Best Practices and Recommendations for Crowdsourced QoE - Lessons learned from the Qualinet Task Force "Crowdsourcing"

Tobias Hoßfeld, Matthias Hirth, Judith Redi, Filippo Mazza, Pavel Korshunov, Babak Naderi, Michael Seufert, Bruno Gardlo, Sebastian Egger, Christian Keimel

Best Practices and Recommendations for Crowdsourced QoE

Lessons learned from the Qualinet Task Force "Crowdsourcing"

Tobias Hoßfeld, Matthias Hirth, Judith Redi, Filippo Mazza, Pavel Korshunov, Babak Naderi, Michael Seufert, Bruno Gardlo, Sebastian Egger, Christian Keimel

Whitepaper version: October 29, 2014

COST Action IC1003 European Network on Quality of Experience in Multimedia Systems and Services (QUALINET)

Preface

Crowdsourcing is a popular approach that outsources tasks via the Internet to a large number of users. Commercial crowdsourcing platforms provide a global pool of users employed for performing short and simple online tasks. For quality assessment of multimedia services and applications, crowdsourcing enables new possibilities by moving the subjective test into the crowd resulting in larger diversity of the test subjects, faster turnover of test campaigns, and reduced costs due to low reimbursement costs of the participants. Further, crowdsourcing allows easily addressing additional features like real-life environments.

Crowdsourced quality assessment however is not a straight-forward implementation of existing subjective testing methodologies in an Internet-based environment. Additional challenges and differences to lab studies occur, in conceptual, technical, and motivational areas [9, 25, 26]. For example, the test contents need to be transmitted to the user over the Internet; test users may have low resolution screens influencing the user experience; also users may not understand the test or do not execute the test carefully resulting in unreliable data.

This white paper summarizes the recommendations and best practices for crowdsourced quality assessment of multimedia applications from the Qualinet Task Force on "Crowdsourcing". The European Network on Quality of Experience in Multimedia Systems and Services Qualinet (COST Action IC 1003, see `www.qualinet.eu`) established this task force in 2012. Since then it has grown to more then 30 members. The recommendation paper resulted from the experience in designing, implementing, and conducting crowdsourcing experiments as well as the analysis of the crowdsourced user ratings and context data. For understanding the impact of the crowdsourcing environment on QoE assessment and to derive a methodology and setup for crowdsourced QoE assessment, data from traditional lab experiments were compared with results from crowdsourcing experiments. Within the crowdsourcing task force, several different application domains and scientific questions were considered, among others:

- video and image quality in general,
- QoE for HTTP streaming [31, 32] and HTTP adaptive streaming [19, 30],
- selfie portrait images perception in a recruitment context [10],
- privacy in HDR images and video [39, 20, 36],
- compression of HDR images [37] [38],
- evaluation of 3D video [38],
- image recognizability and aesthetic appeal [12, 13],
- multidimensional modeling of web QoE [14],
- QoE factors of cloud storage services [21],
- enabling eye tracking experiments using web technologies [41].

From a crowdsourcing perspective, the following mechanisms and approaches were investigated which are relevant to understand for crowdsourced quality assessment.

- Motivation and incentives, e.g., extrinsic motivation scale [2, 12]
- Influence of payments [14, 12]
- Impact of task design [1] and affective crowdsourcing [11]
- Impact of crowdsourcing platforms selection [4, 12, 34]
- Reliability methods and screening mechanisms [5, 6, 31, 24], monitoring result quality [15]
- Development of crowdsourcing frameworks and platforms [3, 6, 7, 8]

As an outcome of the task force, scientific papers on best practices and crowdsourcing for QoE assessment in general were published.

- Challenges in Crowd-based Video Quality Assessment [9, 24, 25, 26, 33]
- Crowdsourcing in QoE Evaluation [25] and best practices for QoE crowdtesting [24, 26]
- Survey of web-based crowdsourcing frameworks for subjective quality assessment [27]

The scope of this white paper is to share practical issues and best practices in crowdsourcing experiments, to summarize the major lessons learned and to give key recommendations from the Qualinet task force. Thereby, the authors especially focus on aspects which are highly important in practice, but often not explained or discussed in scientific research papers for various reasons. Due to the large number of contributors, the document will not reflect the opinion of each individual person at all points. Nevertheless, each section of this white paper briefly formulates an important lesson learned.

Terminology

Crowdsourcing is typically adopted in QoE research to perform Subjective Experiments. The goal of most subjective experiments in QoE research is to quantify the perception, appreciation, satisfaction of users with a set of media. More specifically, subjective testing is deployed to be able to assign **scale** (possibly, interval) values, to a set of so-called **stimuli** (e.g., videos, images, audio excerpts), all varying according to one or more underlying **attributes** (e.g., blurriness, number of stallings in the reproductions and so on). To this purpose, users are asked to perform a **rating task**, which can consist in a more or less explicit assignment of a value to each stimulus in the set. In direct scaling methods, such as the well-known Absolute Category Rating, test participants are asked to assign a value to each stimulus by positioning the stimulus on a **rating scale**. Using indirect scaling methods such as Paired Comparison, the **task** of participants is instead focused on ordering stimuli according to their quality.

The above is true for both lab- and crowdsourcing-based subjective assessments. In this white paper, we will make some distinctions in the use of terms, in order to help the reader distinguishing between lab- and crowdsourcing-based experiments. In particular:

- **Experiment** or **test** will indicate the global subjective assessment activity. In particular, experiment will indicate subjective assessments in the lab, and test will indicate subjective assessments in a crowdsourcing environment.
- People participating in an experiment (thus, lab-based), will be referred to as **participants**.
- People participating in a crowdsourcing test will be referred to as **workers**.
- People deploying an experiment in the lab will be referred to as **experimenters**.
- People deploying a crowdsourcing test will be indicated as **employers**.
- By **task** we will refer to the actual set of actions that participants need to perform to complete an experiment, or workers need to complete a crowdsourcing test. Quality rating is, for example, a task.
- By **campaign** we will refer to group of similar tasks. Every campaign consist of the description of the tasks and additional requirements, e.g., how many quality ratings are required, how many different workers are needed, and amount Workers will earn per task. It should be noted that a campaign may be a subset of a test, as multiple campaigns may be needed to cover the scoring of a large set of stimuli.

Contents

1 Use common software without requiring admin installations!

Crowdsourcing tests can be basically implemented in any programming language and could require an arbitrarily complex setup from the participant. However, this dramatically decreases the number of participating users and also increases the monetary costs to recruit test participants. In order to find a large number of test participants, it is recommended to use easy-to-use software tools, which do not need to be installed and also reduce the amount of data, which has to be downloaded by the users during the test.

One of the most suitable techniques for developing portable crowdsourcing tests is the implementation as a web page or a web application. In such cases, a web browser is the only required software to access the test and to participate. However in many cases, there might exist some additional constraints, e.g., specific to a browser or a browser version, enabled JavaScript, or installed third party extensions like Adobe Flash. Nevertheless, these constraints can be usually tested automatically and appropriate information messages can be provided to the participating users, e.g., to enable JavaScript. The centralized character of this implementation approach also enables easy support and changes of the test implementation. A new version of the test is immediately available to all participants and unlike in the case of the decentralized implementations, no previous versions have to be removed or replaced.

Web based test are highly portable, but still the amount of transferred data can impose problems due to bandwidth limitations on the participants' side. Even worse, such limitations might unintentionally alter the test stimuli. Consider the evaluation of high definition video content. The size of the videos can result in a large amount of data, which has to be transferred to the participant. Transferring of the data can consume a significant amount time and thus must also be taken into account when defining the reward. Moreover, the expected waiting time and the amount of transfered data has to be clearly communicated to the participants before starting the test. When evaluating e.g., stalling pattern of streaming services, streaming via the Internet can also result in unwanted impairments, namely in additional stallings. Therefore, it might be necessary to pre-cache all data required during the test at the client side, before starting the actual test [31].

The server side infrastructure also has to be considered during the implementation. Some Crowdsourcing tests can be easily accessed by several hundreds of participants within a few minutes, imposing significant network and computation load to the server and the reporting infrastructure. This can be mitigated by a careful scaling of the experiment and by using appropriate hardware dimensioning.

