

Relaxed forced choice improves performance of visual quality assessment methods

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Abstract—In image quality assessment, a collective visual quality score for an image or video is obtained from the individual ratings of many subjects. One commonly used format for these experiments is the two-alternative forced choice method. Two stimuli with the same content but differing visual quality are presented sequentially or side-by-side. Subjects are asked to select the one of better quality, and when uncertain, they are required to guess. The relaxed alternative forced choice format aims to reduce the cognitive load and the noise in the responses due to the guessing by providing a third response option, namely, “not sure”. This work presents a large and comprehensive crowdsourcing experiment to compare these two response formats: the one with the “not sure” option and the one without it. To provide unambiguous ground truth for quality evaluation, subjects were shown pairs of images with differing numbers of dots and asked each time to choose the one with more dots. Our crowdsourcing study involved 254 participants and was conducted using a within-subject design. Each participant was asked to respond to 40 pair comparisons with and without the “not sure” response option and completed a questionnaire to evaluate their cognitive load for each testing condition. The experimental results show that the inclusion of the “not sure” response option in the forced choice method reduced mental load and led to models with better data fit and correspondence to ground truth. We also tested for the equivalence of the models and found that they were different. The dataset is available at <http://database.mmsp-kn.de/cogvqa-database.html>.

Index Terms—2-alternative forced choice, psychometric functions, dot images, crowdsourcing, subjective quality assessment

I. INTRODUCTION

Several testing methodologies have been established to assess the visual quality of a source image encoded with different coding parameters, respectively bitrates. In the single stimulus presentation, the quality can be assessed by degradation category rating (DCR) on a discrete scale of five levels or with a slider on a continuous interval scale. In dual presentation mode, two images are displayed sequentially or side-by-side, and observers select the one with better quality,

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and when uncertain, they have to guess. From these pairwise rankings, scale values can be derived, either by scoring, as in sports rating systems, or by fitting parameters of a suitable probabilistic model [1], [2].

The approach to let observers decide which one of two presented stimuli in a pair has a stronger perceptual effect of a certain kind is called two-alternative forced choice (2AFC). It has a long history, having been developed as a method of psychophysics by Gustav Theodor Fechner more than 150 years ago in the first edition of [3]. Already back then, Fechner had relaxed the forced choice, allowing participants of his experiments to give undecided (“zweideutige”) responses that he divided equally between the two alternatives before analyzing the data.

In the research area of image quality assessment, the 2AFC response format has been used almost entirely without such an option for undecided responses. In 2015, JPEG, formally known as ISO/IEC SC29 WG1, issued an international standard for procedures to test compressed images for being visually lossless when compared with the corresponding source images [4]. In its Annex A and B, the forced choice paradigm was prescribed, also without a ternary choice. The first application of this standard was presented by McNally et al. [5] for the subjective evaluation of visually lossless compressed images in the context of JPEG XS, a low-latency, lightweight video coder that is optimized for visually lossless compression. Unlike the JPEG AIC standard [4], however, an undecided response option was offered to the participants. This was justified by stating that “offering a ternary choice to subjects reduces subject stress and fatigue and was deemed beneficial for the reliability of the subjective evaluation results.” However, the authors did not present any experimental evidence for these claims.

In this paper, we present the results of a large and comprehensive user study to investigate the effects of the ternary 2AFC response format for subjective studies to assess a certain visual quality of stimuli. We present paired comparisons in both response formats: 2AFC (referred to as AFC) and RFC (relaxed forced choice). In AFC, subjects are shown two visual patterns side-by-side and have to select the “left” or “right” stimulus. Subjects are instructed to guess when undecided. In RFC, participants may also select the response “not sure”. The

focus of our study is on the following three hypotheses.

Hypothesis 1 *The not-sure option in forced choice quality assessment tasks reduces cognitive load.*

The binary AFC scheme requires subjects to guess when uncertain, which may introduce more noise in the data than equally dividing the responses of the third, undecided category. It is natural to expect that noise reduction would improve the precision of the resulting estimates for scale values or parameters of fitted psychometric functions. If some form of ground truth quality is available, we can also compare the proportions of correct responses and their correlation with the ground truth qualities to assess the performance of the assessment method with and without the not-sure option.

