15] to  
177 estimate the MNREAD parameters. This algorithm iterates over the data searching for an optimal  
178 reading speed plateau, from which MRS and CPS will be derived. To be considered optimal, a  
179 plateau must encompass a range of print sizes that supports reading speed at a significantly faster  
180 rate ( $1.96 \times$  standard deviation) than the print sizes smaller or larger than the plateau range (Fig  
181 2). MRS is estimated as the mean reading speed for print sizes included in the plateau and CPS is  
182 defined as the smallest print size on the plateau. In most cases, several print-size ranges can  
183 qualify as an optimal plateau and the algorithm chooses the one with the fastest average reading  
184 speed. In the present work, the standard deviation method estimation was performed using the  
185 `curveParam_RT ()` function from the `mnreadR` R package.

186

187 **Fig 2: Example of the standard deviation algorithm calculation on a typical dataset.**

188 **On iteration 1 (dark blue), the algorithm selects the first two sentences as *plateau 1* (1.3 and 1.2 logMAR) and**  
189 **calculates a selection criterion for this plateau.  $\text{Criterion}_{\text{plateau 1}} = \text{mean}(\text{reading speed}_{\text{plateau 1}}) - 1.96 \times$**   
190  **$\text{standard deviation}(\text{reading speed}_{\text{plateau 1}}) = 60.5 - 1.96 \times 2.1 = 56.3$  wpm. The point adjacent to *plateau 1* (1.1**  
191 **logMAR) was read at 60 wpm, which is faster than  $\text{criterion}_{\text{plateau 1}}$ , indicating that this point belongs to the**  
192 **optimal plateau. A second iteration is then launched (light blue) with *plateau 2* now encompassing the first**  
193 **three sentences and a new criterion calculation.  $\text{Criterion}_{\text{plateau 2}} = 60.3 - 1.96 \times 1.5 = 57.3$  wpm. Among the**  
194 **points adjacent to *plateau 2*, there is still a value higher than this criterion (59 wpm at 0.9 logMAR), so the**  
195 **algorithm continues to iterate one sentence at a time, including 1.0 logMAR in *plateau 3* and 0.9 logMAR in**  
196 ***plateau 4*. The calculations stop with *plateau 4*, for which selection criterion is higher than any remaining**  
197 **points ( $\text{criterion}_{\text{plateau 4}} = 44.7$  wpm). MRS is estimated as 57.2 wpm and CPS as 0.9 logMAR.**

198

199 The non-linear mixed effects (NLME) modeling method is particularly suited for incomplete  
200 datasets from individuals with reading or visual impairment [19]. The NLME model uses  
201 parameter estimates from a larger group (101 datasets here) to allow suitable curve fits for  
202 individual datasets that contain few data points. In the present work, we used an NLME model  
203 with a negative exponential decay function, as described in details in [19], where a single  
204 estimate of MRS can yield several measures of CPS depending on the definition chosen (e.g.  
205 print size required to achieve 90% of MRS, 80% of MRS, etc.). Therefore, five values of CPS  
206 were estimated, i.e. 95%, 90%, 85%, 80% and 75% of MRS. NLME modeling and parameters  
207 estimation were performed using the `nlmeModel ()` and `nlmeParam ()` functions from `mnreadR`.

208

## 209 **Statistical Analysis**

210 In all three analyses, intra-class correlation coefficient (ICC) was used to assess absolute  
211 agreement between raters and/or algorithms [27]. This reliability index (ranging from 0 to 1; 1  
212 meaning perfect agreement) is widely used in the literature in test-retest, intra-rater, and inter-  
213 rater reliability analyses [28]. In the present work, ICC values estimate the variation between two  
214 or more methods (whether raters or algorithms) in scoring the same data by calculating the  
215 absolute agreement between them. For each analysis, the appropriate ICC form (dependent on  
216 research design and assumptions) was chosen by selecting the correct combination of “model”,  
217 “type” and “definition”, as detailed in Table 1 [29]. ICC values were calculated using SPSS  
218 statistical package and limits of agreement were visualized with Bland-Altman plots. Following  
219 guidelines from [28], ICC values and their 95% confidence intervals (95% CI) were interpreted  
220 as showing: “*poor agreement*” if less than 0.5; “*moderate agreement*” if comprised between 0.5

221 and 0.75; “good agreement” if comprised between 0.75 and 0.9 and “excellent agreement” if  
 222 greater than 0.9.

223

224 **Table 1: Details of the ICC form chosen for Analyses 1, 2 and 3**

	Intra-class correlation coefficient (ICC) form		
	Model	Type	Definition
<u>Analysis 1</u> Agreement among the 7 raters	2-way random effects  Both raters & curves are considered as selected randomly from a larger population	Single rater  Each rater is compared against all others	Absolute  agreement
<u>Analysis 2</u> Agreement between the 2 automated algorithms	2-way mixed-effects  Raters are fixed & curves are considered as selected randomly from a larger population	Single measurement	Absolute  agreement
<u>Analysis 3</u> Agreement between raters and automated algorithms	2-way mixed effects	Mean of 7 raters	Absolute  agreement

225 **Results**

226 **Analysis 1: Agreement between raters (221 words)**

227 For MRS, ICC value was 0.97 (95% CI [0.96, 0.98]), indicating excellent agreement between  
 228 raters (Fig 3). For CPS, ICC value was 0.77 (95% CI [0.69, 0.83]), suggesting good agreement

229 between raters. We hypothesized that the weaker agreement for CPS could be attributed to the  
 230 difference in raters' expertise level. These scores, both before and after evaluating the 101  
 231 MNREAD curves, are reported in Table 2. Prior to rating, one rater had no previous experience in  
 232 rating MNREAD curves (TQ), three raters considered themselves intermediate raters (LM, AM  
 233 and KB), two raters scored themselves as advanced raters (SM and YH) and one rater reported to  
 234 be an expert rater (AC). Among the less experienced raters (score 0-2), CPS estimation reliability  
 235 was only moderate (ICC = 0.70; 95% CI [0.57, 0.80]). Among the most experienced raters (score  
 236 3-4), it was good (ICC = 0.82; 95% CI [0.57, 0.80]). Interestingly, three raters (43%) considered  
 237 that their expertise improved (TQ, LM and AM), whereas the remaining four (57%) did not  
 238 report any change in their expertise level (KB, SM, YH and AC).

