Distributed peer review enhanced with natural language processing and machine learning

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While ancient scientists often had patrons to fund their work, peer review of proposals for the allocation of resources is a foundation of modern science. A very common method is that proposals are evaluated by a small panel of experts (due to logistics and funding limitations) nominated by the grant-giving institutions. The expert panel process introduces several issues - most notably: 1) biases introduced in the selection of the panel. 2) experts have to read a very large number of proposals. Distributed Peer Review promises to alleviate several of the described problems by distributing the task of reviewing among the proposers. Each proposer is given a limited number of proposals to review and rank.

We present the result of an experiment running a machine-learning enhanced distributed peer review process for allocation of telescope time at the European Southern Observatory.

In this work, we show that the distributed peer review is statistically the same as a ‘traditional’ panel, that our machine learning algorithm can predict expertise of reviewers with a high success rate, and we find that seniority and reviewer expertise have an influence on review quality. The general experience has been overwhelmingly praised from the participating community (using an anonymous feedback mechanism).

1 Introduction

All large, ground- and space-based astronomical facilities serving wide communities, like the European Southern Observatory (ESO), the Atacama large Millimeter Array, The Hubble Space Telescope, and the Gemini Observatory, face a similar problem. In many cases the number of applications they receive at each call exceeds 1000, posing a serious challenge to run an effective selection process through the classic peer-review paradigm, which assigns proposals to pre-allocated panels with fixed compositions. Although, in principle, one could increase the size of the time allocation committee (TAC), this creates logistic and financial problems which practically limit its maximum size, making this solution not viable.

Since the referees only have a limited amount of time to perform their task, the heavy load (which at ESO typically exceed 70 proposals per referee; priv. comm. ESO OPC office) has severe consequences on the quality of the review and the feedback that is provided to the applicants. This contributes to increasing levels of frustration in the community and to the loss of credibility in the whole selection process. In addition, although difficult to quantify, this will have consequences for the scientific output of the facilities. Different measures were considered by the various facilities to alleviate the load on the reviewers. This includes quite drastic solutions, like the one deployed by National Science Foundation (NSF) to limit the number of applications (Mervis, 2014a).

In this context, one of the most innovative propositions was put forward by The concept is simple: by submitting a proposal the principal investigator accepts to review proposals submitted by peers, and to have their proposal reviewed by n peers. Also, by submitting proposals, they accept to review proposals, hence virtually limiting the number of submissions. We will indicate this concept as Distributed Peer Review (DPR).

The Gemini Observatory deployed the DPR for its Fast Turnaround channel (Andersen et al., 2019), which is capped to 10% of the total time. The NSF also explored this possibility with a pilot study in 2013, in which each PI was asked to review proposals submitted by peers (Ardabili & Liu, 2013; Mervis, 2014b). The NSF pilot was based on 131 applications submitted by volunteers within the Civil, Mechanical and Manufacturing Innovation Division. The NSF did not publish a report following the study. A similar pilot experiment was carried out in 2016 by the National Institute of Food and Agriculture (see https://nifa.usda.gov/resource/distributed-peer-review-pilot-foundational-program, consulted on April 9, 2019.), but also in this case the results were not published.

We report on an experiment that employed the DPR at European Southern Observatory (ESO) during Period 103 (call for proposals issued on 30 August, 2018) in parallel with the regular Observing Programmes Committee (OPC). We mirrored the deployment of the DPR implementation at Gemini as an example, and enhanced the process using Natural Language Processing (NLP) and machine learning for referee selection (a different method of using NLP for proposal reviews can be found in Strolger et al., 2017). This experiment also added a feedback for individual reviews.

The experiment was designed to test if there is a measurable difference between the DPR and OPC, if the algorithm for referee selection performed well, and if what referee attributes influenced the quality of the referee report (as judged by the feedback to a review).

In Section 2, we describe the general setup of the experiment. Section 3 is devoted to the statistical analysis and divided into Section 3.1 for the comparison between the DPR and OPC outcomes, Section 3.2 for the description of the literature matching, and Section 3.3 for the evaluation of the helpfulness of reviews by the proposers. In Section 4 we summarize and conclude this work.

The supplementary information (SI) gives a more detailed description of the time allocation process at ESO (SI Section 1), a discussion of the demographics of the experiment (SI Section 2), an extended analysis (SI Section 3), and several datasets related to the experiment (see SI Appendices). We will refer the reader to the supplementary material where appropriate.
2 Experiment Overview

We followed a general outline of DPR as described in Merrifield & Saari (2009), but differences were introduced in several key areas. Specifically, we test two different referee selection methods: 1) the first selection method emulates the way that reviews are currently assigned to members of the OPC to make a comparison to the OPC evaluation of the same proposals. 2) an automated machine-learning method to assign referees to proposals (based on the DeepThought-knowledge discovery method; see Kerzendorf, 2019). We believe that the advantages of this method are that it scales easily with the number of proposals and that, due to the automated construction, it might circumvent biases in self-efficacy (e.g., based on gender - see Ehrlinger & Dunning, 2003). Finally, we also asked the participants to assess the reviews of their proposal in order to understand what influences a constructive review and potentially reward helpful referees in the future.

We have tested a DPR scheme on a voluntary basis for the ESO period P103. The outcome of this experiment had no influence on the telescope allocation. The DPR program for ESO P103 recruited 172 volunteers with each submitting one participating proposal (this is 23% of the distinct PIs in P103). These proposals were evaluated in the DPR process as well as with the general OPC methods.

For our experiment, the group of proposers and referees were the same. We selected eight referees for each proposal using several rules (see the Methods Section 6.2 material for an overview of the two selection processes used).

The reviewers assigned the proposed projects through a web application and were given two weeks to assess them. A detailed description of the review options is described in the methods section (see Section 2).

The proposal quartile and the eight unmodified comments were displayed to the proposer. We finally asked the proposer to evaluate the helpfulness of the comments (with details in see Section 2).

Figure 1 summarizes the process as a flow-chart and the detailed description of the process can be found in the Method Section 6.

3 Analysis & Results

We received complete reviews for 167 out of 172 reviewers (97.1%) at the deadline (with these 5 proposals excluded from the further analysis). The individual grades from each review were converted into a global rank for each proposal (with details found in the supplementary material) and translated to quartiles (A, B, C, D).

There are a myriad of statistics available that can be interesting to apply to the dataset (some of them are explored in the supplementary material). We therefore encourage the community to make use the anonymized dataset to run independent analyses (available at https://zenodo.org/record/2634598).

Our main focus in this study is to address three questions: 1) How different is the DPR from a more traditional OPC review? 2) How well can our algorithm predict expertise for a proposal? 3) What reviewer properties influence the helpfulness of their referee report?

