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Analysing Sentiments in Peer Review Reports: Evidence from Two Science Funding Agencies

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Abstract

Using a novel combination of methods and datasets from two national funding agency contexts, this study explores whether review sentiment can be used as a reliable proxy for understanding peer reviewer opinions. We measure reviewer opinions via their review

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sentiments both on specific review subjects and on proposals' overall funding worthiness with three different methods: manual content analysis and two dictionary-based sentiment analysis algorithms (TextBlob and VADER). The reliability of review sentiment to detect reviewer opinions is addressed by its correlation with review scores and proposals' rankings and funding decisions. We find in our samples that 1) review sentiments correlate with review scores or rankings positively, and the correlation is stronger for manually coded than for algorithmic results; 2) manual and algorithmic results are overall correlated across different funding programmes, review sections, languages, and agencies, but the correlations are not strong; 3) manually coded review sentiments can quite accurately predict whether proposals are funded, whereas the two algorithms predict funding success with moderate accuracy. Results suggest that manual analysis of review sentiments can provide a reliable proxy of grant reviewer opinions, whereas the two SA algorithms can be useful only in some specific situations.

Key words

peer review; evaluation report; sentiment analysis; science funding.

1. Introduction

Expert reviewers are central to peer review. Based on their recommendations, scientific journals select manuscripts to publish, hiring committees select faculty to hire, and funding agencies select grant proposals to fund. The latter case, grant peer review, is of special interest as reviewers are asked to assess scientific work that has not yet been performed. Even though grant review procedures can involve a large number of steps to ensure the

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objectivity and fairness of funding decisions, the literature still points to the lack of reliability and transparency in grant review mechanisms (Cicchetti, D. 1991; Pier, Brauer, et al., 2018).

In addition to the many cognitive and social complexities of peer review, the difficulty of obtaining data about peer review processes makes it a difficult topic to study empirically (Squazzoni, Ahrweiler, et al., 2020), further contributing to its opacity. The objective of this paper is to demonstrate how the analysis of review sentiment can supplement our understanding of reviewer opinions both on specific review subjects in the evaluation process and on proposals' overall funding worthiness. To do so, we analyse a corpus of peer review texts and related documents from two national science funding agencies, Science Foundation Ireland (SFI) and the Swiss National Science Foundation (SNSF). We identify and extract reviews of individual subjects and interpret sentiments of the extracted reviews in two ways: (1) manual coding based on content analyses and (2) two dictionary-based algorithms, TextBlob and VADER (Loria, Keen, et al., 2014; Hutto, & Gilbert, 2014). We compare the coding results from the different methods and calibrate the results with other types of data in grant review contexts, such as review scores, rankings and funding decisions of proposals.

We analyse review reports to address three empirical research questions as three dimensions of the reliability of review sentiments to be used in peer review research. First, we ask whether the sentiments of review texts correlate with the review scores. Second, we explore whether automated sentiment analysis (hereafter: SA) of review texts performs similarly to the manual analysis result, usually used as a benchmark for algorithmic tools (Turney 2002). Third, we address whether review sentiments can accurately predict the proposals to be funded or not.

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Our empirical results demonstrate that 1) review sentiments correlate with scores or rankings positively, and the correlation is stronger for manually coded than for algorithmic results; 2) manual and algorithmic results are overall correlated, but the correlations are not strong; 3) manually coded review sentiments can quite accurately predict proposals' funding decisions, whereas the accuracy of the two SA algorithms is moderate. These findings suggest that review sentiments, especially the manually coded sentiments, can be used as a reliable proxy of reviewer opinions in peer review research while the two SA algorithms can be useful in specific situations. To begin with, the following literature review will guide us to understand what characterises grant reviewer opinions and processes, and how reviewer opinions can be measured.

2. Characteristics of grant reviewer opinions

2.1. Reviewer opinions as a processual element of communication

Funding agencies organise peer review very deliberately with multiple review stages, different types of experts, and various evaluation criteria (Hartmann, & Neidhardt, 1990; Reinhart, 2010; Langfeldt, & Scordato, 2016; Schendzielorz, & Reinhart, 2020). As a result, peer review decisions are part of a complex social process in which meaning making and negotiation between multiple actors play a central role (Hirschauer, 2010; Lamont, 2010; Mallard, Lamont, & Guetzkow, 2009).