239

240 **Table 2: Self-reported score of expertise for our 7 raters**

Raters		TQ	LM	AM	KB	SM	YH	AC
Self-reported score of expertise	Prior rating	0	2	2	2	3	3	4
	After rating	1	3	3	2	3	3	4

241

242 **Score of expertise in rating low-vision MNREAD data before and after rating the 101 curves (0 – no prior**  
 243 **experience, 1 – novice, 2 – intermediate, 3 – Advance, 4 – Expert).**

244 **Fig 3: Box and whisker plots of estimated MRS (left) and CPS (right), grouped by raters and sorted in**  
 245 **ascending order of expertise level (from 0 to 4). Boxes represent the 25th to 75th percentiles and whiskers**  
 246 **range from min to max values. Medians (lines) and means (cross) are also represented.**

247

248 **Analysis 2: Agreement between automated algorithms (245 words)**

249 For MRS, the ICC value of absolute agreement between SDev and NLME methods was 0.96  
250 (95% CI [0.91, 0.98]), showing excellent agreement. Contrary to the SDdev method, for which a  
251 single MNREAD test yields only one estimate for MRS and one estimate for CPS, the NLME  
252 method can generate several measures of CPS depending on the reading-speed criterion chosen to  
253 define the CPS (e.g. print size required to achieve 90% of MRS, 80% of MRS, etc.). Therefore,  
254 for each of the 101 MNREAD datasets, we estimated five values of CPS with NLME  
255 (corresponding to: 95%, 90%, 85%, 80% and 75% of MRS) and measured agreement between  
256 SDev and NLME for each of them. The results are reported in Table 3. The strongest agreement  
257 between the two automated methods was found for the 80% criterion, and was good, with an ICC  
258 value of 0.77 (95% CI [0.68, 0.84]). Additionally, limits of agreement between the two  
259 algorithms were estimated using Bland – Altman plots for both MRS and CPS (Fig 4). For MRS,  
260 the average difference (i.e. bias) between the SDev method and the NLME model was 5.8 wpm  
261 (i.e. 4.5%), with 95% limits of agreement of 11.4 wpm (i.e. 10%). For CPS (defined as 80% of  
262 MRS, which showed the best agreement between methods), bias was 0.031 logMAR with 95%  
263 limits of agreement of 0.06 logMAR (1 step unit being 0.1 logMAR). Overall, we concluded that  
264 no significant difference could be observed between the two automated algorithms.

265

266

267 **Table 3: Absolute agreement (ICC values and their 95 % confidence intervals) between CPS values estimated**  
268 **with the SDev method and the NLME model for five different definitions of CPS.**

	ICC value	95% CI	Absolute agreement
95% CPS	0.56	[0.10, 0.77]	Moderate
90% CPS	0.70	[0.53, 0.81]	
85% CPS	0.76	[0.66, 0.83]	Good
<b>80% CPS</b>	<b>0.77</b>	<b>[0.68, 0.84]</b>	
75% CPS	0.76	[0.62, 0.84]	

269

270 **Best agreement is highlighted in grey.**

271

272 **Fig 4: Bland – Altman plots showing agreement between SDev method and NLME model for both MRS (left)**

273 **and CPS (right). x-axes represent the mean estimate for both methods; y-axes represent the estimate**

274 **difference between SDev method and NLME model. Dashed lines show the mean difference (i.e. bias) and the**

275 **dotted lines represent the 95% CI of limits of agreement (i.e. confidence limits of the bias, defined as the mean**

276 **difference  $\pm$  1.96 times the standard deviation of the difference).**

277

### 278 **Analysis 3: Agreement between raters and automated algorithms (139 words)**

279 For MRS, absolute agreement between raters ( $k = 7$ ) and automated algorithms was found to be

280 excellent for both the SDev method (ICC = 0.96; 95% CI [0.88, 0.98] and the NLME model (ICC

281 = 0.97; 95% CI [0.95, 0.98]). For CPS, agreement between raters and the SDev method was only

282 moderate (ICC = 0.66; 95% CI [0.3, 0.80]), whereas agreement between raters and the NLME

283 model was ‘good’ for CPS defined as 90% of MRS (ICC = 0.83; 95% CI [0.76, 0.88] - Table 4

284 shows the ICC values for each of the five CPS definitions). Overall, the NLME model showed

285 better agreement with the raters than the SDev method for both reading parameters. Fig 5 shows  
 286 the MRS and CPS obtained by the automated algorithms and the 7 raters.

287

288 **Fig 5: Box and whisker plots showing the median and average MRS (left panel) and CPS (right panel) from**  
 289 **the two algorithms and the mean of raters. The box represents 25th to 75th percentile with median line and**  
 290 **the + sign represents the mean and the whiskers represent minimum to maximum.**

291

292 **Table 4: Absolute agreement (ICC values and their 95 % confidence intervals) between CPS values estimated**  
 293 **by the raters and with the NLME model for five different definitions of CPS.**

	ICC value	95% CI	Absolute agreement
95% CPS	0.78	[0.61, 0.87]	294
<b>90% CPS</b>	<b>0.83</b>	<b>[0.76, 0.88]</b>	295
85% CPS	0.79	[0.55, 0.71]	296
80% CPS	0.72	[0.18, 0.88]	297
75% CPS	0.66	[0.02, 0.87]	298
			299

300

301 **Best agreement is highlighted in grey.**

302

303

304

305



306 **Discussion (1001 words)**

307

308 In this project we investigated *i*) the agreement between raters for MNREAD parameters  
309 extracted from reading curves (Analysis 1), *ii*) the agreement between SDev and NLME  
310 automated methods extracting reading parameters from raw data (Analysis 2) and *iii*) the  
311 agreement between raters and automated methods (Analysis 3).