3.1 Comparison of the Distributed Peer Review to the Observing Programmes Committee

The proposals used in the DPR experiment were also reviewed through the regular ESO OPC channel. This allows a comparison between the outcomes of the two processes. However, these differ by construction in many aspects, and so a one-to-one comparison is not possible. This is because in the DPR experiment:

1. there is no a priori scientific-seniority selection;
2. the proposals are typically reviewed by \(N_r > 6\) referees (while \(N_r = 3\) in the pre-meeting OPC process);
3. the number of proposals per referee is much smaller;
4. the set of proposals common to different reviewers is much smaller;
5. there is no triage; an early removal of some proposals before the OPC meeting
6. there is no face-to-face discussion.

A robust way of quantifying the consistency between two different panels reviewing the same set of proposals is that of the quartile agreement fraction introduced in Patat (2018, hereafter P18; Section 9.2). Following that concept, one can compute what we will indicate as the panel-panel (p-p) quartile agreement matrix (QAM). The generic QAM element \(M_{ij}\) is the fraction of proposals ranked by the first panel in the \(i\)-th quartile of the grade distribution, that were ranked in the \(j\)-th quartile by the second panel. If we indicate with \(A_i\) and \(B_i\) the events “a proposal is ranked by panel A in quartile \(i\)”, and “a proposal is ranked by panel B in quartile \(j\)”, the QAM elements represent the conditional probability:

\[
M_{ij} = P(A_i|B_j) = \frac{P(A_i \cap B_j)}{P(A_i)}.
\]

For a completely aleatory process \(P(A_i \cap B_j) = P(A_i)P(B_j)\), and therefore all the terms of the QAM would be equal to 0.25, while for a full correlation, all terms would be null, with the exception of the diagonal terms, which would be equal to 1. We note that the matrix elements are not independent from each other as, by definition:

\[
\sum_j M_{ij} = \sum_i M_{ij} = 1.
\]

For the purposes of the main part of this paper, we will compare the internal agreement of the DPR panels with that of the OPC (pre-meeting). Section 10.5 in the supplementary information gives further comparison between the OPC and DPR statistics.

For doing this, we will bootstrap the DPR data extracting a number of sub-sets of three randomly chosen referees.

This choice for the DPR set is particularly interesting as it is directly comparable to the results presented in P18. The procedure is as follows: We first make a selection of the proposals having at least 6 reviews (164). For each of them we randomly select two distinct (i.e. non-intersecting) sub-sets of \(N_r=3\) grades each, from which two average grades are derived. These are used to compute the agreement fractions between the two sub-panels. The process is repeated a large number of times and the average (p-p) QAM is finally obtained.

In Figure 2, we compare the QAM of our subsets with that of the OPC pre-meeting panels. The latter was derived for the OPC process for \(N_r=3\) sub-panels (P18, Table 3 therein). In both cases the first quartile agreement is about 40% (\(k=0.21\)), while for the second and third quartile this is ~30%. The top-bottom quartile agreement is 10% (\(k = -0.60\)). The conclusion is that, in terms of self-consistency, the DPR review behaves in the same way as the pre-meeting OPC process. The two review processes are characterized the same level of subjectivity.

3.2 Domain knowledge inference

Another aim of the DPR experiment is to infer a referee’s domain knowledge for a given proposal using machine learning. “Expertise” is, unfortunately, no objective quantity. However, it is reasonable to
Figure 1: **Overview of the enhanced distributed peer-review process.** The graph shows the flow of the proposal starting with the proposer in the upper left-hand corner. The proposal then goes into the reviewer selection (with the two groups marked), via the review and finally to the grade-aggregation. The loop closes with the proposer giving feedback on the usefulness of the review.

Figure 2: **Comparison of reviewer agreement between both DPR and the classic process.** Comparison between the panel-panel for the OPC subsets (left, from P18 Table 3) and the DPR subsets (right). Each panel shows the probability the second panel (or DPR subset) is grading a specific proposal given the response by the first panel. The probability is highest on the diagonal which suggests there is some correlation between different reviewers grading – albeit a relatively weak one.
Figure 3: Accuracy of DeepThought expertise prediction. Conditional probability $P(\text{Self Reported} | \text{DeepThought})$ for the various combinations of perceived and DeepThought inferred knowledge. The self-reported knowledge came directly from being a required field to answer in the refereeing proposal. The match provided by deepthought was calculated purely algorithmically.

Table: DeepThought inferred knowledge

| Perceived Knowledge | DeepThought Inferred Knowledge |
|--------------------|-------------------------------|
| No Knowledge       | Expert                        |
| General Knowledge  | Expert                        |
| Expert             | Expert                        |

We assume that the self-judgement of expertise (self-efficacy) is a good measure that might approximate such a quantity.

Given:
- “self reported” as the self reported domain knowledge
- DeepThought as the DeepThought inferred domain knowledge

For our experiment, we calculate the joint probability $P(\text{Self Reported} | \text{DeepThought})$ using Bayes theorem:

$$P(\text{Self Reported} | \text{DeepThought}) = \frac{P(\text{DeepThought}) | \text{Self Reported} \cdot P(\text{Self Reported})}{P(\text{DeepThought})}$$

$$P(\text{Self Reported} | \text{DeepThought}) = P(\text{DeepThought}) \cap (\text{Self Reported}) \div P(\text{DeepThought})$$

Figure 3 shows the correlation between self-reported knowledge (see the detailed description of the experiment in the supplementary material) and our predicted DeepThought inferred knowledge (see supplementary material for a detailed description of the method).

We reiterate that we are not comparing to the true domain knowledge but to the self-reported knowledge. We find that DeepThought will predict the opposite of the self-reported knowledge in only $\approx 10\%$ of the cases (predicting expert with self-reported “no knowledge” and vice versa). We emphasize the $\approx 80\%$ success rate of predicting “no knowledge”. These numbers show a high success rate in removing whose expertise does not overlap with the proposal.

### 3.3 Rating the helpfulness of review comments

After the review process, we asked the proposers to evaluate the “helpfulness” of the review comments. A total of 136 reviewers provided feedback.

The review usefulness distribution shows a steady rise, with a sudden drop-off at the ‘very helpful’ bin, as shown in all panels of Fig. 4. About 55% of the users rated the comments in the ‘helpful’ and ‘very helpful’ bins.

To check what factors might influence the ability to write helpful comments we use the statistical method given at the beginning of this section.

The reviewer’s expertise is expected to have an influence on the helpfulness of comments. Figure 4a,b shows the influence of both self-reported knowledge and DeepThought inferred knowledge on the helpfulness of the comment. The probabilities are very similar between the self-reported and inferred knowledge. We highlight that experts seemingly very rarely give unhelpful comments and that non-experts rarely give very helpful comments.

The last test is to see how the comments helpfulness is being evaluated given the ranking of the proposal within the quartiles $P(\text{helpful comment} | \text{proposal quartile})$. This shows a similar distribution to the other panels in Fig. 4. There are some small differences. Comments for proposals from the second to the top quartile often were perceived as relatively helpful. Comments on proposals in the last quartile were rarely ranked as very helpful (Van Rooyen et al., 1999, finds a similar effect).