2 Simplify your questions!

One of the major differences between web based crowdsourcing tests and traditional laboratory experiments is the unsupervised environment. This includes both, the unknown surrounding conditions of the test participants as well as the lack of information about the participants themselves due to the anonymous recruiting process. Moreover, a direct interaction between the participants and the experimenter is usually not given. This makes it hard for participants to clarify questions arising during a test and hard for the experimenter to identify misunderstandings of the test instructions. This issue is even amplified by the diversity of the participants. Compared to

laboratory experiments, crowdsourcing users differ more in terms of spoken languages, cultural background [17], background knowledge, used devices, etc. However, simple guidelines can help to minimize misunderstandings by the test participants.

The usage of simple English or native-language instructions helps non-native speakers to understand the instructions without using additional language resources, e.g., dictionaries. It is not economical for most crowdsourcing users working on micro-tasks to spend a lot of effort on understanding the instructions of an individual task. Consequently, the users will either skip the task if they do not understand the instructions or try to complete the task to the best of their knowledge leading to low quality results.

Besides using a simple language it is also necessary to avoid technical or scientific terms. In an initial iteration of the YouTube QoE study presented in [31] the test participants we asked "to rate how the Quality of Experience of the [presented] video gets worse by stalling". The results obtained from this test indicated that the QoE was independent of the number and length of the stalling events, which is unintuitive. A redesign of the user test, including a reformulation of the task description and a detailed explanation of the word "stalling" resulted in a significant increase of the result quality and a positive user feedback: "Thanks, for including the meaning of Stalling in your survey, as this helped me answer better than previously". A similar issue arising from an complex rating scale can be observed in [11]. Here, the change to a more intuitive rating scale improved the quality of the crowdsourcing result significantly.

In order to test the suitability of a task design it is recommended to apply a preliminary pilot study with a small number of known pilot participants. These participants should not be familiar with the research topic or the purpose of the test in order to exhibit similar background knowledge as a regular crowdsourcing user. One possibility to acquire such pilot participants is asking via social networks.

3 Take the right duration for your experiment!

Participants in crowdsourcing are much less committed than normal in-lab participants and they can withdraw from works at any time. This fact depends on multiple facets. First of all, the experimenter is a stranger to the participants, so they feel much less compelled to do something for her. Second, a large number of other possible crowdsourcing works are available online, so if the ratio of task length and reward is not high enough they will not accept the task. Experiment duration must be correctly estimated and stated in task offers. Workers have the opportunity to report problems and a duration incompatible with declared task can be seen as an employer misconduct, leading to suspension of service from the platform.

Finally, even if a task was accepted but turns out to be lengthy and boring or overstraining, workers simply give up and turn to another task. Some online crowdsourcing platforms monitor participants behaviors, penalizing those who accept a work from which later withdraw. Mostly this metric appears in participants' statistics, however, this metric alone is not enough to discourage withdrawals behavior due to the large availability of small tasks, which are easy to accomplish.

These aspects do not only have an impact on willingness to complete the whole task, but also on reliability and quality of results. This means, in a long crowdsourcing test participants may end up working poorly or hurriedly just to finish as soon as possible.

Thus, not only should tasks be kept as easy as possible, the other factors to be considered are task length and price paid. However, price paid is usually minimized considering other comparable tasks available online (and sometimes suggested/imposed by platforms while posting a task). It is then fundamental to shorten the experiment duration and make the task as attractive as possible (e.g., by using popular or funny content). Different works in literature underlined participants' withdrawal and that a good rule of thumb is to keep duration under five minutes [9, 10, 13]. To achieve this, crowdsourcing test can be split into multiple task and campaigns to be assigned to different users. Moreover, really committed participants can even participate in multiple campaigns.

4 Include proper training sessions!

The conceptual differences between crowdsourced QoE studies and studies conducted in a laboratory environment arise mainly from two issues: Firstly, crowdsourcing tasks are usually much shorter (5–15 minutes) than comparable tests in a laboratory and secondly, the crowdsourcing environment lacks a test supervisor to provide direct and immediate feedback to the test subjects. The test subjects are only guided by a web interface through the tests that provide an explanation of the test, what to evaluate and how to express their opinion and/or ratings. The training of the subjects is mostly conducted by means of qualification tests that on the one hand enable the subjects to practice, but on the other hand also allow the test supervisor to assess to a certain extent the subjects' understanding of the test setup. Nevertheless, if problems due to a lack of understanding of the test procedures by the test subjects occur e.g., uncertainty about rating scales, appropriate mechanisms or statistical methods have to be applied.

In particular, it is more difficult to ensure a proper training of the subjects as no direct feedback between supervisors and subjects during the training phase of the test is possible and thus potential misunderstandings are neither recognised by the test supervisor nor can any clarification questions of the subjects be addressed. Therefore it is essential to address any known issues from similar laboratory-based tests in the training phase with a particular consideration of the fact that no direct feedback is possible e.g., for example by providing short and illustrated (or even animated) explanations of the procedures considering questions commonly encountered in a similar laboratory setup. Still, the already short task duration in crowdsourcing and the fact that the qualification phase for familiarization of the subjects with the test structure and procedures is not included in the analysis, can decrease the efficiency of a test and increase the costs.

Without any worker training and additional quality assurance mechanisms the results are significantly different than in a traditional laboratory environment or when using an advanced crowdsourcing design [25]. Figure 1 shows the results for a video quality assessment conducted in two different test laboratories. The obtained mean opinion scores are normalized by the average of all user ratings. It can be seen that the results from the two laboratories provide the same user ratings. The experiments were also conducted in a crowdsourcing environment. The first experiments did not include proper training phases and it can be seen that the results strongly disagree from the tests conducted in the laboratory. However, after including training phases and additional quality assurance mechanisms in order to confirm if the user understood the test properly, a very good match can be observed which is similar to the agreement between the results from the two laboratories.

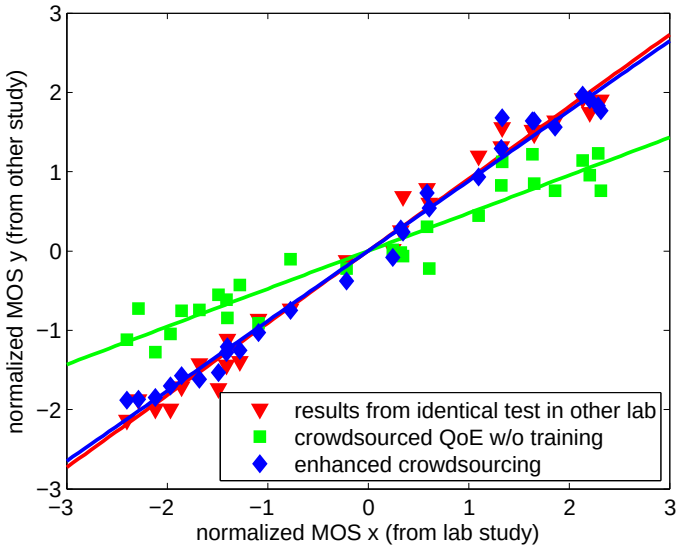


Figure 1: Experiments on video quality were conducted in two different laboratories with identical test setup [25]. The study was crowdsourced a) without training and quality assurance mechanisms and b) with proper test instructions and a training mode as well as quality assurance mechanisms.

5 Integrate a feedback channel!

Even with simplified language, proper instructions, and training sessions test participants might face issues while participating in tests. These issues might either occur due to misunderstandings or other unclear points, but also due to hard- and software issues. Therefore, it is important to provide a feedback channel to the users to contact the experimenter. This feedback channel has to implement three main properties: Accordance with the platform's terms of use (TOS), robustness, and a permanent availability throughout the test.

The accordance with the TOS of the crowd-providing platform can be challenging, because some providers do not allow contact between workers and employers outside the provided system. In this case the platform might provide a messaging system or another platform-specific solutions has to be found. It no feedback possibility is given, the platform provider should be changed.

If custom feedback solutions are possible, they should be implemented in a robust way. This means the feedback channel has to be available, even if the actual task setup is broken, e.g., due to server issues, or the lack of technical requirements at the worker side. Otherwise, workers facing issues are not able to communicate them and the issues remain undetected.

Moreover, the feedback channel should be accessible throughout the whole task, not only at the end of it. Questions might occur at an intermediate step or specific technical issues that hinder the worker to complete the task. If a feedback is only available at the end of the tasks these issues also remain undetected.