Hypothesis 2 *The not-sure option in the forced choice response format improves the performance of quality assessment.*

It is unclear whether the introduction of the ternary response format with the not-sure option leads to the same assessments with respect to image quality. For example, in the study for JPEG XS [5] mentioned above, the obtained thresholds for compression parameters that yielded a just noticeable difference (JND) could have depended on the choice of the answer format of the subjective study.

Hypothesis 3 *The psychometric functions estimated from quality assessment studies using alternative forced choice responses are the same with and without the not-sure option.*

The contributions of our work can be summarized as follows:

- We carried out a large crowdsourcing study with 254 participants using both the traditional two-alternative forced choice and the relaxed forced choice formats. The data will be made available at the time of publication.
- The subjectively reported *Mental Demand* was significantly lower for the relaxed forced choice format.
- We show for a number of criteria that the performance of quality assessment using pair comparisons and maximum likelihood estimation of the psychometric function was improved by the relaxed forced choice format.
- We show that an important parameter, the JND threshold, differed significantly between the two-alternative forced choice and the relaxed forced choice formats, with a very large effect size.

II. RELATED WORK

There have been quite a number of image and video quality assessment studies using standard two-alternative forced choice responses for paired comparison, including [2], [6]–[13]. On the other hand, so far, there are only very few contributions with a relaxed form of the forced choice response format [5], [14], [15]. None of them, however, discuss or study the effect of a not-sure option in detail. However, a study by Punch et al. [16] in audiology compared relaxed force choice with two-alternative forced choice, revealing a higher test-retest reliability in the condition with the not-sure option.

In contrast to user studies in computer science and engineering, in psychophysics, the branch of psychology that deals with the relations between physical stimuli and mental phenomena, the unforced choice response format has been used for a very long time. Recently, the approach gave rise to new theoretical models and was tested in simulations and dedicated experiments. In 2001, Kaernbachs [17] proposed a Bayesian framework of a theory of indecision for experiments applying forced and unforced choice tasks. Responses to the not-sure category were split evenly. Simulations and a behavioral study with six participants were carried out. The task was to detect a brief sinusoid of 1000 Hz centered in 800 ms of white noise. By varying the signal-to-noise ratio and using an adaptive staircase procedure [18], the absolute threshold for detection of the sinusoidal signal was estimated for each of the participants. The results showed that the unforced choice option in the adaptive procedure did not lead to reduced reliability, and a slight gain in efficiency was achieved.

García-Pérez and Alcalá-Quintana [19] presented an even more comprehensive probabilistic indecision model for dual-presentation tasks, which explicitly represents the sensory, decisional, and response components of performance by model parameters. These can be obtained from forced choice responses in pair comparisons by maximum likelihood estimation. It is claimed that the ternary response format provides more accurate estimates of model parameters than data collected with the standard binary forced choice. For a brief historical account of the use the ternary unforced choice, ranging from Hegelmaier and Fechner in the middle of the 19th century until it was discredited and eradicated by signal detection theory 100 years later, see [20].

The intense research in psychophysics on the implications of allowing — or rather ruling out — a not-sure option in forced choice experiments is encouraging for applications in multimedia quality assessment. While in psychophysics the focus lies primarily on the individual performance of a subject, it is just the opposite in multimedia quality assessment; the collective experience of quality has to be assessed. Therefore, it is unclear whether the conclusions drawn in the recent works in psychophysics can simply be transferred one-to-one to our domain of research.

III. EXPERIMENTAL DESIGN AND SETUP

For our experiments, we have chosen the so-called dot-guessing game [21]. In this game, subjects are presented with pairs of images consisting of black dots of the same size, but with differing numbers, for example, 300 and 320. The question asked is which of the two images in a pair contains more dots. Thus, the number of dots is regarded as the “quality” of an image that is to be assessed.

Why are we not using source images compressed at different bitrates? It has been observed that slightly compressed images may be judged to have better visual quality than the source images. This may be due to the denoising effect of some compression methods at high bitrates. This is also the reason why in the paired comparisons in Annex A of the JPEG

standard [4], the reference image is displayed a second time above the pair so that the question for better image quality could be recast as “Please select the lower image that is the closest match to the reference.”

With the dot images, we do not have this problem and may safely assume that the perceived number of dots on the observer’s sensory scale is monotonically related to the number of dots in the stimulus. In expectation, more dots will be perceived when the number of dots is increased. This is an advantage that offers a wider spectrum of criteria when comparing assessment performance between the AFC and RFC response formats.