We checked whether seniority has an influence on the ability to create helpful comments. Figure 4c shows some correlation between the seniority and the ability for the referee to give helpful comments. Most interesting is the apparent inability of graduate students to give very helpful comments. This might be a training issue and can be resolved by exposing the students to schemes such as DPR.

We have also asked about the helpfulness of the comment in our general feedback (Supplementary Information). The distribution of comment usefulness follows the distribution of helpfulness for individual comments relatively closely (see statistics in Supplementary Information). The comments given in the DPR compare very favourably with the OPC (see details in Supplementary Information).

### 4 Summary and Conclusions

The main advantages of the DPR paradigm (coupled to the DeepThought approach) over the classic panel concept can be listed as follows.

**Advantages:**

- it allows a much larger statistical basis (each proposal can be easily reviewed by 8-10 scientists), enabling robust outlier rejection;
- it removes possible biases generated by panel member nominations;
- the larger pool of scientists allows a much better coverage in terms of proposal–expertise matching;
- the smaller number of proposals per reviewer allows for more careful work and more useful feedback;
- coupled to the DeepThought approach for proposal–referee matching, it is suited to be made semi-automatised; it also gives an objective criteria for ‘expertise’ removing biases in self-reporting;
- it removes the concept of panel, which adds rigidity to the process;
- it addresses the problem of maximising the proposal–referee match while maximising the overlap in the evaluations, which is a typical issue in pre-allocated panels (see Cook et al., 2005, and references therein);
Figure 4: **Influence of various factors on the perceived quality of the review** We show a number of factors that can influence the (perceived) quality of the review that was graded by the proposers in the feedback step. **Upper Row:** Evaluation of the helpfulness of the comment given expertise (inferred by DeepThought on the left panel and self reported on the right panel). **Lower Left:** We show the conditional probability $P(\text{helpful comment} | \text{seniority})$ for the various combinations of helpful comment rating and reported gender. **Lower Right:** We show the conditional probability $P(\text{helpful comment} | \text{proposal quartile})$ for the various combinations of helpful comment rating and proposal quartile.

- the lack of a face-to-face meeting greatly simplifies the logistics and the costs, making it attractive for small, budget-limited facilities;
- the absence of the meeting prevents strong personal opinions from having a pivotal influence on the process;
- it involves a larger part of the community, increasing its democratic breadth;
- all applicants are exposed to the typical quality of the proposals. This allows them to better understand if their request is not allocated time by placing it in a much wider context, and helps improving their proposal-writing skills (comment by Arash Takshi: “The ability to see what my competitors were doing filled a blind spot for me. Now I know that if I don’t get funded, it’s because of the quality of the other proposals, not something I did wrong.” Mervis, 2014b);
- it trains the members of the community without additional effort.

Disadvantages:

- The lack of a meeting does not allow the exchange of opinions and the possibility of asking and answering questions to/from the peers;
- exposition of proposal content to a larger number of individuals (167 vs. 78 in the real case of the DPR experiment) increases the risk of confidentiality issues.

The two major disadvantages can, however, be easily addressed: barring the fact that its effectiveness remains to be demonstrated and quantified (see above), the social, educational and networking aspects of the face-to-face meeting should not be undervalued. In this respect, we notice that the resources freed by the DPR approach can be used by the organizations for education and community networking (training on proposal writing, fostering collaborations, ...). Another possibility to enable the interaction between the reviewers is to allow them to up-vote or down-vote the comments by other reviewers (the Science journal employs such an approach) which could be used to exclude comments and grades that were down-voted by a very significant fraction of the other referees.

We conclude that the participating community has reacted extremely positively to this (see Section B in the supplementary mate-
rial). The presented approach to infer expertise works very well (see Figure 3). On an individual level, the behavior of the DPR referees conforms to the statistical description of the regular OPC referees (P18), and there is no statistically significant evidence that junior reviewers systematically deviate from this (see Section 3.1). The introduction of the possibility to rate the helpfulness of comments provides a new avenue to potentially reward helpful referees and train referees in general on giving useful feedback.

We encourage other organizations to run similar studies, to progress from a situation in which the classic peer-review is adopted notwithstanding its limitations in the lack of better alternatives. As scientists, we firmly believe in experiments, even when these concern the way we select the experiments themselves.

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This paper is fruit of independent research and is not to be considered as expressing the position of the European Southern Observatory on proposal review and telescope time allocation procedures and policies.

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METHODS

6 Description of the DeepThought DPR experiment

For an overview of the process see Section 2. In the next sections, we will give a detailed description of the process of the DeepThought DPR experiment.

6.1 Reviewer exclusion and selection

Reviewer selection is a core part of the experiment. We separated this step into reviewer exclusion and reviewer selection. We tested two different strategies for reviewer selection: one based on a standard methodology (called “OPC emulate” [OE]), the other based on a machine-estimated of the domain-specific knowledge (called “DeepThought” [DT]), which are described in detail in Section 6.2.2.

We describe the reviewer exclusion and selection using the abstract concept of a matrix. The matrix has a row for each proposer and a column for each referee. In our case, the referees and proposers are the same set, and thus we have a square matrix.

Our exclusion matrix was constructed in a way that would mark a referee ineligible to review a proposal where any of the investigators were from the same institute as the referee

\[
A_{\text{exclusion}} = \begin{pmatrix}
  p_1 & 1 & \cdots & 0 \\
  1 & 1 & \cdots & 0 \\
  0 & 1 & \cdots & 0 \\
  \vdots & \vdots & \ddots & \vdots \\
  1 & 0 & \cdots & 0 \\
  0 & 0 & \cdots & 1
\end{pmatrix}
\]

where \( p_\text{r} \) stands for proposer, 1 indicates conflict and 0 no conflict.

For the OPC-emulate group, we also constructed an additional matrix (that was combined to the previous exclusion matrix using the logical or) that marks a referee ineligible to review a proposal that was submitted to the same unit telescope as the referee’s submitted proposal.

We constructed a reviewing matrix that marks a reviewer-proposal combination with 1 (and the rest of the matrix with 0). We then used a round-robin selection process to iterate through the referees. For each referee, we use the exclusion matrix to determine eligible proposals and then the specific selection criterion for each of the groups (outlined in Section 6.1) to assign one of the remaining available proposals (taking into account the exclusion matrix). This process was repeated until all referees had been assigned eight proposals. If the process failed before completion, it was restarted with a different random number seed until we found a solution. A solution matrix needs to have all row sums and column sums equal to eight. For future projects, we strongly suggest to research algorithms from operations research (or combinatorial optimization) that have been optimized for the given process.

6.2 Reviewer selection methodology

We separated the volunteer base into two groups for our two experiments. The first group was 60 randomly chosen volunteers out of the 172. This group was assigned proposals that would closely emulate the current way ESO assigns proposals in the OPC (which is a variant of the common time-allocation strategy present in the astronomy community).

The second group of the remaining 112 volunteers was assigned by predicting their expertise of a proposal based on their publication history using machine learning.