Central to this process are peer reviewer opinions. A typical grant review process comprises a postal review stage, also called an independent, remote, or postal panel followed by a collective panel review stage, or a sitting panel. These two stages are adopted by many

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funders including the two funders studied in this paper, SFI and SNSF, the U.S. National Institutes of Health (NIH) (Pier, Brauer, et al., 2018), and the European Research Council (ERC) (Van den Besselaar, Sandström, & Schiffbaenker, 2018). Postal review is conducted first by peer experts who, independently of one another, review an assigned proposal. Reviewers communicate their opinions via (often semi-structured) textual reviews to collective panels which synthesise the individual reviews and rank the proposals within competing pools to make their funding recommendations. Finally, agencies base their final funding decisions on the ranking provided by the panel, along with other considerations such as organisational goals, policy objectives, and available budget. Reviewers may even anticipate such considerations, e.g., by overly emphasising criticism or praise (Reinhart, 2010). Therefore, while postal peer reviewer opinions on individual proposals are one (early) processual element of communication in the grant review process, they are often reserved for later uses in the process.

In our study, we analyse the review reports from the postal review stage. In most cases including SFI and SNSF, postal reviewers cannot update or revise their reviews after submission, nor can they interact with other reviewers or applicants during their individual evaluation process. Thus, postal reviews serve as a one-way transformation of reviewer opinions into a standardised format comprising *texts* and *scores*, typically structured following the review guidelines set by the agency.

2.2. Two carriers of reviewer opinions: texts and scores

Review texts can be a few words, sentences, or paragraphs. They can be written in a structured way in a form requested by agencies (for instance, via a checklist of evaluation

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criteria or a section-separated review report) or organised by reviewers themselves based on their interpretations of the guidelines and own (epistemological and writing) styles (Reinhart, 2010). Before giving their overall judgement of the proposals' funding worthiness, reviewers are usually asked to comment on and grade the individual review subjects set by the agency, such as scientific excellence and non-scientific impact. Each subject can be assessed and graded separately from others via section-separated review reports (e.g., in SFI, some panels in SNSF, and EU H2020 programmes (European Commission, 2015)) or, assessed distinctly but without separate grades for the overall score of each proposal (e.g., some panels in SNSF and some programmes in the U.S. National Science Foundation, NSF). In the case of section-separated forms, reviewer evaluations on individual subjects can also be aggregated into one overall review, for example by taking the mean of the review scores, or by commenting on a proposal as a whole. Aggregation is usually done by the reviewers themselves when they are asked to provide one overall review for each proposal. For review scores specifically, this can also be done by the agency as a way to summarise a multifaceted review into one overall score.

With respect to scores, many agencies design their postal review reports to supplement the textual reviews with categorised grading scales and provide reviewers with labels and explanations of the scales for them to use (Langfeldt, & Scordato, 2016). For instance, SFI and many EU programmes use a 5-point grading scales (1=*poor*, 5=*excellent*); SNSF uses 6-point scales (1=*schlecht/bad*, 6=*sehr gut/very good*), and the NIH uses 9-point scales (1=*exceptional*, 9=*poor*).

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Review scores are a very convenient source of data for research on peer review. For one, they are more amenable to statistical analysis whereas review texts require more interpretative work. Much of the existing literature on peer review thus focuses on scores rather than texts. For instance, variation in scores is often used as a measurement of reviewers' disagreement and inter-reviewer reliability (Cicchetti, 1991; Obrecht, Tibelius, & D'Aloisio, 2007; Fogelholm, Leppinen, et al., 2012; Pier, Raclaw, et al., 2017; Pina, Buljan, et al., 2021). However, people with similar or even identical underlying views of proposals may express their opinions using a different grade due to reviewers' different interpretations of the grading scales (Cole, Cole, & Simon, 1981). This issue is called "grading heterogeneity" (Morgan, 2014). Also, different reviewers might use the same grade despite having different underlying views of the same proposal. Both cases can colour our understanding of reviewers' consensus or disagreement if one looks at scores only.

Fewer studies on peer review focus exclusively on review texts (Reinhart, 2010; Kretzenbacher, 2017; Ma, Luo, et al., 2020); even fewer explored both. Pier, Brauer, et al. (2018) compared (simulated) NIH panel reviewers' scores and texts and found the numbers of strengths and of weaknesses reported in the review texts did not generally agree with the scores. Van den Besselaar, Sandström, and Schiffbaenker (2018) studied the linguistic characteristics of ERC review texts (e.g., length and frequency of positive and negative emotions) in relation to the corresponding review scores and funding decisions. They found negative reviews had a stronger effect on the panel scores confirming earlier work that suggested negative comments are significant in breaking the overall positive tone of review texts (Reinhart, 2010).

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2.3. Sentiment as a proxy of reviewer opinions

Sentiment analysis (SA) is the computational treatment of subjectivity in a given text in order to classify this textual opinion as positive, negative, or neutral (Turney, 2002). SA is a common method for the estimation of opinions and emotions in a variety of domains such as online reviews of commercial products or services and in research areas (e.g., psychology, philosophy, sociology) (Liu, 2010). In this regard, peer review texts in research evaluation are similar to other types of reviews and can be analysed by SA tools.