Moreover, random dot images have been used in subjective studies for various other applications, including human computation tasks [21], aggregate predictions using the wisdom of crowds [22]–[24], and information aggregation [25]. So these works have shown that the dot guessing game may indeed be considered as a basic task that can serve as a “fruit fly for human computation research” as Horton has expressed it [21].

We conducted a crowdsourcing user study to collect responses for the AFC and RFC paired comparisons, using a within-subjects design in which all participants responded to both conditions. The presentation order of AFC and RFC was randomized to avoid the potential for presentation order bias.

We measured participants’ cognitive load using the NASA task load index (TLX) questionnaire [26]. The TLX is a multi-scale questionnaire to assess participants’ perceived subjective workload – split into six sub-scales: *Mental Demand*, *Physical Demand*, *Temporal Demand*, *Performance*, *Effort*, and *Frustration*. Although the original analysis procedure includes an individual weighting of the sub-scales, it is common to skip the weighting and only average participants’ ratings for the sub-scales to create scores for each sub-scale and the overall task load (known as *raw TLX*) [27]. Scores rank between 0 and 100; lower values indicate a lower task load.

A. Image generation and procedure

In our experiment, each dot image contained a relatively large number of non-overlapping dots and had a resolution of 640×480 pixels to facilitate side-by-side display on crowdworkers’ screens. We defined a *question* as showing a participant a pair of images side-by-side and asking to select the image that contains more dots. We compared a reference image with 300 dots to 20 test images with a greater number of dots, ranging from 302 to 340 with a step size of 2. For each question, the reference image was presented on either the left or the right side, with the test image on the opposite side. This resulted in 40 study questions for each of the two conditions, AFC and RFC, for a total of 80 study questions presented to each subject. Each image was generated with a random dot pattern.

To mitigate the influence of learning from previous comparisons or random dot patterns on participants’ responses, we ensured that no dot pattern was repeated in the 80 study questions evaluated by a subject in the two test conditions. For example, the 80 reference images, each containing 300 dots,

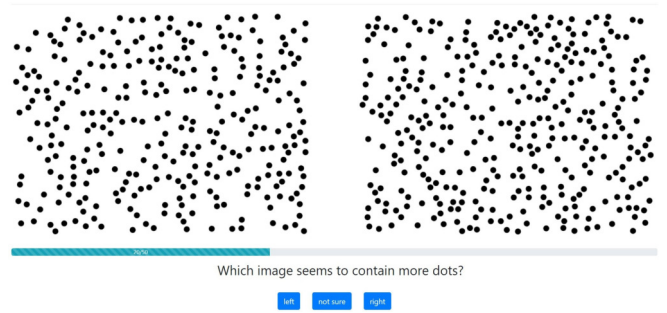


Fig. 1: User interface with relaxed forced choice answer options and a progress bar.

had unique patterns. Moreover, the dot patterns also differed between subjects. The order of the conditions used, AFC or RFC, was also randomly assigned to participants.

To identify and filter out unreliable participants, e.g., line clickers, we included 10 trap questions for each test condition, comparing a reference image with 300 dots to a test image with about 450 dots. In these trap questions, the test image was easily distinguishable. Each participant was presented with 10 trap questions in each experimental condition.

B. Crowdsourcing study

We conducted our experiment on the Amazon Mechanical Turk (MTurk) platform. We posted a human intelligence task (HIT) with 254 assignments. However, each MTurk worker was only allowed to do one assignment. In each assignment, a worker had to answer 50 questions (40 questions for the study experiment and 10 trap questions) for the AFC experiment and 50 questions for the RFC experiment. The order of the experiment types and the order of the questions in each experiment were randomized. Figure 1 shows a screenshot of the user interface.

To ensure reliable responses, participants were required to have at least 500 previously approved HITs with a 95% or higher approval rate on MTurk. Additionally, participants were required to use a PC or laptop with a minimum logical resolution of 1366×768 pixels and the Google Chrome browser to complete the experiment. Participants who did not meet these requirements received a warning message, and the experiment was terminated.

A brief instruction was shown to the eligible workers, explaining the steps of the experiment, and the worker was asked to sign a consent form. The presentation order of the two conditions, AFC and RFC, was chosen randomly. More detailed instructions, the training session, and the main part of the experiment were given for the first chosen condition, and then this was repeated for the other condition.