6.2.1 OPC emulate Group

We aim with this selection process to emulate the OPC process. The members of the OPC assign themselves to expert groups in four categories

- A - Cosmology and Intergalactic Medium
- B - Galaxies
6.2.2 DeepThought Group

The general idea behind this selection process is to use the published papers of each participant to predict how knowledgeable they were for each proposal. This made extensive use of the dataset and techniques presented in Kerzendorf (2019). This required identifying their publications, construct knowledge-vectors for each referee, construct proposal vectors from the submitted latex document, construct a knowledge matrix for each of the combination of referee and proposal, and use this matrix in the selection process.

Name disambiguation The first part of this process was to uniquely identify participants in ADS to infer their publications. Milojević (2013) has shown using the last name and the first initials only 6.1% of author’s identities are contaminated (either due to splitting or merging) which is sufficient for the statistical requirements of our experiment.

We then used the Pynio package as (available at https://ads.readthedocs.io) to access the ADS API to search for the participant’s papers (and their arxiv identifiers) without regard for position of authorship. We excluded participants (moved them to the OPC emulate group) that have less than 3 papers (9 participants) or more than 500 papers (4 participants).

Knowledge Vectors Kerzendorf (2019) shows in Section 4 the construction of vectors from publication (using a technique called TF-IDF). We used the document vectors from Kerzendorf (2019) given of all publications identified for each participant in the previous step. These document vectors were summed up and then normalized. We call such a vector sum for each referee a “knowledge vectors”.

Proposal vectors We use the machinery described in Kerzendorf (2019) to process several sections of the latex representation ('Title', 'Abstract', 'ScientificRationale', 'ImmediateObjective’) of the submitted proposal. These were then converted to normalized document vectors which we refer to as “proposal vectors”.

Knowledge Matrix We then construct a knowledge matrix similar to the exclusion matrix and fill each of its elements with the dot-product between the proposal vector and referee knowledge vector (cosine distance; see Equation 4).

\[ A_{\text{knowledge}} = \begin{pmatrix}
    p_1 & p_2 & \cdots & p_n \\
    \text{referee}_1 & 0.8 & 0.4 & 0.1 \\
    \text{referee}_2 & 0.5 & 0.9 & 0.5 \\
    \vdots & \vdots & \ddots & \vdots \\
    \text{referee}_n & 0.6 & 0.2 & 0.7
\]  

(4)

where \( p_n \) stands for proposer.

As opposed to the OPC emulate case, we do not assign proposals randomly to the referees during the selection step in the referee selection process (see Section 6.1). The proposals are picked according to the following algorithm with different steps for the first four, subsequent two and last two proposals picked for each referee:

1. from the available proposals choose the one with the highest cosine distance for the first four proposals assigned to each referee
2. from the available proposals choose the proposal closest to the median of all cosine scores for that particularly referee for the next two proposals
3. from the available proposals choose the one with the lowest cosine distance for the last two proposals assigned to each referee

The process was repeated with a different random if there were no eight suitable proposals available for each referee. Depending on the number of constraints and participants it took on the order of three times too find a suitable solution.

6.3 Review process

The participants were given a login to evaluate the proposals. After signing a Non Disclosure Agreement (which is identical to the one signed by the OPC members), the participants could view the proposals assigned to them. They were first given the option to indicate a conflict of interest (removing them from making an eligible vote on the proposal). Then were asked for their expertise on the proposal’s topic. They were tasked to review the proposals by giving them a score (1 - 5; same as in the OPC), their assessment of their knowledge of the proposal, and a comment.

We outline the steps in more detail in the following. The following options were given to indicate a conflict:

- No, I do not have a conflict.
- Yes, I have a close personal or professional relationship with the PI and/or team.
- Yes, I am a direct competitor to this proposal.

The referees were instructed to consider the following questions when evaluating a proposal:

- Is there sufficient background/context for the non-expert (i.e., someone not specialized in this particular sub-field)?
- Are previous results (either by proposers themselves or in the published literature) clearly presented?
- Are the proposed observations and the Immediate Objectives pertinent to the background description?
- Is the sample selection clearly described, or, if a single target, is its choice justified?
- Are the instrument modes, and target location(s) (e.g., cosmology fields) specified clearly?
- Will the proposed observations add significantly to the knowledge of this particular field?

They were then asked to assess their expertise of the proposal:

- This is my field of expertise.
- I have some general knowledge of this field.
- I have little or no knowledge of this field.

They were instructed to use the following general grading rules:
• 1.0 outstanding: breakthrough science
• 1.5 excellent: definitely above average
• 2.0 very good: no significant weaknesses
• 2.5 good: minor deficiencies do not detract from strong scientific case
• 3.0 fair: good scientific case, but with definite weaknesses
• 3.5 rather weak: limited science return prospects
• 4.0 weak: little scientific value and/or questionable scientific strategy
• 4.5 very weak: deficiencies outweigh strengths
• 5.0 rejected

The referees then had to write a comment with a minimum of 10 characters.

6.4 Grade Aggregation

In the experiment design, each proposal was assigned to $N_p = 8$ peers, and each PI was assigned $N_e = 8$ proposals. In practice, because of the declared conflicts, proposals were evaluated by 4 to 8 referees, with $N_p \geq 6$ in 95% of the cases. For the same reason, each referee reviewed between 5 and 8 proposals, with $N_e \geq 6$ in 98% of the cases. This guarantees statistical robustness in the grade aggregation.

In the OPC process, the grades given by the distinct referees are combined using a simple average, after applying the referee calibration. This operation is described in Patat (2018) (Sect. 2.4 and Appendix A therein), and aims at minimizing the systematic differences in the grading scales used by the reviewers. In the current implementation, the calibration consists in a shift-and-stretch linear transformation, by which the grade distributions of the single referees are brought to have the same average and standard deviation (grades $\geq 3$ are excluded from the calculations). This operation is justified by the relatively large number of proposals reviewed by each referee (>60), which makes the estimate of the central value and dispersion reasonably robust.

The case of the DPR is different in this respect, as a given person would have reviewed at most $N_p = 8$ proposals. Especially for the dispersion, this limitation certainly weakens its statistical significance. For this reason, following the example of the Gemini Fast Turn Around channel (Andersen et al., 2019), and for the purposes of providing feedback to the users, the raw grades were combined without applying any referee calibration (the effects of calibration in the DPR experiment are presented and discussed in the main text).

6.5 Review evaluation

After the review deadline the participants were given access to a page with the peer-reviews (most of the time seven or eight) of their proposal. The applicants are given the quartile rank as a letter (A–D; as calculated in Section 6.4). For each comment, they were asked to rank its helpfulness:

We would be grateful if you could rate each review on a scale of 1 (not helpful) to 4 (very helpful) how much this comment helps improve your proposal (positive comments like “best proposal I ever read” - can be ranked as not helpful as it does not improve the proposal further). These ratings will not be distributed further but help us for statistical purposes.