312

313 Our first main result was that inter-rater reliability can be classified as excellent for MRS (ICC of  
314 0.97) and good for CPS (ICC of 0.77). Because they are lower than 1, these agreement indexes  
315 reveal the existence of discrepancies when extracting MNREAD parameters visually from  
316 reading curves. Whilst the variability for MRS can be considered residual, the CPS estimation  
317 may be questionable. On average, the range of difference in CPS estimates was 0.19 logMAR  
318 (i.e. almost 2 lines on a logMAR chart), implying that the variability among raters can be  
319 considered clinically significant and potentially problematic, for example when CPS is used to  
320 prescribe optimal magnifying power. To identify the underlying factors of the discrepancies  
321 observed in CPS rating, we considered whether the data itself could be involved, hypothesizing  
322 that the modest ICC value that we found (0.77) was largely due to the presence of highly noisy  
323 data. To confirm this hypothesis, we identified extreme outliers for which CPS values were three  
324 times larger than the standard deviation of the mean. A total of five curves (5%) were identified  
325 as extreme outliers (#2, #31, #58, #70 and #89 in S1 Appendix). What these curves have in  
326 common is: the lack of a clear plateau and/or the lack of a clear drop point. After removing these  
327 five outliers, the resulting ICC value for CPS improved to 0.82 (95%CI [0.76, 0.87]). This

328 increased value suggests that, to increase inter-rater reliability, ambiguous cases of noisy data  
329 should be discussed before final estimates of CPS are reached. Therefore, the advice for our  
330 fellow researchers is to inspect our 5 ambiguous samples and define how to deal with such cases  
331 on an individual basis whilst maintaining consistency in data extraction. The tips provided in S2  
332 Appendix on how to score ambiguous data can serve as a starting point. When possible,  
333 measurements should be repeated to help interpret problematic data.

334

335 We also found that for CPS inter-rater reliability was poorer among less experienced raters  
336 compared to experienced ones. We speculate that this tendency may be related to both the lack of  
337 experience in administering and rating the test that would lead more naïve raters to follow  
338 strictly the definitions of CPS and MRS. Taking the example of curve #2 (see S1 Appendix),  
339 raters SM and AC (self-reported expertise scores of 3 and 4) estimated CPS to be 0.7 logMAR  
340 (MRS = 68 wpm, both) whilst TQ and KB (self-reported expertise score of 0 and 2) estimated  
341 CPS to be 1.3 and 1.1 logMAR (MRS = 85 and 75 wpm, respectively). In this case, the more  
342 experienced raters (SM and AC) may have decided to ignore the outlier initial data point,  
343 assuming that this measure resulted from experimental noise.

344

345 Our second main result is the excellent agreement between the two automated methods for MRS.  
346 Regarding CPS estimation, the NLME method provides more flexibility over the SDev method,  
347 since it allows to determine CPS for different levels of MRS. For instance a higher, more  
348 conservative criterion, can be chosen for fluent reading while a lower criterion would be  
349 preferred for spot reading. However, there is no rule yet on how to set this criterion optimally to

350 increase reliability. Our results show that the reading speed cut-off to determine CPS yielding the  
351 best reliability between methods is 80% MRS. This result resonates with conclusions from [19],  
352 who showed that agreement between NLME models using a two-limb function and an  
353 exponential decay function was greater if CPS was set at 80% MRS. On the question of test-retest  
354 reliability, [11] also reported that using a criterion of 80% yield improved repeatability of the  
355 CPS (when compared to 90%). While an optimal criterion should be chosen on a case-by-case  
356 basis depending on the clinician or researcher's motivations, all these evidence suggest that a  
357 criterion close to 80 % would increase both inter-rater and test-retest variability.

358

359 Our third result is that raters and automated methods show excellent agreement for MRS values  
360 (ICC of 0.96 and 0.97 for the SDev and NLME respectively). The agreement for CPS was more  
361 variable. It was found to be poor for the SDev (ICC of 0.66) and good for the NLME (ICC of  
362 0.83 with a CPS criterion set to 90% MRS). It is worth noting that ICC values were almost  
363 identical when measuring agreement between raters and agreement between algorithms for both  
364 MRS and CPS. This observation is quite interesting and somehow indicates the robustness and  
365 efficacy of human visual inspection of MNREAD curves.

366

367 The present work presents some limitations. First, despite the relatively large sample of  
368 MNREAD data considered in the present work, it is hard to predict to what extent the different  
369 shaped curves are representative of the curves found in typical clinical practice. Second, it is  
370 likely that the new instructions helped reduce inter-rater variability, but there are no data to  
371 support this assumption. While all raters used these extended instructions, the ICC value for CPS

372 was still low, suggesting that additional fixes should be considered to help increase reliability. It  
373 is possible to run participants through the test more than once, at least with the English version  
374 [16,30]. Repeated measures would make it easier for the rater to determine whether a measure  
375 should be considered as noise or not. Another possibility might be to pool estimates from  
376 multiple raters or in combination with curve fits. Third, the finding that 80% MRS yields the  
377 most reliable CPS using the NLME method is convenient to parameterize the curve in research  
378 studies using curve fitting. But for low vision rehabilitation the goal ought to be to enlarge text so  
379 that it can be read at the reader's MRS, not at the 80% of the reader's MRS.

380

## 381 **Conclusions**

382 In summary, our study shows that extraction of the maximum reading speed from MNREAD data  
383 is highly consistent across methods and researchers. It also reveals that for low-vision data, it is  
384 difficult to obtain excellent inter-rater reliability for CPS estimates. Future studies, such as  
385 rehabilitation interventions aiming at improving reading ability in people with low vision, can  
386 now follow the advices and instructions resulting from our investigation. Using a standard set of  
387 instructions and criteria to analyze reading curves may help increase the reliability of the results.  
388 Additional ways to improve inter-rater reliability should also be considered, e.g. use the curve  
389 fits, collect multiple runs per participant or combine the estimates of multiple raters.