There exist multiple possibilities to implement feedback channels for a crowdsourcing task. The easiest option is adding a feedback form. However, this is usually only added at the end

of a test and because of this neither robust nor always accessible. Moreover it is only a one-way communication from worker to employer. External, interactive feedback channels, which are independent of the task execution are more suitable here. These feedback channels could include e.g., live chat or email support for small tests or forum threads for larger test groups. The contact details, respectively the links to the forum threads can easily be integrated in every step of the task enabling both robustness and availability of the channel.

In general, all questions from the users should be answered. An intensive discussion with the workers and a reasonable support helps to improve the task design and respectively the task results. Moreover, it helps to increase the employer's reputation, as workers tend to gather in virtual communities and share their experiences with certain employers and tasks.

6 Use event logging!

One approach to increase the result quality of crowdsourcing tests is integrating automatic and semi automatic measures in the task. Analysing user interactions with the test is a recommended way to find out what really happened during the test execution. Thereby, the user's actions and test conditions, e.g., available bandwidth, are be monitored and logged. User actions/interactions that are part of the test, e.g., clicking behavior, are as important as user actions which modify the test environment, e.g., window focus, window resize, page reload, switching of tab. The typical web browsing behavior of switching between different tabs could for example lead to the miss of a test condition because the user was watching another tab.

Besides estimating the reliability of users, event logging can also help to debug crowdsourcing tasks. Tests are usually implemented as web applications and are consequently executed in a very diverse software and hardware environment. Different browsers might render a test page differently which might result in unexpected test conditions. Moreover, tests might require a third party plugin, e.g., Adobe flash player for video tests, which could work in some browsers only, or which could be available in several versions which work slightly differently. The resulting test conditions should be logged, include overall test conditions like page load times, but also specific conditions, e.g., start of video playback in a video test. Also extraordinary events, which can alter or disturb a test condition, have to be logged, e.g., stalling events in a video test.

The automatic evaluation of the event logs during the test can then be used to give immediate feedback to the worker. For example an error message can be displayed if a missing plugin is detected. Moreover, a user can also be warned if she or he did not watch the video as expected but switched to another tab instead [31]. During the analysis of the test results, the logged events can be used to apply filter rules [24]. Here it can be checked whether the desired test conditions actually were perceived by the test user. Furthermore, more sophisticated reliability checks can be performed to find out whether the test users conducted the test in an expected way [15]. In case the event logs show an unusual test or user behavior, the results for this user should be excluded from the overall analyses. Moreover, abnormalities in the event logs provide valuable insights for further tests. If a systematic error of test execution is visible, e.g., because of browser compatibility, the test can be improved. If user behavior is consistently unexpected for some parts or even the whole test, the test design has to be improved. For example, long response times for a specific question could indicate that the question was too hard and should be reformulated.

Extensive user monitoring can provide valuable insights in the task interactions of the participants. However, it can also be considered as intrusive as a large amount of data about the user is gathered, sometimes including personal data, e.g., the IP address. Even if the implementation of the monitoring in a web application guarantees a certain amount of privacy, because only the interactions with the test page can be observed, the gathered data should be handled carefully.

7 Include reliability checks! In the test design...

The remoteness of the test participants does not only impose challenges, because of misunderstanding and technical problems. The anonymity also encourages some participants to work sloppy or to cheat in order to increase their income, by maximizing the number of completed tasks per time. Numerous approaches already exist to identify these users, however, most of them require objective tasks, like text transcription. The results of these tasks can easily be categorized in either "correct" or "incorrect". In contrast, QoE evaluations are highly subjective and may differ significantly among the participants. Consequently, it is impossible to identify "correct" subjective ratings.

To overcome this issue, reliability checks have to be added to a task in order to estimate the trustworthiness or reliability of a user. This in turn can be used to estimate the reliability of the ratings given by the very user. Reliability tests may include consistency checks, content questions, gold standard approaches or tests verifying the user's attention or familiarity with the test. During or after the test, the results from those checks and additional questions are then analyzed in order to identify unreliable users. The reliability checks aim at identifying unreliable users and the rejection of all ratings from those unreliable users. This in turn requires that the identification of unreliable users is mainly based on information which is not related to the user ratings. In particular, the following elements may be added in the test design to check the reliability of the users. Combining these elements also leads to an improved reliability of the results [24].

1. Verification tests [43, 44], including captchas or computation of simple text equations: "two plus 3=?", "Which of these countries contains a major city called Cairo? (Brazil, Canada, Egypt, Japan)". Captchas and the computation of simple equations help to identify scripts and bots automatically submitting results. Further verification questions might be added as indicators for sloppy workers or random clickers.
2. Consistency tests: At the beginning of the test, the user is asked "In which country do you live?". Later after several steps in the test, the user is asked "In which continent do you live?". Here it is important that the user cannot look up the previous answer. This approach helps to estimate the validity of the users answers, as random clickers might not remember their first answer.
3. Content questions about the test: "Which animal did you see in the video? (Lion, Bird, Rabbit, Fish)". This type of question can be used as an indicator of the participants attention during the test. The content questions should be rather easy so that misunderstandings or language issues are avoided, but still should not be answerable with pure guessing.

4. Gold standard data [45]: "Did you notice any stops to the video you just watched? (Yes, No)", when the actual test video played without stalling. Usually gold standard data refers to tasks for which the correct result is known in advance, e.g., the correct transcription of a text on a picture. However, as discussed above it is not meaningful to define e.g., a gold standard MOS rating for a given impairment as this is a subjective rating. In contrast, gold standard data in QoE evaluation should aim at checking obvious impairments like the number of stallings or the presence of (significant) graphical distortions, not the resulting ratings.
5. Repetition of test conditions to check consistent user rating behavior: This can be seen as a special kind of consistency check but based on user ratings instead of additional information. Repetition of test conditions might be used to minimize the need of additional consistency questions, however, during the evaluation familiarization and memory effects have to be considered.

The important thing to keep in mind is not to add too many reliability items and questions, as otherwise the assessment task will become too lengthy. Further, too many questions may give a signal of distrust to the users. As a result, users may abort the survey. In general, incentives and proper payment schemes depending on the actual work effort are the key to high quality work.

8 Include reliability checks! . . . during the test . . . !

The majority of crowdsourcing tests relies on reliability checking and examination of the results after the campaign finished i.e. a-posteriori checks. Using such an approach, however, reliable users are only discovered after the test is finished and the advantage of engaging reliable users with more tasks directly in the current test is lost. An alternative approach has been proposed in [6], where a reliability profile of each user is built continuously in real-time during the test a user is working on. This *in momento* reliability checking offers not only a quicker execution of campaigns, but also also increases the reliability of the results.

A-posteriori designs often rely on repetitive hiring schemes, re-inviting reliable users to participate in further campaigns of the employer. It has been shown, however, that this might also lead to the exhaustion of the crowd at the risk of declining motivation and poor rating performance. The *in momento* approach successfully addresses this problem by avoiding repetitive hiring of the users and utilizing the advantages of the huge workforce available on crowd-providing platforms. The campaign is offered to thousands of users at the same time and reliable users are directly engaged by additional tasks for extra rewards.

Moreover, reliability checks during the test and their direct evaluation reduce the administrative overhead introduced by the traditional a-posteriori approaches that require extensive data cleaning and group generation with repeated campaign runs. Also the *in momento* approach allows for building a rapid feedback component for better communication with test participants. Such a component is used to directly communicate any suspicious behaviour to the users and thus enables the users to reflect on their performance, allowing them to choose whether to stop or to continue the test.

In momento reliability checking utilizes the recommended multi-stage design of crowdsourcing tests including a training-phase and relies on numerous reliability checks during the test.