6.6 Questionnaire

Each participant in the DPR experiment was asked to fill out a questionnaire after performing the reviews and receiving the feedback on their own proposal:

Also, after reading the reviews, please take 10-15 minutes to fill the final questionnaire (see the link at the bottom of this page). Although it is optional, it is your chance to give us feedback on any aspect that you liked/disliked and to shape a future DPR process. It will also greatly assist us in understanding how the experiment went, learn about what works and not, which biases are still present etc. It will allow us to build better tools for you in the future.

Out of 167 participants, 140 returned a completed on-line questionnaire (83.8%). Most of the questions were multiple choice (see supplementary material Section A) with many of the answers used in the following sections in the evaluation of the DPR experiment.

The questionnaire also included 5 free-format questions: (i) What suggestions do you have to improve the software?, (ii) What suggestions do you have to improve the assessment criteria and/or review process?, (iii) Do you have concerns about your proposals being evaluated through distributed peer review?, (iv) Do you have any further feedback or suggestions regarding distributed peer review?, and (v) Would you like to give any further feedback and/or suggestions regarding earlier raised points on securing confidentiality, external expertise, and robustness versus bias?

Each of the 5 free-form questions was answered on average by 50 persons with a sentence or more. The answers were very helpful in specific suggestions for improvement and to get an overall feedback as summarized in the main text).

6.7 Data Collection

The proposals were distributed to the participated on 8 October, 2018. The participants were given until Oct 25 (17 days) until the deadline to submit the reviews. At the time of the deadline 2 of 112 participants in the DearWoudr group and 3 of 60 participants in the OPC emulate group had not completed their reviews and were excluded from the further process (completion rate 97.1%). We received a total of 1336 reviews (from 167 reviewers for 172 proposals).

On 30 October the 167 remaining participants were given access to their evaluated proposals and were given two weeks to provide feedback. Of these, 136 (81.4%) completed the questionnaire.

We aim to allow further study of this dataset by the community. We also want to ensure the privacy of our participants and thus have anonymized and redacted some of the dataset. In particular, we have given the participants randomized IDs and only give some derived products from the DearWoudr machinery (we are not sharing properties knowledge vectors as they might allow the reconstruction of the individuals). In addition, we have removed any free text data the participants entered (such as the comments on the proposal). We have also removed all participants that did not reveal their gender. This is a very small number and might be used to de-anonymize individuals.

The anonymized dataset is available at https://zenodo.org/record/2634598.

7 Statements

Author Contributions: We use the CRT standard (see https://casrai.org/credit/) for reporting the author contributions:

• Conceptualization: Kerzendorf, Patat, van de Ven
• Data curation: Kerzendorf, Patat
• Formal Analysis: Kerzendorf, Patat
• Investigation: Kerzendorf, Patat
Methodology: Kerzendorf, van de Ven, Pritchard
Software: Kerzendorf, Bordelon
Supervision: Kerzendorf, Patat
Validation: Kerzendorf, Patat, van de Ven, Pritchard
Visualization: Kerzendorf, Patat, Pritchard
Writing original draft: Kerzendorf, Patat, Pritchard
Writing review & editing: Kerzendorf, Patat, van de Ven, Pritchard

Competing Interests: The authors declare no competing interests.

Data Availability: The anonymized data is available at https://zenodo.org/record/2634598.

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Supplementary Information
The Supplementary information is structured in the following way. In Section 8, we described the general process of ESO Time allocation. Section 9 gives an overview of the demographics of the experiment and discusses self-efficacy based on several criteria. Section 10 provides further analysis of the data. Appendix A gives the exact wording of the questions including some statistics. Appendix B provides additional statistics for the feedback survey.

8 Time allocation at ESO

ESO is an intergovernmental organization established in 1962, and runs one of the largest ground-based astronomical facilities world-wide. Every semester, about 900 proposals including more than 3000 distinct scientists from 50 different countries are submitted to ESO, requesting time on a large suite of telescopes: the four 8.2 m units of the Very Large Telescope (VLT), VISTA (4.2 m), 3.6 m, NTT (3.5 m), VST (2.6 m), and the Atacama Pathfinder Experiment (APEX), placed on three different sites in Chile. The total time request for Period 103 (the one relevant for the DPR experiment), was about 23 000 hours. The oversubscription rate varies with telescopes, and for the VLT is typically around 4 (a detailed oversubscription statistics can be found at https://www.eso.org/sci/observing/phase1/p96/pressure.html).

The proposal review process at ESO is extensively described in Patat & Hussain (2013), and is summarized in Patat (2018). The reader is referred to those publications for more details. Here only a very brief summary is given.

The members of the ESO TAC (the Observing Programmes Committee; OPC) who review the proposals are mostly nominated by the Users Committee, in turn composed by representatives of all member states. The nominations are reviewed by the OPC Nominating Committee, which makes a final recommendation to the Director General. As a rule, the panel members are required to have a minimum seniority level, starting with scientists at their second post-doc onward. The current implementation includes 13 Panels with 6 referees each, and cover the four scientific categories (Cosmology; Galaxy structure and evolution; Interstellar medium, Star formation and planetary systems; Stellar evolution). The panels are composed in such a way to maximize the expertise coverage (while also taking into account other constraints, like affiliations, gender, and seniority). Although some panels are created to cover special cases (e.g. interferometry), the proposals are distributed randomly within the panels of a given scientific category. Institutional conflicts are taken into account by the distribution software, while scientific conflicts are declared by the referees during the initial phases of the review.

The process is composed of two steps: 1) asynchronous at home, and 2) synchronous face-to-face. In the first step (which is called pre-meeting), the proposals are assigned to 3 referees, who are asked to review and grade the proposals using a scale from 1 to 5. The pre-meeting grades are used to compile a first rank list, and triage is applied to the bottom 30% (in time) for each telescope separately. At the meeting, the surviving proposals are discussed and graded by all non-conflicted members. The final rank lists per telescope are compiled based on the meeting grades, and the time is allocated following this final rank.

9 Demographics of the Experiment

The participants were asked to voluntarily give feedback and statistics about themselves and their experience in the experiment. We received this information from 140 out of 167 final participants.

Before Period 102 all non-conflicted members of a panel (up to 6) would review all proposals assigned to their panel. As of Period 102, in order to alleviate the work-load, this was reduced to 3.

Figure 5: Gender distribution of Principal Investigators comparing this work participants and the general community.

Figure 6: Career level distribution of Principal Investigators. We chose to plot the Patat (2016) postdoc fraction for both the “less than 4 years after PhD” and “between 4 and 12 years”. We chose the professional astronomer category to plot over the “more than 12 years” past PhD column.
Figure 5 and Figure 6 suggest that the self-selected participants of this study are representative of the ESO community at large. The PI gender distribution in the DPR experiment is 32.4% (F) and 67.6% (M), to be compared to the values derived from a sample of about 3000 PIs (Patat, 2016): 29.0% (F), 71.0% (M). In terms of scientific seniority, the DPR PIs are distributed as follows: 8.9% (no PhD), 18.3% (<4 years after PhD), 33.8% (between 4 and 12 years after PhD), 39% (more than 12 years after PhD). For the sample discussed in Patat (2016) the distribution is: 18.7% (PhD students), 33.9% (post-docs), 47.4% (senior astronomers). Although the two studies have a different seniority classification scheme, the overall comparison shows that the DPR includes a fair amount of junior scientists, properly sampling the underlying population.