390 **Acknowledgments**

391

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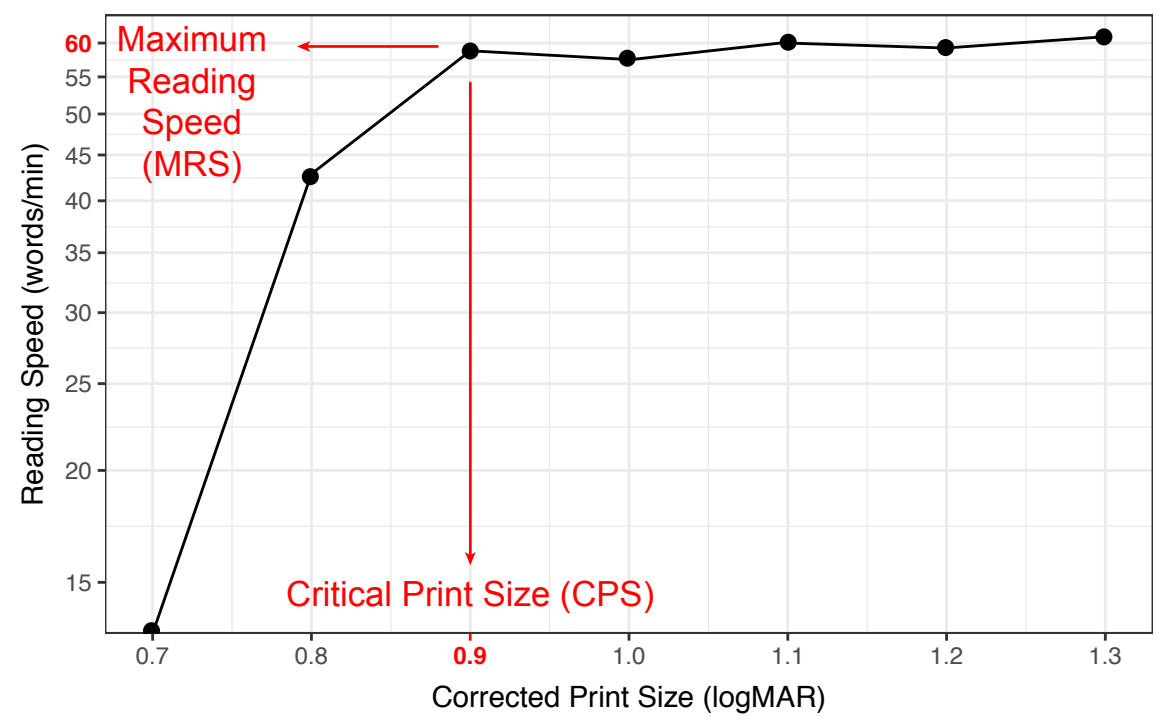
498 **Supporting information captions**

499 **S1 Appendix. Individual MNREAD curves from the 101 MNREAD measurements.**

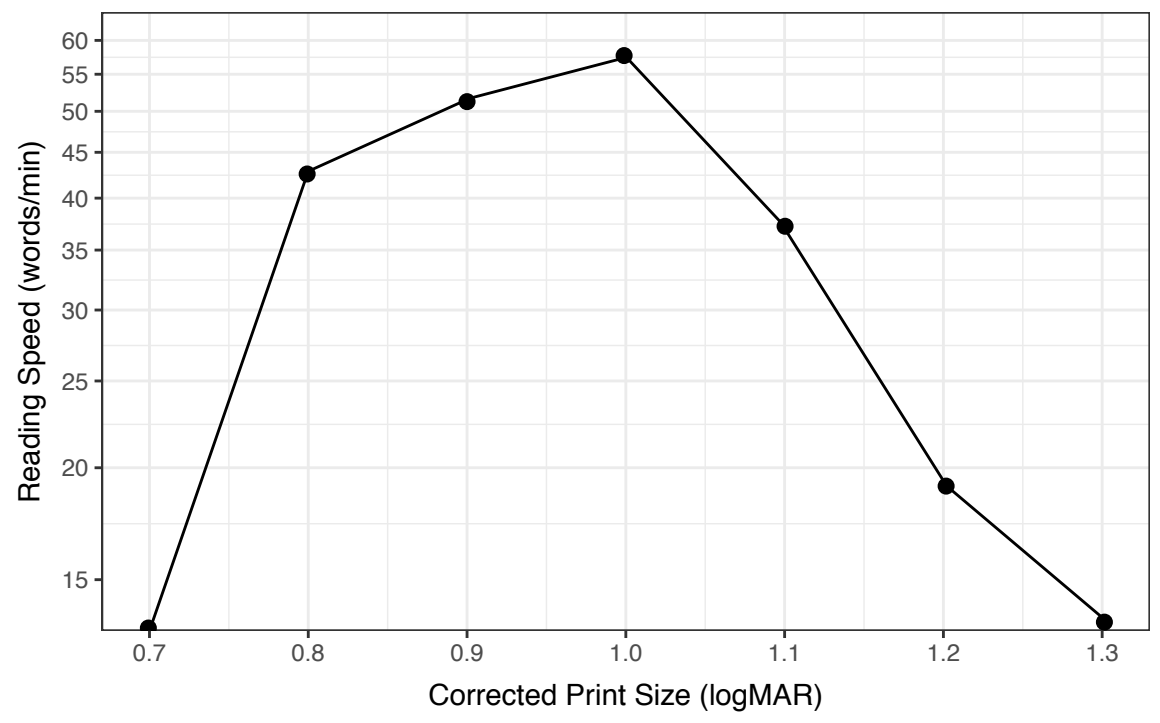
500 **S2 Appendix. Detailed scoring instructions provided to the raters.**