For each test condition, participants received detailed instructions with examples of paired comparisons specific to that test condition, followed by an explanation of the NASA task load questionnaire. After reading the instructions, workers went through a training session consisting of five questions of varying levels of difficulty. After answering each training

TABLE I: Summary of the responses to the study questions in the two test conditions collected from 235 participants.

Test condition	Number of dots	302	304	306	308	310	312	314	316	318	320	322	324	326	328	330	332	334	336	338	340
AFC	Correct answers	254	256	284	269	306	294	309	320	318	339	359	370	349	367	383	374	382	366	392	404
	Wrong answers	210	208	183	197	160	175	158	149	150	129	108	97	118	99	83	93	85	101	70	64
RFC	Correct answers	210	230	239	251	254	264	274	285	306	303	323	319	321	330	362	350	352	385	357	377
	“not sure” answers	64	53	70	62	56	54	61	61	49	45	39	45	40	38	39	31	35	22	38	29
	Wrong answers	190	181	158	153	156	151	132	123	113	120	105	103	106	98	65	86	80	60	67	62

question, the worker was given feedback indicating which image had more dots.

Then the worker was asked to do the main experiment with 50 questions for the first selected test condition (40 study and 10 trap questions). For each question, the paired images were shown for five seconds. If the worker did not make a decision during these five seconds, a blank page was displayed in place of the paired images, and the worker was given three more seconds to answer. If the worker did not give an answer, the next question was shown. After the 50 questions, the NASA task load questionnaire was shown. After answering the questionnaire, the experiment for the other condition was carried out in the same manner.

The experimental procedures and protocols used in the study were ethically approved by the Institutional Review Board of the local university.

IV. EXPERIMENTAL RESULTS

In the crowdsourcing study, 254 crowdworkers responded to 25,400 paired comparisons and provided 3,048 answers to the NASA TLX questions. The response times for the paired comparisons were recorded. In this section, we present the filtering of unreliable participants, the data analysis for our hypotheses.

A. Data and model

1) *Data cleansing*: We used two criteria to eliminate unreliable participants. First, the responses of participants who answered incorrectly three or more trap questions were discarded. Second, the responses of participants who skipped five or more questions from the 100 (study and trap) questions in the main study were disregarded. Consequently, 19 participants were excluded, and their responses were not considered in the analysis. The analysis was conducted based on the responses of the remaining 235 participants. In order to maintain a strict within-subject design, if a participant did not answer a study question in one test condition, the corresponding question from the other test condition was excluded. The summary of the remaining data is presented in Table I.

2) *Model and MLE fitting*: In psychophysics, maximum likelihood estimation (MLE) is applied to fit a psychometric function to the proportions of correct paired comparison responses. Commonly, the cumulative distribution function $\Phi(x; \mu, \sigma)$ of a normal distribution is used as follows [28],

$$\psi(x; \mu, \sigma) = \frac{1}{2} + \frac{1}{2}\Phi(x; \mu, \sigma). \quad (1)$$

The additive constant 1/2 is required here to accommodate the guessing, which can be expected to give the correct answer

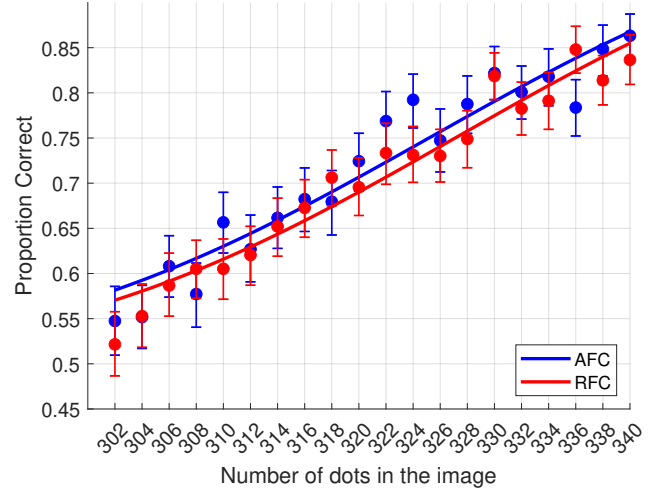


Fig. 2: The psychometric function in Equation (1) is fitted to the proportions of correct responses in each test condition.

half of the time. To analyze the responses collected through the RFC method, we divided the “not sure” responses into two halves, correct and incorrect, as usual. Figure 2 shows the resulting psychometric functions. The parameters for the psychometric functions were $\mu = 25.18, \sigma = 23.61$ for AFC, and $\mu = 27.10, \sigma = 23.33$ for RFC. Thus, the estimated JNDs were 25.18 and 27.10, respectively.