We cannot guarantee that there are not specific attributes that lead our participants to self-selection, but if they exist they are well hidden.

Most participants are relatively experienced submitting proposals (see Figure 13). However, most of them have not served on a TAC (see Figure 7).

![Fraction of participants served on TAC](image)

Figure 7: Combined fractions from the feedback questions (see Section A) of Have you served on another time allocation committee? and How often have you been a panel member of the ESO Observing Programmes Committee (OPC)?

### 10 Supplementary Analysis

#### 10.1 Self-Efficacy

The DeepThought algorithm described in this work is built to predict domain expertise. However, domain expertise is not a measurable attribute of reviewers. A close approximator might be the self-reported domain expertise but this comes with its own biases when compared with an actual – but immeasurable – domain knowledge. Evaluating one’s ability to perform a task (in this case reviewing a proposal) is called self efficacy. We can use our dataset to study the self efficacy of our participants before moving onto testing the DeepThought algorithm against the self-reported expertise.

Seniority is expected to have an impact on expertise. Figure 8 shows that the self-reported domain expertise is significantly lower for junior scientists compared to senior scientists. Junior scientist, also often suggest that they have little to no knowledge about a field. This might suggests that self-reported knowledge is a useful proxy for actual knowledge.

![Expertise distribution](image)

Table 1: Bootstrapped DPR r-r QAM.

| 1st referee quartile | 2nd referee Quartile |
|----------------------|----------------------|
| 1                    | 0.33 0.26 0.24 0.18  |
| 2                    | 0.26 0.26 0.25 0.23  |
| 3                    | 0.24 0.25 0.25 0.26  |
| 4                    | 0.18 0.23 0.26 0.34  |

Huang (2013) is a large meta-study of academic self-efficacy and shows that women tend to under-predict their performance in certain STEM fields. Figure 8 suggests that in the domain of astrophysics, and for post-grad individuals, the difference between the self-efficacy of men and women is relatively small.

#### 10.2 Expertise influence on Review

An important question is whether expertise has an influence on the review process itself.

Statistics shows that experts take tentatively less time to review proposals than non-experts (see supplementary material for statistics).

We also study how expertise influences the grade distribution. Figure 9 shows that the difference in the shapes related to experts and referees with little to no domain knowledge is relatively small. The distributions show an extended tail towards poor grades, similarly to what is seen in Figure 4 of Patat (2018) for the large OPC sample.

In their study on the effects of reviewer expertise on the evaluation of funding applications, Gallo et al. (2016) concluded that "reviewers with higher levels of self-assessed expertise tended to be harsher in their evaluations". That study was based on a sample of 1044 reviewers, i.e. 6 times larger than ours. Although our data may contain some indication of this trend, the differences are statistically marginal.

#### 10.3 Influence of gender on helpfulness of referee report

We study if gender of the referee has an influence on the helpfulness of the comments in Figure 10 and find that there is no statistically significant difference between the helpfulness of comments by male and female referees. There were very few participants that used the option "prefer not to say" on the gender question (see Figure 5). We thus did not report the helpfulness statistics on those participants as the statistical noise is too large to draw conclusions.

#### 10.4 Comparison of DeepThought Distributed Peer Review to the Observing Progr

We will use the concept of the quartile agreement matrix (QAM) and related statistics as described in Section 3 of the main paper. We will present additional statistics such as individual referee comparison in this supplementary information.

We first compute the agreement fractions between pairs of sub-sets of reviews within the DPR sample. In a first test, for each of the 172 proposals we extract a random pair of reviews, which are then used to produce two rank-lists, from which the QAM is derived. The process is then repeated a large number of times, leading to the construction of an average QAM and the standard deviation matrix. Since this is constructed for simple reviewer pairs, we will indicate it as the referee-referee (r-r) QAM. The result is presented in Table 1 for the calibrated grades (very similar values are obtained using the raw grades). The typical standard deviation of single realizations is 0.06, while the uncertainty (using poisson statistics) on the average values is below 0.01.

The values are statistically indistinguishable from those reported in P18 (Table 2) for the OPC sample including ~15,000 proposals. This
shows that the average r-r agreement is identical in the two processes. On average, the ranking lists produced by two distinct referees have about 33% of the proposals in common in their first and last quartiles. This corresponds to a Cohen’s kappa coefficient κ=0.11 (Cohen, 1960).

In the central quartiles the intersection is compatible with a purely random selection. This extends to the mixed cases (i ≠ j), with the exception of the extreme quartiles: the fraction of proposals ranked in the first quartile by one referee and in the fourth quartile by another referee is ~18%, which deviates in a statistically significant way from the random value (κ = −0.28). No meaningful difference is seen in the QAMs computed for the OPC-Emulate (OE; 60 proposals) and Deep-Thought (DT; 112 proposals) sub-samples.

As a further test, we have investigated the possible dependence on the scientific seniority level. In the feedback questionnaire we asked the participants to express it in terms of the years after PhD, specified within 4 groups (0=no PhD; 1=less than 4 years; 2=between 4 and 12; 3: more than 12). Of the 167 reviewers, 136 provided this information, which we used to divide the reviewers in two classes: junior (groups 0 and 1) and senior (groups 2 and 3). These classes roughly correspond to PhD students plus junior post-docs (37), and advanced post-docs plus senior scientists (99). We then computed the r-r QAM for the two classes. The first quartile terms are 0.22 and 0.32 for the two classes, respectively. At face value this indicates a larger agreement between senior reviewers. However, the small size of the junior class (37 people) produces a significant scatter, and therefore we do not attach too much confidence to this result.

We have defined the panel-panel (p-p) agreement fraction in the main text (see Section 3). For the OE and DT sub-samples yield statistically indistinguishable values. Finally, the numbers derived from the bootstrap procedure fully agree with the results presented in P18 for different panel sizes. For N=1, 2, and 3 the first quartile agreement fractions are 0.34, 0.37 and 0.41, respectively. These match (within the noise) the corresponding P18 values (Table 8): 0.33, 0.39 and 0.45.

The conclusion is that, in terms of self-consistency, the DPR review behaves in the same way as the pre-meeting OPC process.