1. Reversed rating scale order for questions not related to the test content [6]: For better engaging the users' attention, a simple test asks for the maximum and minimum number of visible objects in a picture shown during the test. The rating scales used for providing the answers are presented in reversed order e.g., lowest to highest during the non-test-content related questions instead of highest to lowest for questions related to the test content, and also includes false answers, which are not presented in the test picture at all. Random clickers and users not focusing enough on the test are thus quickly discovered and penalized.
2. Questions about artefacts not discoverable by a reliable user: The user is asked to mark several visible objects images on the screen. However, besides the visual objects, the images presented to the user include also invisible, but clickable shape. These shape are not detectable for reliable user but might be discovered by random clickers. Random clicker can additionally be identified by multiple clicks in areas without visual shapes or by their high number of clicks. These suspicious behaviours are recorded into the user's reliability profile.
3. Altering test patterns for each test execution: Random movement of the control shapes and changing the number of shapes prevents cheating by sharing of correct locations amoung participants.
4. Checking execution and focus time: Each stage of the test has a certain minimal duration i.e., time needed to finish the test properly. If the time spent on the page is very short or several magnitudes longer than usual, the user is considered unreliable (cf. Section 6).
5. Additional tests related to the stimuli and its representation: Depending on the type of the stimuli and its representation, specific tests can be included. For example, in audio-visual quality testing the playback can be checked: Was the video played to the end, did the user pause the playback, was the sound volume adequate etc.

9 Include reliability checks! . . . after the test!

Reliability checks can be performed also based on the outcomes of the test. A typical approach, developed already for lab-based testing, is the detection of outlier participants. Outlier participants are those which provided evaluations that significantly depart from the average evaluations, typically the Mean Opinion Scores, expressed by the crowd, and in a non-systematic way. In this context non-systematics means, their evaluations are not systematically above or below the average, which may simply indicate a different usage of the scoring method rather than a poor understanding of instruction or a sloppy performance of the task. To detect scoring outliers when using categorical or interval scales, the procedure proposed in the ITU BT.500 recommendation [46] is most suitable, and widely adopted also for lab participant screening. For paired-comparison based experiments, instead, it was proposed by [47, 48] to check for inversions in the judgment of pairs involving the same images.

Outlier detection should be also deployed to control for a second essential indicator of reliable task completion, which is task execution time. Whereas in Lab-based experiments the presence of an experimenter forces the participant to fully commit to the task, dedicating to it the proper attention, in crowdsourcing it is impossible to control for this. It may therefore happen that:

1. Workers skip across stimuli as fast as possible, without taking the time to properly evaluate them
2. Workers intertwine the execution of the task with other tasks, e.g., surfing the web or playing a game, thus being constantly distracted and taking longer in their evaluations
3. Workers get distracted at a specific point in time by a different task, such as talking on the phone or preparing a coffee, thereby taking an unusually long time for evaluating one stimulus in particular.

Should any of these three scenarios be verified, the corresponding evaluations cannot be trusted to be reliable. To identify scenario (1) and (2), the outlier detection procedure advised in ITU BT.500 can be applied using as a dependent variable the scoring time per participant and per stimulus. Participants identified to repeatedly score in an amount of time which is significantly lower or higher than average, can then be deemed unreliable and excluded from further analysis. To identify scenario (3), it is necessary to capture unusually high evaluation times for a single stimulus.

In [13] and [12] it was proposed to observe this through the standard deviation of the time taken by each participant to evaluate each stimulus. In [13] for example, a test was run in three different regions (Europe, US and Asia), consisting in the evaluation of the aesthetic appeal of 20 images on an Absolute Category Rating scale. The authors observed that the Asian participants took on average much longer than the other participants to complete the entire test.

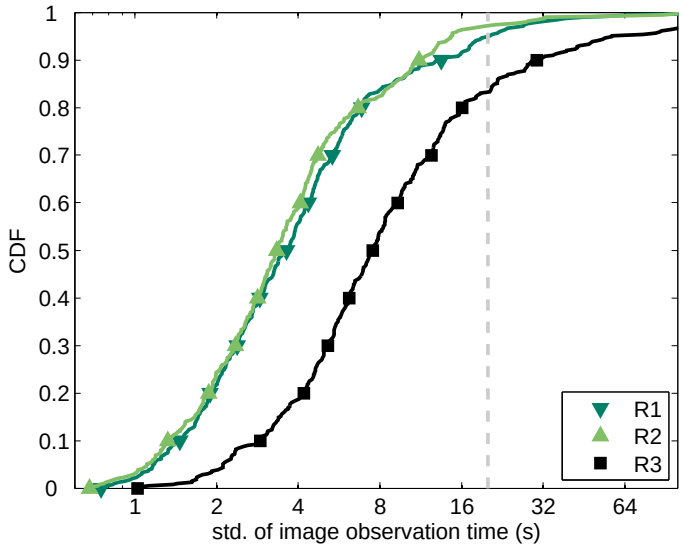


Figure 2: Cumulative distribution of the standard deviation of the image evaluation time in [13]. It can be seen that for several Asian users (R3 curve) such variability in time taken to evaluate a single image becomes quite pronounced. In fact, some users were found to take up to 5 minutes to score a single image, where on average they took about three seconds to score the remaining images in the test. In [12], this procedure was found to exclude from the analysis about 13 % of the participants that completed the whole test.

Taking a closer look at the mean test completion time, authors found that for European and US participants the median test completion time was close to the mean completion time, but in the case of Asian participants the mean was significantly larger than the median. This hinted the authors that some of the Asian participants may have had with very large evaluation times for some images, as measured from the moment when the image was displayed until the time the evaluation was inserted is given. Such differences were captured by computing the standard deviation of the image evaluation time, as shown in Figure 2. In order to filter out participants being distracted during the subjective test, all participants with a standard deviation of the image observation time larger than 20 s were rejected. This value was determined empirically and chosen to accommodate possible variations in download speeds of different users but reject users with significantly high variations in completion times.

Some other techniques for filtering out the unreliable users can rely on such metrics like time it took for a worker to complete the overall test and the mean time spent on each stimulus as discussed in [20]. Similarly, to the standard deviation in time per stimuli, the empirical thresholds can be found for these additional metrics and workers that do not fit into these thresholds can be filtered out.

10 The crowd consists of human beings!

The question arises why we should care about ethics in the context of crowdsourcing.[1] We are actors in crowdsourcing systems to directly benefit from an environment that respects ethics. In general, long run altruism beats greed. An ethical system is more sustainable (everyone is empowered to reach full capacity). Also, according to most of the state laws, including European Directive 95/46/EC [49], governing processing of personal data, one has to be very careful about handling subjective information provided by the online workers in an ethical and privacy respecting way.

The next question is when we should care about ethics. The answer is simple: always. In cases where crowdwork income is not essential: What are people not doing when they are crowdsourcing? Does crowdsourcing have an addictive side? In cases where people are subsisting on crowdwork income: Is the crowdwork paying only money, without building a longer term future? Is the money enough? Is the timing of the payment ok?

Followings is a list of suggestion for experimenters to take ethics into consideration:

General

- Try some crowdwork.
- Do not reveal identity of the workers. Abide the law on processing and storage of personal data: Anonymize the workers, restrict access to any personal data, and then delete such data upon completion of the related research project.

[1] In the Dagstuhl seminar 13361 "Crowdsourcing: From Theory to Practice and Long-Term Perspectives", the ethical aspects in crowdsourcing were discussed in a special session which are summarized in [35]. Some results, suggestions, and opinions from [35] are included in this section.

Job Design

- Use contracts to clearly define your relationships.
- Validate the functionality of the test implementation carefully, to make sure the worker can complete the task. Be available during the test via your feedback channels.
- Don not engage in the "race of bottom" and pay appropriately for requested work. Be honest about the time your job takes and have realistic expectations.
- Be very specific about your needs, use clear questions, and make the instruction with clear explanation.
- Avoid test designs that have too many complex details, keep them short.
- Tell to the workers what's required up front.
- In case of any sensitive issues or checks you may require for your experiments, explain them to workers and allow them to opt out of the experiment early if they do not want to engage in the test.