501

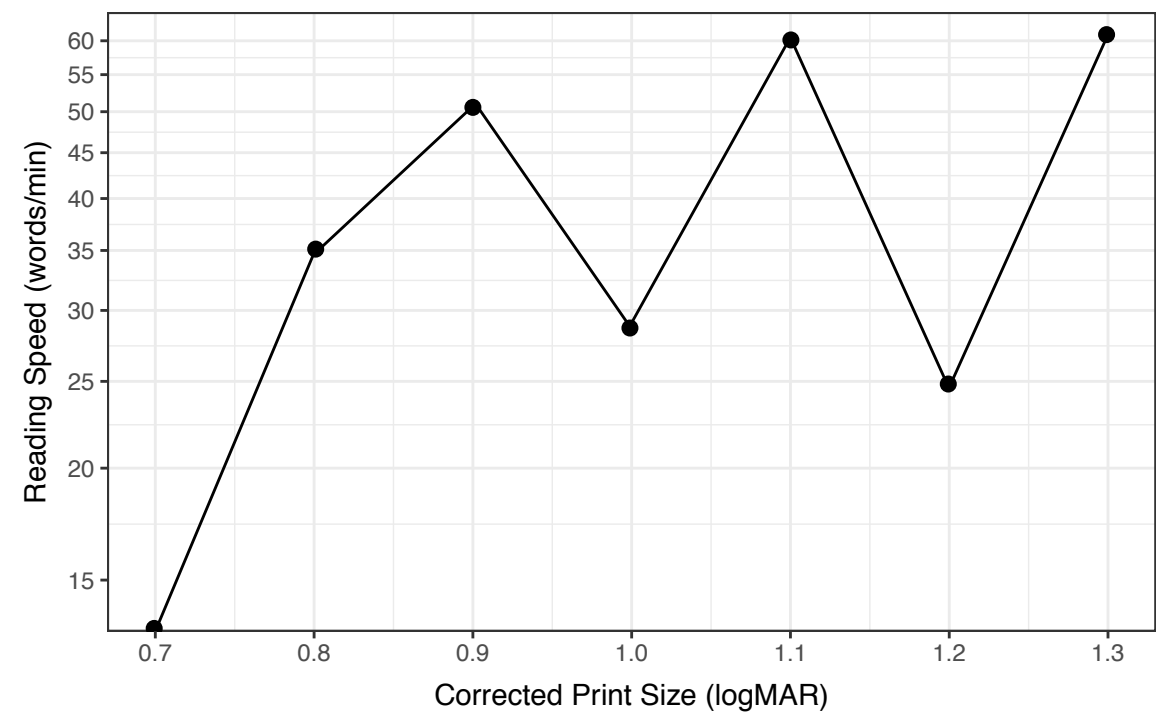
Figure A - Standard-shaped MNREAD curve



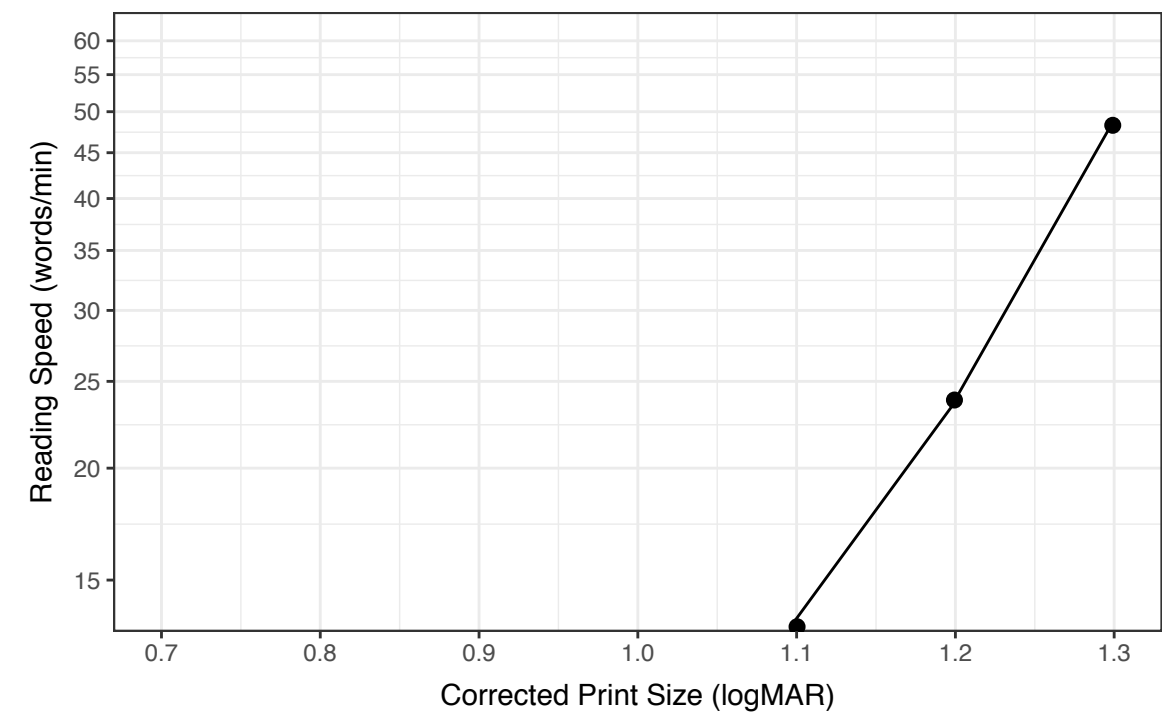
B - MNREAD curve example in presence of a ring scotoma