### 10.5 The DPR-OPC agreement fraction

As anticipated, the proposals used in the DPR experiment were also subject to the regular OPC review. This enables the comparison between the outcomes of the two selections, with the caveats outlined above about their inherent differences.
Table 2: DPR-OPC (pre-meeting) r-r QAM.

| DPR ref. quartile | OPC referee quartile |
|------------------|---------------------|
|                  | 1                   |
|                  | 2                   |
|                  | 3                   |
|                  | 4                   |

For a first test we used a bootstrap procedure in which, for each proposal included in the DPR, we randomly extracted one evaluation from the DPR (typically one out of 7) and one from the OPC (one out of 3), forming two ranking lists from which a QAM was computed. The operation was repeated a large number of times and the average and standard deviation matrices were constructed. This approach provides a direct indication of the DPR-OPC agreement at the r-r level, and overcomes the problem that the two reviews have a different number of evaluations per proposal (see below). The result is presented in Table 2. The typical standard deviation of single realizations from the average is 0.06.

This matrix is very similar to that derived within the DPR reviews (Table 1), possibly indicating a DPR-OPC r-r agreement slightly lower than the corresponding DPR-DPR. A check run on the two sub-samples for the junior and senior DPR reviewers (according to the classification described in the previous section) has given statistically indistinguishable results.

As explained in the introduction, the proposals were reviewed by \(N_r=3\) OPC referees in the pre-meeting phase. This constitutes a significant difference, in that the DPR ranking is typically based on \(\sim 7\) grades, whilst the pre-meeting OPC ranking rests on 3 grades only. With this caveat in mind, one can nevertheless compute the QAM for the two overall ranking lists.

The result (computed using calibrated grades) is presented in Table 3. At face value, about 37% of the proposals ranked in the 1st quartile by the DPR were ranked in the same quartile by the OPC, with a similar fraction for the bottom quartile. When looking at these values, one needs to consider that this is only one realization, which is affected by a large scatter, as one can deduce from the comparatively large fluctuations in the QAM. These are evident when comparing, for instance, to the average values obtained from the bootstrapping procedures described in the previous section; or considering that the average matrix is expected to be symmetric.

To quantify the expected noise on a single panel-panel realization, we have run a set of simulations along the lines described in P18, which are based on the statistical description of the reviewers and on the True Grade Hypothesis (see P18; Section 7 therein). For the purposes of this analysis we modified the original code to allow the calculation of the QAM for pairs of panels with different sizes. We emphasize that the P18 code was designed to simulate the OPC process, i.e. it deals with panels reviewing the same set of proposals which, in turn, are reviewed by all referees in the panels. It therefore does not fully reproduce the DPR side, in which each proposal is reviewed by a virtually different panel in the DPR sample. For this reason the results should be considered only as indicative. More sophisticated simulations will be presented elsewhere.

The outcome is presented in Table 4 (top), which also shows the standard deviation of the single realizations (bottom). For the DPR simulated panels we have used \(N_p=7\), which is close to the actual average number of reviewers per proposal in the experiment. For the OPC we have set \(N_p=3\). The numerical calculations predict a top and bottom quartile agreement of about 50%, while in the central quartiles this drops to about 30%. The statistical significance of the deviations of the observed QAM from the average QAM can be quantified using the predicted dispersion. For the first and fourth quartile, the observed value (0.37) differs at the 1.3\(\sigma\)-level from the average value. For the central quartiles the difference is at the 1.5\(\sigma\)-level.

Therefore, although lower than expected on average, the observed DPR-OPC agreement is statistically consistent with that expected from the statistical description of the pre-meeting OPC process (P18).

One important aspect to remark is that, given the large noise inherent to the process, a much larger data-set (or more realizations of the experiment) would be required to reach a statistical significance sufficiently high to make robust claims about systematic deviations.

### 10.6 Comparison with the post-meeting outcome

The fact that in the real OPC process there is a face-to-face meeting constitutes the most pronounced difference between the two review schemes. In the meeting, the opinions of single reviewers are changed...
by the discussion, so that the grades attributed by the single referees are not completely independent from each other (as opposed to the pre-meeting phase, in which the possible correlation should depend only on the intrinsic merits of the proposal).

The effects of the meeting can be quantified in terms of the quartile agreement fractions between the pre- and post-meeting outcomes, as outlined in Patat (2019, hereafter P19). Based on the P18 sample, P19 concludes that the change is significant: on average, only 75% of the proposals ranked in the top quartile before the meeting remain in the top quartile after the discussion (about 20% are demoted to the second quartile, and 5% to the third quartile). P19 characterizes this effect introducing the Quartile Migration Matrix (QMM). For the specific case of P103, the QMM is reported in Table 5 for the 683 proposals that passed the triage (top), and for the sub-set of the DPR experiment (bottom).²

As anticipated, the effect of the discussion is very pronounced. In the light of these facts one can finally inspect the QAM between the DPR and the final outcome of the OPC process. This is presented in Table 6. With the only possible exception of \( M_{4,4} \), which indicates a relatively marked agreement for the proposals in the bottom quartile, the two reviews appear to be almost completely uncorrelated. By means of simple Monte-Carlo calculations one can show that for two fully aleatory panels the standard deviation of a single realization around the average value (0.25) is 0.10. Therefore, the majority of the \( M_{i,j} \) elements in Table 6 are consistent with a stochastic process at the 1σ level.

The main conclusion is that while the pre-meeting agreement is consistent with the DPR and OPC reviewers behaving in a very similar way (in terms of r-r and p-p agreements), the face-to-face meeting has the effect of significantly increasing the discrepancy between the two processes. We remark that the sample is relatively small, and therefore the results are significantly affected by noise.

²Of the initial 172 proposals included in the DPR sample, 36 were triaged out in the OPC process.

### Feedback questionnaire

The following is the multiple choice questions that were presented to the participants in the questionnaire at the end of the experiment. The bold numbers after the multiple choice answers are the number of the participants that selected this answer.

A.1 What is your gender?
- Male 96
- Female 46
- Prefer not to say 5
- (no answer given) 0

A.2 How many years are you after your PhD?
- Negative; I don’t have my PhD yet. 12
- Less than 4 years 27
- Between 4 and 12 years 51
- More than 12 years 57
- (no answer given) 0

A.3 How many proposals have you submitted to ESO as PI in the past?
- None; this is my first proposal as PI. 0
- Less than 3 proposals 14
- Between 3 and 10 proposals 55
- More than 10 proposals 78
- (no answer given) 0

A.4 How often have you been a panel member of the ESO Observing Programmes Committee (OPC)?
- Never; I have not yet been on the OPC. 112
- I am currently OPC panel member. 3
- I served as OPC panel member for one term. 12
- I served more than one term on the OPC. 20
- (no answer given) 0

A.5 How easy was it to navigate and use the interface to review the proposals?
- Easy, no problems in usage 117
- Mostly easy; some improvements possible 28
- Rather difficult; some improvements needed 2
- Difficult; several problems in usage 0
- (no answer given) 0
A.6 How much time did you spend, on average, per proposal (including writing comments)?
- Less than 15 minutes 0
- Between 15 and 30 minutes 41
- Between 30 and 45 minutes 62
- Over 45 minutes 44
- (no answer given) 0