Checking Responses

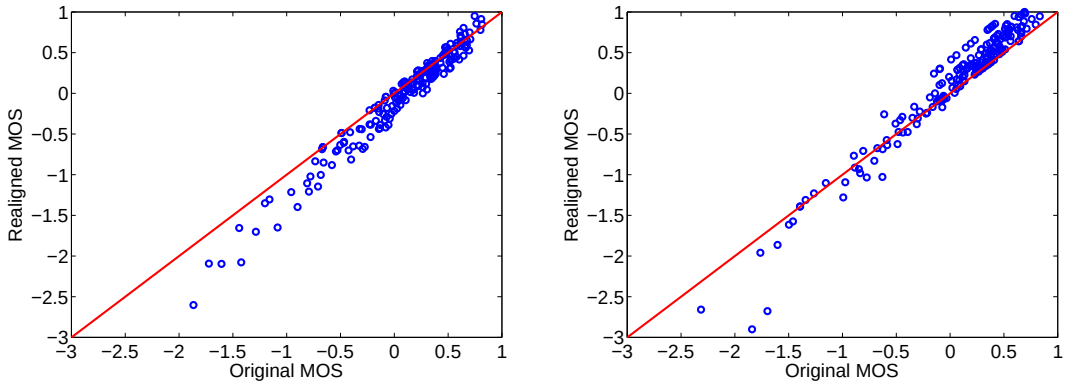
- Review work promptly. Realize there is an investment of time and not only money.
- If you are in doubt of paying the worker or not, pay the worker.
- Address workers politely (and apologize if you goof up).
- Respond to inquiries (even the ones with horrible grammar).
- Take a look at worker's communities like turkopticon [50]. See their concerns and how do they rate you.

11 Lessons learned from lab test. Use them in Crowdsourcing too!

Although performed out in the open, by thousands of different users across the world, crowdsourcing-based QoE tests still remain psychometric experiments, which aim at quantifying user perceptions and preferences. To this purpose, there is a large body of literature that can be accessed to tackle the challenges that crowdsourcing-based testing poses. One such challenges is that of keeping the tests to a minimum duration (see also lesson 3). Whereas in lab-based experiments participants can take over one hour to perform the rating of a full stimulus set, in crowdsourcing it is recommended to keep the duration much shorter. This, poses an obvious limitation to the number of stimuli that can be evaluated in each test. To be able to still obtain quality scores for a large set of stimuli, researchers typically segment the latter into subsets, to be scored by different users in different campaigns. This practice is prone to a major drawback. Especially when using direct scaling e.g., the most popular Single Stimulus or Absolute Category Rating Stimulus scoring [46], participants tend to use the whole scale for scoring, independent on the absolute quality of the stimuli visualized. In other words, if the quality range covered by the images in a campaign A is a subset of the quality range covered by the images in campaign B, still the best and the worst images in both campaigns, although representing different values in terms of absolute quality, will get similar scores. Thus, the quality scores of images in A will be represented on a "stretched" scale with respect to those in campaign B. This phenomenon is commonly known as "context" or "range" effect [51], and is usually countered by re-aligning

MOS scores a posteriori. This can be done by means of the known scores of a subset of stimuli either kept constant (anchors) throughout all campaigns, or collected from all campaigns and then re-evaluated in an extra campaign altogether [52].

In their aesthetic appeal assessment experiments, Redi et al. [13] adopted the method of using anchor stimuli common to all campaigns. They chose 5 anchor images so that they would space the entire quality range of the test stimuli, and so that they would span it in a uniform way based on previous evaluations run in the lab. They then added these anchors to the 13 campaigns, of 15 images each, making up their 200-image test set. This practice turned out to keep context effects to a minimum. When attempting at re-aligning the MOS of images of all campaigns to the scale of a reference campaign c*, authors of [13] found re-alignment almost useless. Figure 3 shows the aesthetic and recognizability scores obtained throughout the 13 campaigns of [13] against their realigned values with respect to campaign c*, selected as the one with stimuli spanning the widest quality range. As it can be seen, the effect of re-aligning is quite limited, indicating a strong robustness of the original MOS to context effects.



(a) Aesthetic quality **(b)** Recognizability

Figure 3: Original (from 13 different campaigns) and re-aligned (a) aesthetic quality and (b) recognizability MOS for experiment [13]. Range effects seem minimal in both cases.

Another consideration that is useful to make when designing crowdsourcing experiment is that, by dividing the traditional design over many users and campaigns, we intrinsically generate mixed-subjects designs. So, it may be the case that the measurements themselves loose in accuracy, because one cannot fully exploit within-subjects variance. An interesting solution to that has been proposed in [47], which involves randomized paired comparison [53] to accommodate incomplete and imbalanced data. Paired Comparison has been found to be an effective methodology for measuring QoE via crowdsourcing, due to the simplicity of the task and the availability of tools for the analysis of incomplete preference matrices. Furthermore, it allows easy embedding of worker reliability checks [47, 48] (see lesson 9). On the other hand, for scaling large sets of stimuli in the order of hundreds, the applicability of paired comparison is still limited, as the number of pairs to be judged may be intractable also for such a far-outreaching methodology.

12 Use the appropriate scale for your problem!

A common issue in subjective measurement tasks even beyond QoE assessments are scale usage heterogeneity problems for Absolute Category Rating scales [54]. On the one hand users tend to avoid using both ends of the scales, thus the votes tend to saturate before reaching the end points as shown in [40, 9] On the other hand language and cultural differences regarding the "distance" between scale labels for a given ITU scale as reported in [55, 56] make it difficult to compare results across cultural or international boundaries. Typically, these problems are tackled by either ensuring that scale labels and designs are clearly understood in the respective language or culture (cf Absolute Category Rating scale labels for different languages as described in [57]), or by using extensive training sessions that educate the subjects regarding proper scale usage.

However, both of these solutions cannot be directly applied to crowdsourcing campaigns. Training sessions can be used (cf. lesson 4), but not as elaborate as in related laboratory trials due to the limited number of sequences that can be used, in order not to lose crowd workers attention and ensure reliable results [24]. Another possible solution would be paired testing for eliminating offsets between different crowdsourcing campaigns and laboratory tests as proposed by [48, 58]. Although this minimizes offsets between different test campaigns, it only provides relative ratings instead of absolute category ratings. This is useful for comparing different implementations of algorithms or codecs, but provides less insight in the actually perceived quality of the customer. Therefore, industry and research are interested in Absolute Category Ratings as they compare well to several other customer satisfaction measures that are typically used to assess product offerings, as well as questions about various aspects of the customer's interaction with the company [54, 40].

In terms of language and scale design crowdsourcing workers are quite heterogeneous regarding their native language and their cultural background. Therefore, they often receive instructions and scale descriptors not in their native language. As the language cannot be relied on in terms of scale description, different scale designs can influence the scale usage and the resulting mean opinion scores. Therefore, the unambiguous design of rating scales is essential for acquiring proper results from crowdsourcing tests.

Based on these assumptions a comparison of different scale types and designs in [42] has revealed that an Absolute Category Rating 5 scale with non-clickable anchor points and traffic-light semaphore design as depicted in Figure 4 yields reliable results and is most efficient in terms of the relative number of outliers.

Figure 4: Absolute Category Rating 5 scale with non clickable anchor points and a traffic-light semaphore design. The scale designs is available under Creative Commons Attribution 3.0 Austria License at `https://github.com/St1c/ratings`.

13 Look a gift horse in the mouth!

The use of a crowdsourcing-based approach for testing the visual appeal of websites [14] resulted into many diverse insights. Firstly, it became clear that crowdsourcing does provide a valuable mechanism for quickly and cheaply conducting these types of experiments while still obtaining meaningful results. In that sense, the results obtained are encouraging.

On the other hand, a number of issues were also noticed. Firstly, and contrary to possible expectations, an increase in payments will not necessarily lead to better results. In fact, in our results, it led to an increase in the number of unreliable users, most likely due to increased financial incentive to participate. This effect is illustrated by the table below where in the campaign shown in the right column workers were paid three times more than in the campaign on the left. At the same time, the average ratio of reliable users is less in the more expensive campaign. Taking this into account, it is clear that additional incentives, e.g., gamification or designing the task in an interesting way, might result in a better result quality then simply increasing the payment.

Another apparent impact of the increased payments was the much faster completion of the test campaign. While this is in some cases desirable, it also results in a narrower variety of users in terms of demographics, for example due to the influence of time-zones. It might be worth taking this into account when proposing the campaigns, and possibly throttling their execution in order to obtain more representative population samples. The effects of time-zone differences also affects the reproducibility of the results, as it is hard, if not impossible to obtain similar demographics distributions in different test runs.

In terms of the actual scores we notice that while payment level influences absolute MOS values for given assessment tests, it does not influence qualitative relations, i.e., main effects, interactions, or shape of curves. Thus there does not appear to be a severe impact on models built from the campaign data, if such models exist. However, user ratings may have to be normalized to cope with the payment effect and to merge data from different studies with different payments.