To determine the confidence intervals (CI) of the proportions of correct responses, non-parametric bootstrapping with 1000 trials was used. The 235 subjects were sampled with replacement. For each bootstrap sample, all of the responses of the sampled subjects were included in computing the proportions of correct responses, thereby preserving the within-subject design. The percentile bootstrap intervals for 1000 trials produced 95% CIs for the 20 proportions (Figure 2).

B. Cognitive load analysis (Hypothesis 1)

We used a Wilcoxon matched pairs signed ranks test to analyze the overall TLX scores and the sub-scales. The analysis of the overall TLX scores did not show statistically significant differences ($z = -1.65, p > .05$) with median values of 57.50 for AFC and 57.50 for RFC. The analysis of the sub-scale *Mental Demand* revealed a statistically significant difference between AFC and RFC ($z = -2.19, p < .05$), showing higher median values regarding Mental Demand for AFC (77.50) than for RFC (75.00). None of the other sub-scales showed a statistically significant difference between the conditions.

TABLE II: McNemar test results for paired proportions at each stimulus level in the two test conditions.

Number of dots	302	304	306	308	310	312	314	316	318	320	322	324	326	328	330	332	334	336	338	340
Chi square	0.504	0.001	0.362	0.679	2.784	0.019	0.061	0.059	0.687	0.856	1.516	5.025	0.269	1.806	0.002	0.418	1.054	6.276	1.875	1.155
p-values	0.478	0.972	0.548	0.410	0.095	0.89	0.806	0.808	0.407	0.354	0.218	0.025	0.604	0.179	0.965	0.518	0.305	0.012	0.171	0.282

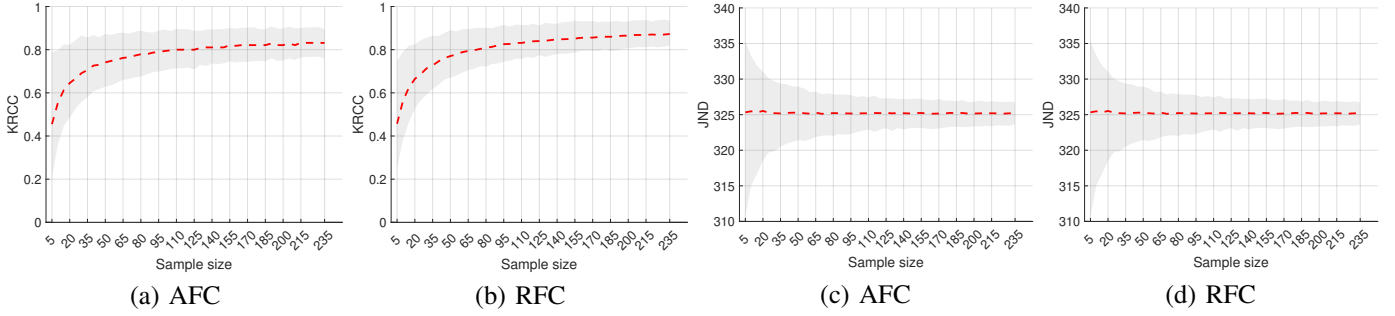


Fig. 3: The first two plots illustrate the correlation (KRCC) between the proportions and the stimulus levels, while the second two plots illustrate the estimated JND values, both with 95% CI. These statistics were calculated using 1000 bootstrap samples.

C. Performance analysis (Hypothesis 2)

We checked whether the not-sure option in our forced choice experiment with the dot-guessing game improved the goodness of fit of the psychometric function, increased the correlation with the ground truth ordering of the stimuli according to dot numbers, and reduced the confidence intervals for the estimated JND. To indicate the degree by which some of these criteria differed between AFC and RFC, we used Cohen's effect size d for paired observations [29].