Scholars have examined review sentiments in linguistic studies of grant reviews (Kretzenbacher, & Thurmair, 1992, 1995; Van den Besselaar, Sandström, & Schiffbaenker, 2018; Buljan, Garcia-Costa, et al., 2020), in bibliometric studies of literature review citation (Zhang, Ding, & Milojević, 2013; Yan, Chen, & Li, 2020), and in altmetrics of scientific articles (Liu, & Fang, 2017; Hassan, Aljohani, et al., 2020). These studies either rely on purely qualitative linguistic methods or use algorithmic methods and manual annotations without assessing the reliability of the algorithmic methods. The generalisability of results from existing studies is limited in at least two ways: first, multi-method designs that use more than one type of data are rare; second, comparative studies that apply their research questions and methods across different organisational and policy contexts are non-existent to our knowledge. In light of the variability and complexity of grant review procedures at different agencies (Schendzielorz, & Reinhart, 2020), several issues remain overlooked, e.g., how review scores are contextualised with textual reviews, and how high and low funding rates may affect reviewers' assessments as well as agencies' use of reviewer opinions.

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The ways in which peer reviews are written make them amenable to automated SA methods since dictionary-based SA algorithms are at less of a disadvantage when classifying texts that, like scientific reviews, are written in a formal and straightforward language, with relatively scarce use of harder-to-classify figures of speech such as metaphors, antiphrasis, sarcasm, etc. Scientific reviews tend to be longer and more detailed than other types of reviews and require professional experience to understand scientific and technical details. Yet, they are generally written without hidden meaning or nuance as reviewers' overall opinions on whether to recommend a paper be published or a proposal be funded often need to be written in lay language for sometimes non-specialist decision-makers. Earlier studies on SNSF and SFI review data show that grant review texts are written in direct and factual language. Despite some use of technical jargon, the choice of words to describe the (de)merits of the evaluated proposals are mostly colloquial and refrain from concealing the evaluative meaning (Reinhart, 2010).

In addition, the accuracy of algorithmic SA results is often measured by how well the results agree with human analysers. The existing peer review literature that addressed review sentiment, to our knowledge, relies on either manual or algorithmic methods without testing or calibrating their accuracy and reliability against each other. Our study is novel in that we apply both manual and algorithmic coding approaches consistently across different funding programmes, review sections, languages, and agencies, as well as across different units of analysis, and then compare the results.

3. Research design, methods, and research questions

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Funding agencies apply their own review procedures and criteria (Langfeldt, & Scordato, 2016), leading to very different characteristics and forms of review data that can be very difficult to compare explicitly. Our research is designed to incorporate the different forms of data that were shared by SFI and SNSF, especially the structure of review reports. Standardised section-separated review reports where each section represents one subject to be commented upon (such as impact) makes it easy to extract review texts on specific subjects. We call these "section-level reviews". In the case of non-standardised review reports, manual analysers extract and code individual statements on particular subjects. We call these "statement-level reviews". Both section-level and statement-level reviews extracted from review reports represent reviewer opinions on individual subjects and are considered as two different units of analysis in this study.

We apply manual and two algorithmic coding tools to measure sentiments of extracted reviews. Five human analysers in the team read, interpreted, and coded textual reviews into one of five sentiment categories: very negative (-1), moderate negative (-0.5), neutral (0), moderate positive (0.5), and very positive (1). This five-point category was expanded from the three frequently used categories of sentiments (negative, neutral, and positive) to be more accurate by separating "very" or "moderate" degrees. This five-point scale is also compatible with the actual grading scales applied by SFI where 1 indicates "very bad" to 5 for "outstanding". We conducted manual coding of section-level reviews from standardised review reports at SFI and some SNSF cases. All manually coded reviews were independently coded by two team members. Internal training and a pilot exercise ensured a satisfactory level of inter-coder reliability. All instances where the two coders disagreed were resolved through

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discussion. We also re-utilised the manual coding results of statement-level reviews from the same SNSF pools conducted ten years ago (Reinhart 2010).

Two open-source SA algorithms were applied: TextBlob (Loria, Keen, et al., 2014) and VADER (Valence Aware Dictionary and sEntiment Reasoner—Hutto, & Gilbert, 2014), both from the NLTK.org (Natural Language Toolkit) library for Python 3.x (Loper, & Bird, 2002). Both algorithms rely on pre-trained dictionaries where each word is assigned a sentiment weight based on the sign and intensity of its emotion. The sentiment of a text (such as a review) is then the sum of the weights of its words. Sentiment scores range between -1 (the most negative) and +1 (the most positive). Although more sophisticated tools for SA have emerged in the literature (e.g., BERT, see Devlin, Chang, et al. 2019), here we focus on intuitive dictionary-based algorithms to make the point that even simple and accessible tools for SA might have sufficient validity to be useful additions to the peer review research.