Table 1: Two identical crowdsourcing campaigns on web QoE assessment were conducted which only differ in the reward to the participants. Subjects completing campaign C_2 earned three times more money than the participants in campaign C_1.

Measure	C_1 with payment P_1	C_2 with payment $P_2 = 3P_1$
Number of countries	45	30
Ratio of completed tests	90.26 %	89.34 %
Campaign completion time	173.05 h	2.74 h
Avg. #correct content questions	8.27	7.48
Ratio of reliable users	71.54 %	66.10 %
Mean user rating	3.60	3.81

Since monetary incentives can have a negative effect on the reliability of the crowdsourcing results, it might appear meaningful to attract participants through social networks. The disadvantage of using social networks is the limited access to the crowd and the fact that more effort is needed to pursue people from social networks to participate in a crowdsourcing experiment. One example of using social network in the crowdsourcing is presented in [39], where Facebook users were used in the evaluation of different privacy filters applied on video.

A Facebook application was build and the call to participate in the subjective test was disseminated via social networks like Facebook, Twitter, and LinkedIn, as well as various research mailing lists. With an estimated outreach to more than 1,500, some 120 participants used the application and submitted subjective scores. The resulting scores were compared with the results from a similar evaluation conducted by a conventional approach in a designated research test laboratory. The results depicted in Figure 5 demonstrate a high correlation with only some minor differences favoring the crowdsourcing method, which means that it can be considered as a reliable and effective approach for subjective evaluation of visual privacy filters.

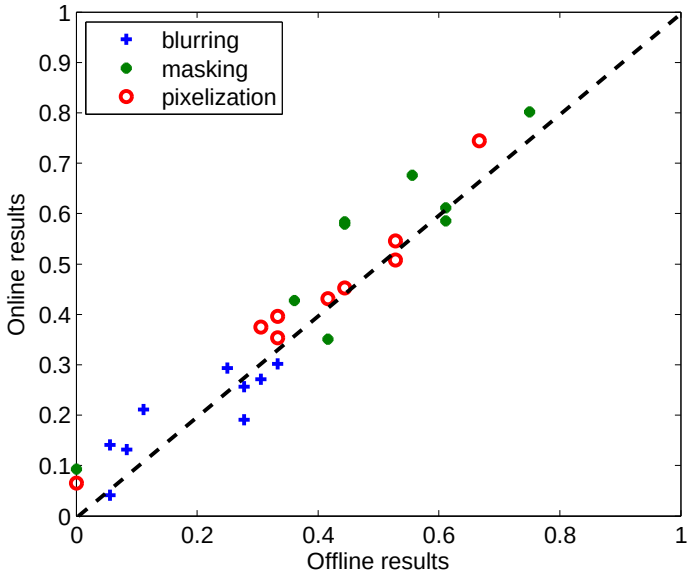


Figure 5: Privacy of Online vs. Offline Evaluations in Facebook-based crowdsourcing.

Note that no reliability checks or any filtering was applied on the participants from Facebook, while the results appeared to be highly reliable with high correlation to the lab-based evaluation. Such high reliability is due to the fact that Facebook users are generally verified individuals with very little number of them with fake IDs. Since the application was disseminated only to either friends, family, or friends of friends, it was in a way, propagated in a trusted way. Such measures insured significantly more reliable results of the subjective tests, compared to a classical crowdsourcing scenario.

14 Motivate your users!

Often employers in crowdsourcing micro-task platforms assume workers to be motivated to complete tasks by small monetary rewards. However, previous studies show that workers are at least partly motivated by aspects other than monetary rewards such as killing time or having fun [59, 60].

In [12] Redi and Povoa showed how monetary reward can have a multifaceted impact on the quality of the data collected. They set up a Facebook app, Phototo, for users to rate the aesthetic appeal of images processed with Instagram-like filters. Scores were expressed on a scale from 1 to 5 through a playful, star-based rating system. The app was launched through the Facebook networks of the experimenters. Users would then access it on a voluntary basis, out of curiosity or personal invitation from the experimenter, and without receiving any monetary rewards for performing the experimental task. Simultaneously, a Microworkers campaign was also launched, through which crowdsourcing workers could access Phototo and perform the experiment under a 0.30 $ compensation. Table 2 shows some striking differences between the behavior of users receiving a monetary compensation and volunteer users. A wide majority of the latter did not get to perform the experimental task, i.e., did not complete the training phase. About half of those did not even access the experiment introduction, possibly because they decided not to grant Phototo the permission to access their personal data. Microworkers users, instead, were more than twice as likely to complete the first experimental task (67 %). On the other hand, when running a set of reliability checks to screen the remaining users, a higher percentage of paid users was ruled out, with respect to Facebook volunteer users, see Tabel 2. From this analysis, the authors of [12] conclude that paid users are more likely to commit to the execution of a crowdsourcing task. However, they may not perform it as reliably as volunteer users may do, driven by their intrinsic motivation. Furthermore, the authors found, as already noticed in [4] and lesson 13, a strong bias of paid users to rate image towards the top-end of the quality scale, see Figure 6. This was less true for volunteer users.

Table 2: Two identical crowdsourcing campaigns on image quality were conducted with paid users (Microworkers) and volunteers (Facebook).

Measure	Facebook recruited participants (volunteers)	Microworkers recruited participants (paid)
No. registered users	414	258
Did not complete the training	63 %	31 %
Finished scoring the first set of images	32 %	67 %
No. users considered in the analysis	133	172
No. users considered after the filtering	96	113

Naderi et al. [2] introduced a scale for measuring continuum of worker motivation from Amotivation to internic motivation based on Self-determination theory (SDT). The SDT distinguishes one's motivation based on its locus of causality and how far it is internalized meaning "taking in" underlying regulation and the value of the activity. Moreover, SDT addresses the relation between work motivation, i.e. degree of internalization and the quality of outcome. As a result, the more internalized motivation, the higher quality has the outcome.

We recommend to motivate workers by providing more insight about what they are doing and how important their performance and response quality are for you and for community.

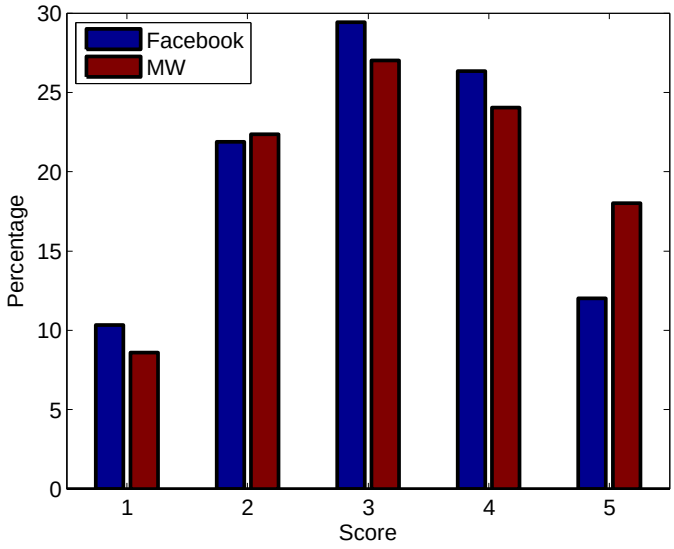


Figure 6: Strong bias of paid users (labeled "MW") to rate images towards the top-end of the quality scale in contrast to voluntary users ("Facebook").

15 Crowdsourced lessons learned

In the Qualinet community there have been many exchanges between members on different related topics, of course crowdsourcing is one of these. Both its strengths and flaws suscitated interest in the community and many different works have been done as said before. In this concluding paragraph we sum up all the different opinions and suggestions that came out from these exchanges. Future works and interactions between members will maybe translate some of these lessons learned into useful rules as the previous ones.

First of all it appears clear in the community that while in theory it is a relatively easy technique, crowdsourcing actually hides many pitfalls. Small details can be overlooked and ruin your experiment easily: lack of direct visual and participants' feedback can hide problems that would have been easily found in a laboratory environment. Related to this point, many issues have been found and solved by people that adopted crowdsourcing. Technical solutions have been implemented in different software frameworks; while some are ready for the WWW and available online [48, 27], others are private [10] or need additional security add-on to allow crowdsourcing[2]. The community agrees that a common framework including all solutions proposed – based on experience – would be a useful tool in reducing implementation pitfalls and time to experiment. However, this common all-in-one solution is far from being easy, as important technical discrepancies between solutions developed exist.