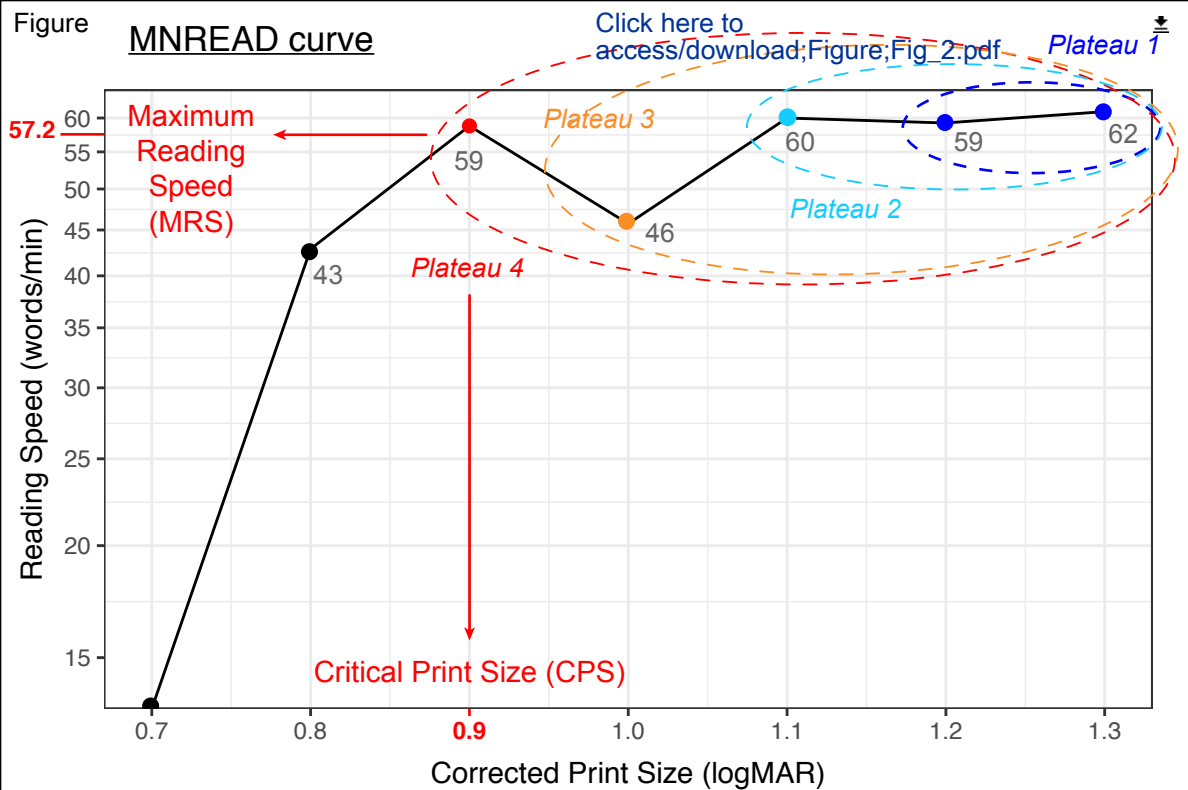


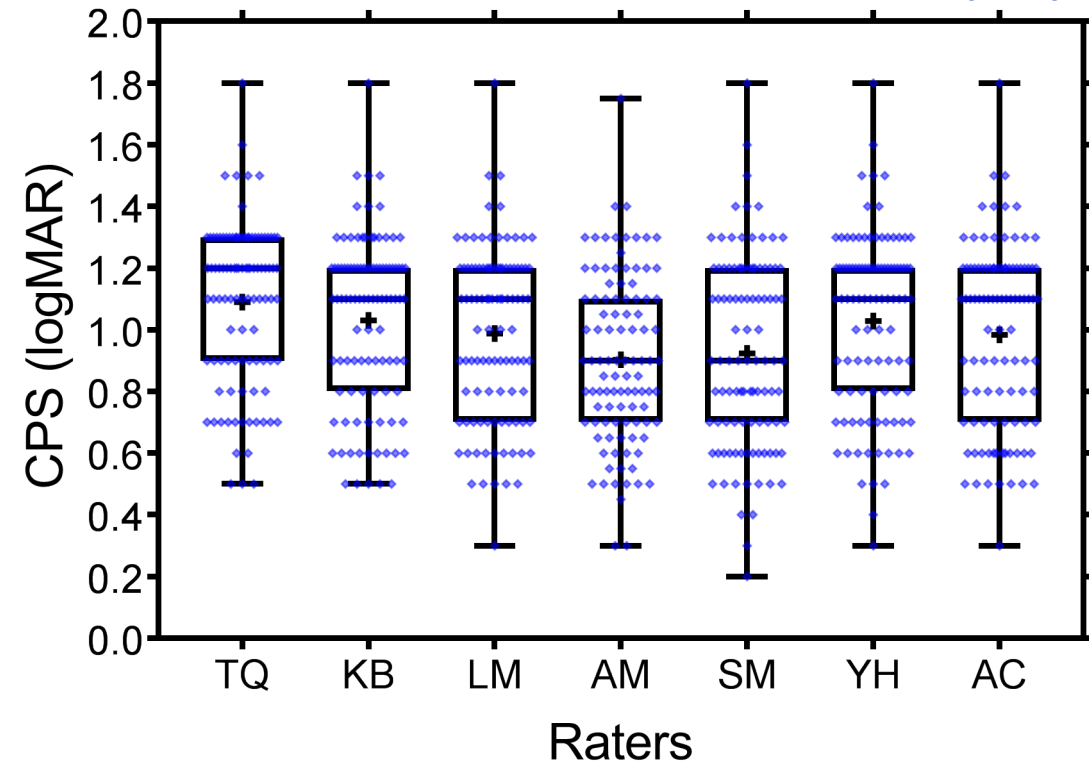
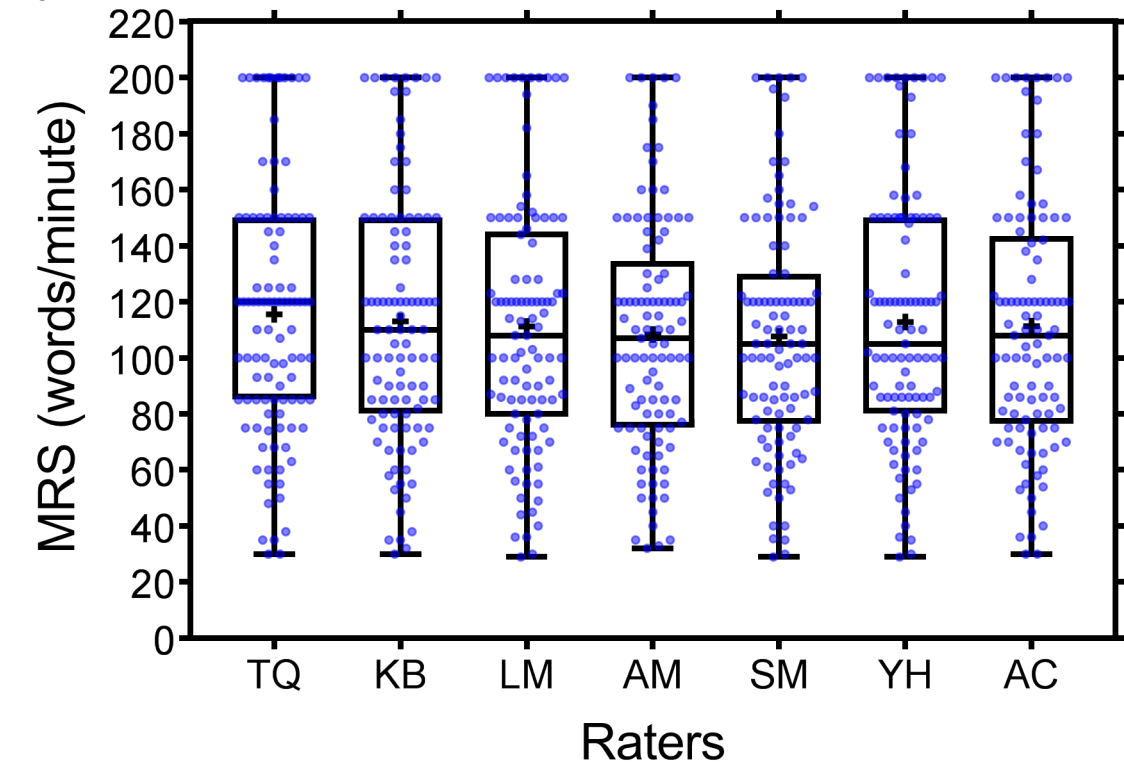
C - MNREAD curve example when using multiple fixation sites