1) *Goodness of fit*: The goodness of fit assesses the accuracy of the fitted psychometric function in predicting the proportion of responses in each condition. To evaluate the goodness of fit of the psychometric function, we applied the procedure of analysis by bootstrapping given by Wichmann and Hill [30]. The deviance was calculated from the observed and predicted proportions at each of the 20 stimuli levels for each condition and summed to form the overall metric values. The total deviance value was 37.00 for the AFC condition and 23.31 for the RFC condition.

A smaller deviance indicates better goodness of fit. From an analysis with 1000 bootstrap samples, we also calculated the p-values and found that they were equal to 0.008 for AFC and 0.270 for RFC. The p-value is the estimated probability that a random sample of the psychometric model leads to a deviance greater than that from the observed data. Thus, the p-value of only 0.008 for AFC suggests that the AFC model should be rejected. Furthermore, the difference in deviance between AFC and RFC was large, with an effect size of 0.98.

2) *Correlation with ground truth*: As explained in Section I, we can use the rank order correlation between the observed proportions of correct responses and the numbers of dots in the test stimuli to assess the performance of AFC and RFC. Methods with larger correlations can be considered more efficient. We have used Kendall's rank order correlation (KRCC) which is less sensitive to ties and assumptions about the distribution than Spearman's rank order correlation.

Fig. 3 (a, b) shows the mean KRCC values with 95% CIs,

computed for sample sizes from 5 to 235 from 1000 bootstrap samples as outlined in Section IV-A2. The correlation for RFC was larger and had smaller CIs. For the maximal sample size of 235, the mean KRCC value of 1000 bootstrap samples for AFC was 0.83 with a CI length of 0.13, while the KRCC for RFC was 0.87 with a CI length of 0.11. The difference in correlation between AFC and RFC was of medium effect size, 0.79. Thus, in terms of correlation with ground truth, the quality assessment with the not-sure option was superior to the alternative forced choice.

3) *Convergence and precision of the JND*: Fig. 3 (c,d) shows the JND estimates and their CIs for various sample sizes computed using 1000 bootstrap samples again. For the sample size 235, the CI of the JND was 3.11 for AFC and 3.40 for RFC. The AFC experiment resulted in a slightly smaller CI length.

D. Homogeneity of psychometric functions (Hypothesis 3)

We applied three criteria for testing the homogeneity of the models derived from AFC and RFC data, one for each of the predicted proportions of correct responses, one for all of them together, and one for equality of the estimated JNDs.

(1) For the first task, we conducted the McNemar test for the statistical analysis of the 2×2 contingency tables that summarize the binary responses for each stimulus level. The test statistic is used to test the null hypothesis of no difference. The resulting chi-square and p-values are presented in Table II. The critical value at a 95% significance level was 3.84. If the McNemar chi-square value is greater than the critical value, it indicates a significant difference with 95% confidence. The results suggest that there was weak evidence for rejecting the null hypothesis of equality for 18 paired proportions in the two test conditions. However, two paired proportions showed a significant difference.

(2) To compare the psychometric functions fitted to the proportions of correct responses at all stimuli levels together, we applied the nonparametric generalized Mantel-Haenszel test

[31]. The p-value was 0.02, rejecting the null hypothesis of homogeneity of the psychometric functions in the compared test conditions.

(3) Finally, the difference between the JNDs estimated with AFC and RFC was significant as the effect size was huge, estimated at 2.29 from 1000 bootstrap samples.

In summary, the statistical tests conducted indicate that the data collected with the AFC and RFC were significantly different, and Hypothesis 3 has to be rejected.

V. CONCLUSIONS AND FUTURE WORK

This study examined the effects of including the “not-sure” response option for pair comparisons on subjects’ cognitive load and efficiency. The task was to assess the perceptual quality for a set of visual stimuli of dot patterns that may well serve as a paradigm for visual quality assessment. The experimental results show that compared to alternative forced choice, the relaxed force choice with the not-sure option yielded a model with a better fit and a higher correlation between the proportions of correct responses and the physical scale. Moreover, the cognitive load assessment indicates that the *Mental Demand* was significantly lower. In conclusion, the results of our study support the use of the relaxed forced choice response format over the standard two-alternative forced choice.

The results also show that the fitted distributions differed significantly between the two test conditions. This gives rise to a fundamental open research question, namely, to determine whether the improved performance of the RFC format also leads to a more accurate estimate for the collective JND in visual quality assessment studies. This is beyond the scope of our contribution and will be considered in future research.

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