[2] http://www.its.bldrdoc.gov/resources/video-quality-research/web-enabled-subjective-test-(west).aspx

Below are some quotes from some Qualinet members about crowdsourcing and its usage for QoE assessment.

- *"The most important thing I learned is that it could be a very effective tool but you have to be extremely careful when designing the experiment."*
- *"...uncontrolled conditions (a free for all scenario)."*
- *"...large no. of observers possible (typically not the case with lab studies) ...good for statistical reasons."*
- *"You get a lot of data, but not necessarily good quality data"*
- *"I don't know what factors actually played a role into the experiment when people participated in the crowdsourcing test."*
- *"You need many filters to make sure that you get the reliable participants and filter out the unreliable ones."*
- *"You need to pay particular attention to experiments conditions that vary."*
- *"Can be very effective."*
- *"You have to ask participants explicitly to stay quiet in front of the camera, switch on the lights and so on."*

From our experiences in the field, the community underlines that while crowdsourcing is fairly uncontrolled under many aspects – as, i.e. there is no direct control on participants behaviour or hardware – this technique can be highly rewarding if well prepared. The collected data is not good quality data unless with a proper strategy to filter outliers. This really important point has been widely reported and many studies dealt with it. Many effective data analysis approaches have been proposed and adopted by the community.

A final important issue that has been underlined within the community is the importance of considering socio/demographic unbalances. These have been suggested to be linked to economical unbalances in the world, as crowdsourcing rewards have not the same importance in every part of world. Participants would be more likely to belong to specific regions and social classes and this could influence the outcome of some studies.

Figure 7: Tag cloud of different opinions collected from Qualinet about crowdsourcing and crowdsourced QoE assessments.

In summary, there is no simple recommendation how to crowdsource QoE studies. But there are many lessons learned and practices gained through own crowdsourcing experiments which we share with the research community in this whitepaper. Researchers utilizing crowdsourcing need to carefully consider the crowdsourcing environment, the crowdsourcing users, and all emerging consequences. It should be clear why crowdsourcing is used to answer a certain research question and whether crowdsourcing is the right approach. Still there are many open questions, e.g., if crowdsourcing provides us more realistic data, or if crowdsourced data is too noisy. Crowdsourcing for QoE assessments is an evolving research topic!

Publications from Qualinet Crowdsourcing Task Force

[1] Andreas Sackl, Michael Seufert, and Tobias Hoßfeld. "Asking costs little? The impact of tasks in video QoE studies on user behavior and user ratings". In: *4th International Workshop on Perceptual Quality of Systems (PQS 2013)*. Vienna, Austria, Sept. 2013.

[2] Babak Naderi et al. "Asking costs little? The impact of tasks in video QoE studies on user behavior and user ratings". In: *3rd International ACM workshop on Crowdsourcing for Multimedia (CrowdMM 2014)*. Orlando, FL, USA, Nov. 2014.

[3] Babak Naderi et al. "Crowdee: Mobile Crowdsourcing Micro-Task Platform for Celebrating the Diversity of Languages". In: *Fifteenth Annual Conference of the International Speech Communication Association (Interspeech 2014)*. Singapore, Sept. 2014.

[4] Bruno Gardlo et al. "Microworkers vs. facebook: The impact of crowdsourcing platform choice on experimental results". In: *Fourth International Workshop on Quality of Multimedia Experience (QoMEX 2012)*. IEEE. Yarra Valley, Australia, July 2012.

[5] Bruno Gardlo, Michal Ries, and Tobias Hoßfeld. "Impact of screening technique on crowdsourcing QoE assessments". In: *22nd International Conference Radioelektronika*. IEEE. Brno, Czech Republic, Apr. 2012.

[6] Bruno Gardlo et al. "Crowdsourcing 2.0: Enhancing execution speed and reliability of web-based QoE testing". In: *IEEE International Conference on Communications (ICC 2014)*. IEEE. June 2014.

[7] Christian Keimel et al. "Qualitycrowda framework for crowd-based quality evaluation". In: *Picture Coding Symposium (PCS 2012)*. IEEE. Krakow, Poland, May 2012.

[8] Christian Keimel et al. "Video quality evaluation in the cloud". In: *19th International Packet Video Workshop (PV 2012)*. IEEE. Munich, Germany, May 2012.

[9] Christian Keimel, Julian Habigt, and Klaus Diepold. "Challenges in crowd-based video quality assessment". In: *Fourth International Workshop on Quality of Multimedia Experience (QoMEX 2012)*. IEEE. Yarra Valley, Australia, July 2012.

[10] Filippo Mazza, Matthieu Perreira Da Silva, and Patrick Le Callet. "Would you hire me? Selfie portrait images perception in a recruitment context." In: *IS&T/SPIE Electronic Imaging*. International Society for Optics and Photonics. San Francisco, CA, USA, Feb. 2014.

[11] Isabelle Hupont et al. “Is affective crowdsourcing reliable?” In: *5th International Conference on Communications and Electronics (ICCE 2014)*. Da Nang, Vietnam, July 2014.

[12] Judith Redi and Isabel Povoa. “Crowdsourcing for Rating Image Aesthetic Appeal: Better a Paid or a Volunteer Crowd?” In: *3rd International ACM workshop on Crowdsourcing for Multimedia (CrowdMM 2014)*. Orlando, FL, USA, Nov. 2014.

[13] Judith Redi et al. “Crowdsourcing-based multimedia subjective evaluations: a case study on image recognizability and aesthetic appeal”. In: *2nd International ACM workshop on Crowdsourcing for Multimedia (CrowdMM 2013)*. Barcelona, Spain, Oct. 2013.

[14] Martin Varela et al. “Increasing Payments in Crowdsourcing: Don’t look a gift horse in the mouth”. In: *4th International Workshop on Perceptual Quality of Systems (PQS 2013)*. Vienna, Austria, Sept. 2013.

[15] Matthias Hirth et al. “Predicting Result Quality in Crowdsourcing Using Application Layer Monitoring”. In: *5th International Conference on Communications and Electronics (ICCE 2014)*. Da Nang, Vietnam, July 2014.

[16] Matthias Hirth, Tobias Hoßfeld, and Phuoc Tran-Gia. “Analyzing Costs and Accuracy of Validation Mechanisms for Crowdsourcing Platforms”. In: *Mathematical and Computer Modelling* 57.11 (2013), pp. 2918–2932.

[17] Matthias Hirth, Tobias Hoßfeld, and Phuoc Tran-Gia. “Anatomy of a crowdsourcing platform-using the example of microworkers. com”. In: *Fifth International Conference On Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS 2011)*. IEEE. Seoul, Korea, June 2011.

[18] Matthias Hirth, Tobias Hoßfeld, and Phuoc Tran-Gia. “Cost-optimal validation mechanisms and cheat-detection for crowdsourcing platforms”. In: *Fifth International Conference On Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS 2011)*. IEEE. Seoul, Korea, June 2011.

[19] Michael Seufert et al. ““To pool or not to pool”: A comparison of temporal pooling methods for HTTP adaptive video streaming”. In: *Fifth International Workshop on Quality of Multimedia Experience (QoMEX 2013)*. IEEE. Klagenfurt, Austria, July 2013.

[20] Pavel Korshunov et al. “The effect of HDR images on privacy: crowdsourcing evaluation”. In: *SPIE Photonics Europe 2014, Optics, Photonics and Digital Technologies for Multimedia Applications*. Brussels, Belgium, Apr. 2014.

[21] Philipp Amrehn et al. “Need for speed? On quality of experience for file storage services”. In: *4th International Workshop on Perceptual Quality of Systems (PQS 2013)*. Vienna, Austria, Sept. 2013.

[22] Phuoc Tran-Gia et al. “Crowdsourcing and its Impact on Future Internet Usage”. In: *it-Information Technology Methoden und innovative Anwendungen der Informatik und Informationstechnik* 55.4 (2013), pp. 139–145.

[23] Simon Oechsner et al. “Visions and Challenges for Sensor Network Collaboration in the Cloud”. In: *Eigth International Conference On Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS 2014)*. IEEE. Birmingham, UK, July 2011.

[24] Tobias Hoßfeld et al. “Best Practices for QoE Crowdtesting: QoE Assessment with Crowdsourcing”. In: *IEEE Transactions on Multimedia* 16.2 (Feb. 2014), pp. 541–558.