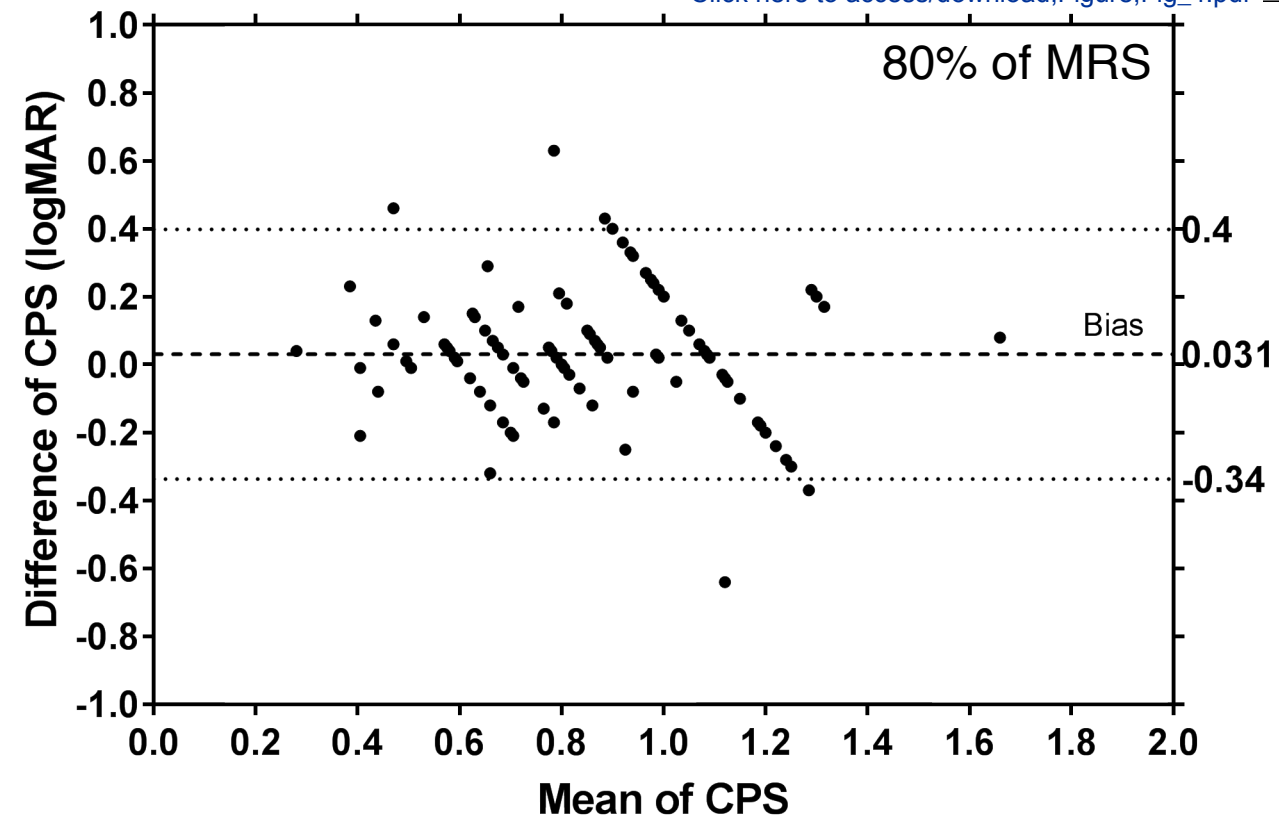
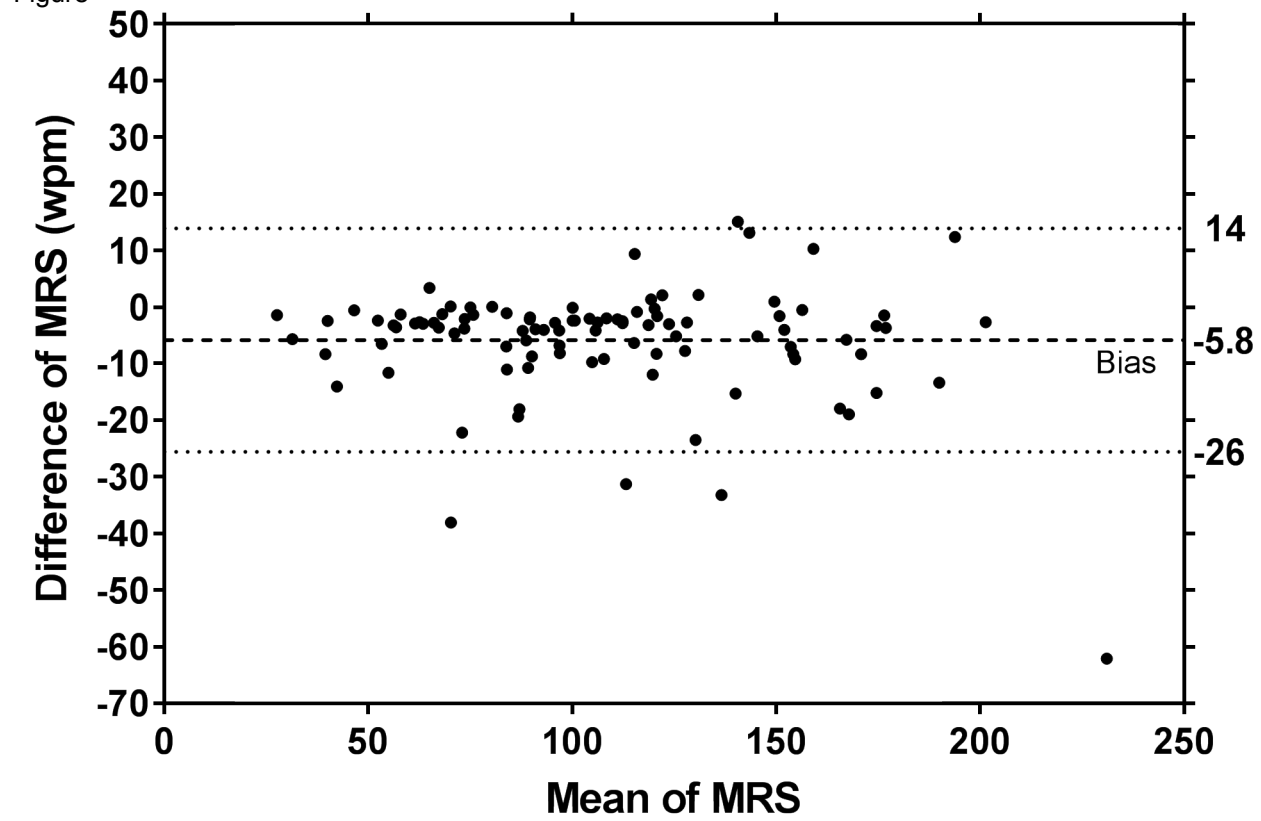