A.7 Was the time spent for proposals for which you are an expert versus a non-expert different?
- More time on proposals for which I am an expert 15
- About the same 62
- Less time on proposals for which I am an expert 69
- (no answer given) 1

A.8 How appropriate were the assessment criteria to evaluate the proposals?
- Fully appropriate; the criteria were clear and easy to apply 53
- Mostly appropriate; the criteria were clear but not easy to apply 73
- Somewhat appropriate; the criteria can be clarified but were applicable 18
- Not appropriate; the criteria should be changed 2
- (no answer given) 1

A.9 How satisfactorily were you able to evaluate the proposals for which you were a non-expert?
- Fully; I could evaluate well and fairly as a non-expert 3
- Mostly; I sometimes missed the expertise but was still able to evaluate fairly 53
- Somewhat; I struggled and might not always have been able to evaluate fairly 75
- Not satisfactorily; I might have unintentionally provided an unfair evaluation 16
- (no answer given) 0

A.10 How useful were the comments that you received on your proposal?
- Fully; overall the comments will allow me to improve my proposed project 17
- Mostly; several comments will help me to strengthen my proposed project 70
- Somewhat; some comments might help me to strengthen my proposed project 53
- Not useful; the comments will not help me to improve my proposed project 6
- (no answer given) 1

A.11 How clear and appropriate were the comments that you received on your proposal?
- Fully; overall the comments were clear and appropriate 36
- Mostly; some comments were not fully clear but mostly appropriate 72
- Somewhat; several comments were unclear or not fully appropriate 36
- Not; several comments were unclear and inappropriate 3
- (no answer given) 0

A.12 How do these raw comments compare to the edited comments from the OPC in the past?
- These raw comments were better; the OPC edited comments were less helpful. 62
- Of similar quality 66
- These raw comments were less helpful; the OPC edited comments were better. 18
- Not applicable; I have not received OPC edited comments before. 1
- (no answer given) 0

A.13 For which types of proposals do you think distributed peer review would be beneficial? (multiple answers possible)
- Short proposals, with total requested time less than 20 hours 0
- Regular proposals, with total requested time between 1 and 100 hours 0
- Large proposals, with total requested time more than 100 hours 0
- None 0
- (no answer given) 4

A.14 The ESO Time Allocation Working Group recommended to introduce in addition to the existing calls for proposals a 'Fast Track' channel with a fraction of the time allocated through (two) monthly calls. If implemented, would distributed peer review be appropriate for this time allocation? (multiple answers possible)
- I would support distributed peer review being used for the 'Fast Track' calls. 105
- I have concerns with distributed peer review being used for the 'Fast Track' calls. 23
- I am indifferent. 19
- (no answer given) 0
A.15 Securing confidentiality in the process:

- I am neither more nor less concerned about confidentiality issues in the DPR process than in the OPC process. 73
- I am more concerned about confidentiality issues in the DPR process than in the OPC process. 42
- I am less concerned about confidentiality issues in the DPR process than in the OPC process. 8
- I have no strong opinion on this point. 24
- (no answer given) 0

A.16 External expertise in the review process:

- I think that the pool of eight peer reviewers (including some non-experts) are sufficient to assess the proposals. 43
- I think that the pool of eight peer reviewers are sufficient to assess the proposals, provided that they have some expertise in the field. 73
- I think that external experts (non-ESO facility users) are critical to the assessment of the proposals and must be added as reviewers. 22
- I have no strong opinion on this point. 8
- (no answer given) 1

A.17 Robustness of the review process against any biases:

- I think that DPR review process is as robust against biases as the OPC review process. 38
- I think that DPR review process is more robust against biases than the OPC review process. 39
- I think that DPR review process is less robust against biases than the OPC review process. 25
- I have no strong opinion on this point. 43
- (no answer given) 2

B Feedback questions statistics and overview

Statistics figures of the feedback overview.

Figure 11: The referee was asked the question What is your gender?

Figure 12: The referee was asked the question How many years are you after your PhD?

Figure 13: The referee was asked the question How many proposals have you submitted to ESO as PI in the past?
Never; I have not yet been on the OPC. I served as OPC panel member for one term.

I served more than one term on the OPC. I am currently and OPC panel member.

Figure 14: The referee was asked the question *How often have you been a panel member of the ESO Observing Programmes Committee (OPC)?*

0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Never; I have not yet been on the OPC.
I served as OPC panel member for one term.
I served more than one term on the OPC.
I am currently and OPC panel member.

Figure 16: The referee was asked the question *How easy was it to navigate and use the interface to review the proposals?*

0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

Easy, no problems in usage
Mostly easy; some improvements possible
Rather difficult; some improvements needed

Figure 15: The referee was asked the question *Have you served on another time allocation committee?*

0.0
0.1
0.2
0.3
0.4

This is my first experience reviewing observing proposals.
I have served on a time allocation committee before.
I have served on multiple time allocation committees for various facilities

Figure 17: The referee was asked the question *How much time did you spend, on average, per proposal (including writing comments)?*
Figure 18: The referee was asked the question *Was the time spent for proposals for which you are an expert versus a non-expert different?*

Figure 19: The referee was asked the question *How appropriate were the assessment criteria to evaluate the proposals?*

Figure 20: The referee was asked the question *How satisfactorily were you able to evaluate the proposals for which you were a non-expert?*

Figure 21: The referee was asked the question *How useful were the comments that you received on your proposal?*
Figure 22: The referee was asked the question *How clear and appropriate were the comments that you received on your proposal?*

Figure 23: The referee was asked the question *How do these raw comments compare to the edited comments from the OPC in the past?*

Figure 24: The referee was asked the question *For which types of proposals do you think distributed peer review would be beneficial?*

Figure 25: The referee was asked the question *The ESO Time Allocation Working Group recommended to introduce in addition to the existing calls for proposals a ‘Fast Track’ channel with a fraction of the time allocated through (two) monthly calls. If implemented, would distributed peer review be appropriate for this time allocation?*
I am less concerned about confidentiality issues in the DPR process than in the OPC process.

I am neither more nor less concerned about confidentiality issues in the DPR process than in the OPC process.

I am more concerned about confidentiality issues in the DPR process than in the OPC process.

I have no strong opinion on this point.

Figure 26: The referee was asked the question *Securing confidentiality in the process:*

I think that the pool of eight peer reviewers are sufficient to assess the proposals, provided that they have some expertise in the field.

I think that the pool of eight peer reviewers (including some non-experts) are sufficient to assess the proposals.

I think that external experts (non-ESO facility users) are critical to the assessment of the proposals.

I have no strong opinion on this point.

Figure 27: The referee was asked the question *External expertise in the review process:*

I think that DPR review process is more robust against biases than the OPC review process.

I think that DPR review process is as robust against biases as the OPC review process.

I think that DPR review process is less robust against biases than the OPC review process.

I have no strong opinion on this point.

Figure 28: The referee was asked the question *Robustness of the review process against any biases:***