[25] Tobias Hoßfeld and Christian Keimel. “Crowdsourcing in QoE Evaluation”. In: *Quality of Experience: Advanced Concepts, Applications and Methods*. Ed. by Alexander Raake Sebastian Mller. Springer: T-Labs Series in Telecommunication Services, ISBN 978-3-319-02680-0, Mar. 2014.

[26] Tobias Hoßfeld and Christian Timmerer. “Quality of Experience Assessment using Crowdsourcing ”. In: *IEEE COMSOC MMTC R-Letter* 5 (June 2014).

[27] Tobias Hoßfeld et al. “Survey of Web-based Crowdsourcing Frameworks for Subjective Quality Assessment”. In: *16th International Workshop on Multimedia Signal Processing (MMSP 2014)*. Jakarta, Indonesia, Sept. 2014.

[28] Tobias Hoßfeld, Matthias Hirth, and Phuoc Tran-Gia. “Aktuelles Schlagwort: Crowdsourcing”. In: *Informatik Spektrum* 35 (Apr. 2012).

[29] Tobias Hoßfeld, Matthias Hirth, and Phuoc Tran-Gia. “Modeling of crowdsourcing platforms and granularity of work organization in future internet”. In: *23rd International Teletraffic Congress (ITC 2011)*. International Teletraffic Congress. San Francisco, CA, USA, Sept. 2011.

[30] Tobias Hoßfeld et al. “Assessing Effect Sizes of Influence Factors Towards a QoE Model for HTTP Adaptive Streaming”. In: *6th International Workshop on Quality of Multimedia Experience (QoMEX 2014)*. Singapore, Sept. 2014.

[31] Tobias Hoßfeld et al. “Quantification of YouTube QoE via crowdsourcing”. In: *IEEE International Symposium on Multimedia (ISM 2011)*. IEEE. Dana Point, CA, USA, Dec. 2011.

[32] Tobias Hoßfeld et al. “Initial delay vs. interruptions: between the devil and the deep blue sea”. In: *Fourth International Workshop on Quality of Multimedia Experience (QoMEX 2012)*. IEEE. Yarra Valley, Australia, July 2012.

[33] Tobias Hoßfeld. “On Training the Crowd for Subjective Quality Studies”. In: *VQEG eLetter* 1 (Mar. 2014).

[34] Valentin Burger et al. “Increasing the Coverage of Vantage Points in Distributed Active Network Measurements by Crowdsourcing”. In: *Measurement, Modelling, and Evaluation of Computing Systems and Dependability and Fault Tolerance (MMB & DFT 2014)*. Bamberg, Germany: Springer, Mar. 2014.

[35] Tobias Hoßfeld, Phuoc Tran-Gia, and Maja Vucovic. “Crowdsourcing: From Theory to Practice and Long-Term Perspectives (Dagstuhl Seminar 13361)”. In: *Dagstuhl Reports* 3.9 (2013). Ed. by Tobias Hoßfeld, Phuoc Tran-Gia, and Maja Vukovic, pp. 1–33. ISSN: 2192-5283. DOI: http://dx.doi.org/10.4230/DagRep.3.9.1.

[36] Martin Rerabek et al. “Evaluation of privacy in high dynamic range video sequences”. In: *SPIE Optical Engineering + Applications*. International Society for Optics and Photonics. San Diego, CA, USA, Aug. 2014.

[37] Philippe Hanhart, Pavel Korshunov, and Touradj Ebrahimi. “Crowdsourcing evaluation of high dynamic range image compression”. In: *SPIE Optical Engineering + Applications*. International Society for Optics and Photonics. San Diego, CA, USA, Aug. 2014.

[38] Philippe Hanhart, Pavel Korshunov, and Touradj Ebrahimi. “Crowd-based quality assessment of multiview video plus depth coding”. In: *IEEE International Conference on Image Processing*. Paris, France, Oct. 2014.

[39] Pavel Korshunov, Shuting Cai, and Touradj Ebrahimi. “Crowdsourcing approach for evaluation of privacy filters in video surveillance”. In: *1st International ACM workshop on Crowdsourcing for Multimedia (CrowdMM 2012)*. ACM. Nara, Japan, Oct. 2012.

[40] Bruno Gardlo. “Quality of experience evaluation methodology via crowdsourcing”. PhD thesis. Zilina, Slovakia: University of Zilina, 2012.

[41] Pierre Lebreton et al. “Bridging the Gap Between Eye Tracking and Crowdsourcing”. In: *Proceedings of the SPIE 9394, Human Vision and Electronic Imaging XX*. San Francisco, USA, Feb. 2015.

[42] B. Gardlo, S. Egger, and T. Hoßfeld. *Does Scale-Design matter for assessing Video QoE through Crowdsourcing?* Tech. rep. FTW, 2014.

Other references

[43] Omar Alonso, Daniel E Rose, and Benjamin Stewart. “Crowdsourcing for relevance evaluation”. In: *ACM SigIR Forum*. Vol. 42. 2. ACM. 2008, pp. 9–15.

[44] Julie S Downs et al. “Are your participants gaming the system?: screening mechanical turk workers”. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM. 2010, pp. 2399–2402.

[45] Pei-Yun Hsueh, Prem Melville, and Vikas Sindhwani. “Data quality from crowdsourcing: a study of annotation selection criteria”. In: *Proceedings of the NAACL HLT 2009 workshop on active learning for natural language processing*. Association for Computational Linguistics. 2009, pp. 27–35.

[46] BT.500-13 (01/2012). “Methodology for the subjective assessment of the quality of television pictures”. In: *Recommendation ITU-R* (2012).

[47] Qianqian Xu et al. “HodgeRank on random graphs for subjective video quality assessment”. In: *IEEE Transactions on Multimedia* 14.3 (2012), pp. 844–857.

[48] Kuan-Ta Chen et al. “A crowdsourceable QoE evaluation framework for multimedia content”. In: *17th ACM International Conference on Multimedia*. ACM. Beijing, China, Oct. 2009.

[49] European Parliament Directive. “95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data”. In: *Official Journal of the EC* 23.6 (1995).

[50] Lilly C Irani and M Silberman. “Turkopticon: Interrupting worker invisibility in amazon mechanical turk”. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM. Paris, France, Apr. 2013.

[51] Huib de Ridder. “Cognitive issues in image quality measurement”. In: *Journal of Electronic Imaging* 10.1 (2001), pp. 47–55.

[52] Yohann Pitrey et al. “Aligning subjective tests using a low cost common set”. In: *QoE for Multimedia Content Sharing* (2011).

[53] Alexander Eichhorn, Pengpeng Ni, and Ragnhild Eg. “Randomised pair comparison: an economic and robust method for audiovisual quality assessment”. In: *20th international workshop on Network and operating systems support for digital audio and video*. ACM. Amsterdam, The Netherlands, June 2010.

[54] Peter E Rossi, Zvi Gilula, and Greg M Allenby. “Overcoming scale usage heterogeneity: A Bayesian hierarchical approach”. In: *Journal of the American Statistical Association* 96.453 (2001), pp. 20–31.

[55] Bronwen L Jones and Pamela R McManus. “Graphic scaling of qualitative terms”. In: *SMPTE journal* 95.11 (1986), pp. 1166–1171.

[56] MT Virtanen, N Gleiss, and M Goldstein. “On the use of evaluative category scales in telecommunications”. In: *Human Factors in Telecommunications*. Melbourne, Australia, Mar. 1995.

[57] International Telecommunication Union. “Methods for Subjective Determination of Transmission Quality”. In: *ITU-T Recommendation P.800* (Aug. 1996).

[58] Chen-Chi Wu et al. “Crowdsourcing multimedia QoE evaluation: A trusted framework”. In: *IEEE transactions on multimedia* 15.5 (2013), pp. 1121–1137.

[59] Judd Antin and Aaron Shaw. “Social desirability bias and self-reports of motivation: a study of amazon mechanical turk in the US and India”. In: *ACM SIGCHI Conference on Human Factors in Computing Systems*. ACM. Austin, TX, USA, 2012.

[60] Panagiotis G Ipeirotis. *Demographics of mechanical turk*. Tech. rep. http://hdl.handle.net/2451/29585. New York University, Mar. 2010.