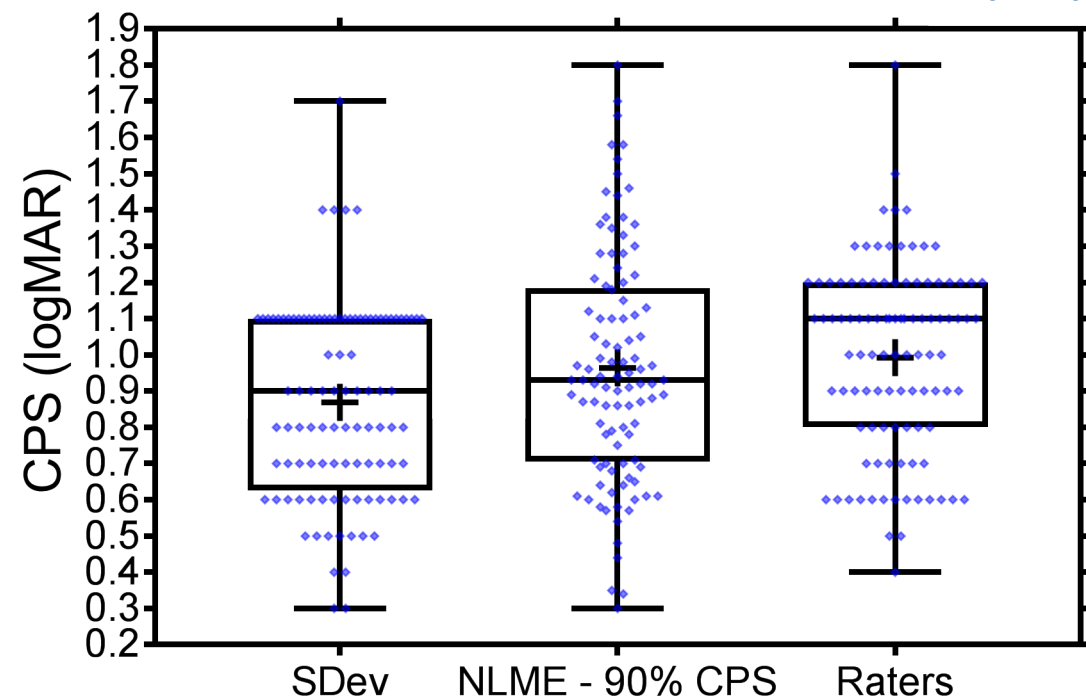
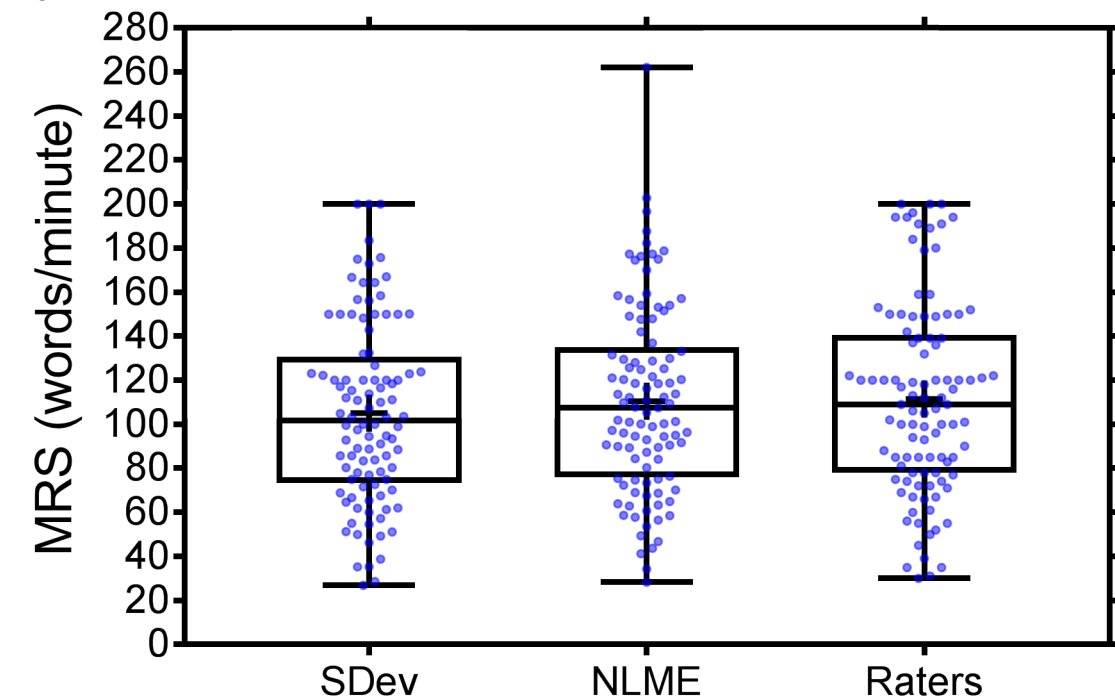
D - MNREAD curve example with a noisy incomplete dataset













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