In Table 1, we summarise how we use these approaches with our empirical data to explore three research questions.

Data	*Source*	*For each proposal*	*For each review section*	*Manual content analysis*	*SA: TextBlob, VADER*[2]	*Ranking of proposals*	*RQ1*	*RQ2*	*RQ3*
Review scores[3] *(from the reviewers)*	SNSF	✓	✓			Ranking by review scores	•		
Review texts	SNSF/ SFI	✓	✓	✓	✓	Rankings by	•	•	•

[2] VADER dictionary is only supported for the English language. As explained in the next section, one of the two datasets (SNSF) contains review texts in several languages, so not all reviews could be assigned a VADER sentiment score.

[3] In a few instances, SNSF reviewers only commented but did not grade, and the officer graded instead based on the review texts. In this study we assume all scores came from reviewers.

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(from the reviewers)						sentiment scores: manual, TextBlob, and VADER			
Funding decision *(from the agency)*	SNSF/ SFI	✓							•

Table 1 Research design and three research questions.

RQ1: Do review sentiment scores correlate with review scores?

When review scores are available, such as in the SNSF case, section-level review sentiments can be compared with section-level scores to explore similarities and differences between the two carriers of reviewer opinions: texts and scores. Such similarities/differences can also be used to measure the consistency between reviewing and grading behaviours of either one single reviewer or multiple reviewers evaluating the same proposals. A correlation analysis between review scores and sentiment scores is a straightforward way to measure such consistency: The stronger the correlation is, the higher the consistency between the variables. We use Spearman's rank correlation coefficient because the review score data is ordinal (1=*bad*, 6=*very good*). We explore further the correlation between review sentiments and scores under groups of different disciplines, review sections, languages etc.

When review scores themselves are not available for study but the proposals' rankings by review scores are (which is the case for SFI data), we instead compare the similarity between two types of ranking positions of the proposals: actual ranking based on review scores and sentiment ranking based on sentiment scores. We use the Spearman rank correlation

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coefficient to measure the similarity between the two types of rankings. A stronger correlation indicates a higher similarity between the two types of rankings.

RQ2: Do algorithmic SA results correlate with manually coded sentiment scores?

Human coders do not act like algorithms that count words and attribute valency based on a pre-defined lexicon; instead, they interpret reviewer opinions using knowledge and awareness of context. As a rule of thumb, an achievement of 70% similarity in replicating manual classifications is often considered an acceptable performance (Turney, 2002). Therefore, if our algorithmic results suggest a satisfactory correlation to manual analysis across different subjects and units of analysis, the reliability of some quick and low-cost SA algorithms for peer review studies is supported.

RQ3: Can review sentiment scores predict funding decisions?

Focusing next on proposals as the unit of analysis, we ask how strong the links are between proposals' review sentiments, measured by the review texts, and their funding decisions (awarded or rejected) made by agencies. If the links are strong, we infer that review sentiment works as a reliable proxy of reviewer opinions to predict proposals' funding worthiness. To explore this question, we label each proposal (1) as either "awarded" or "rejected"; (2) as either "relatively positive" or "relatively negative". By "relatively positive/negative", we refer to the sentiment score for each proposal (assigned by aggregating all the review sentiments it received). As funding decisions are usually made upon the relative rather than absolute (perceived) merits of proposals, we rank proposals based on their review sentiment scores from the highest (the most positive) to the lowest (the most negative). We classify the top-ranking proposals as "relatively positive" group, and the bottom-ranking as "relatively

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negative"[4], and the threshold line between the two groups is the funding rate of the programme.

Ideally, awarded proposals should have received "relatively positive" reviews, whereas rejected proposals should have received "relatively negative" reviews. A standard way to investigate the agreement between two dichotomous variables is a confusion matrix like the one depicted in Table 2 (Kohavi, & Provost, 1998). Thus, we construct a confusion matrix for each set of proposals in the same competition pool.

	Review sentiment	
	Relatively positive	Relatively negative
Proposal awarded	TP: True positive scenario	FN: False negative scenario
Proposal rejected	FP: False positive scenario	TN: True negative scenario

Table 2 A confusion matrix captures the relationship between (binary) review sentiment and proposals funding decisions.

The literature offers several standard metrics calculated on the confusion matrix to measure the predictive power of the model (Kohavi, & Provost, 1998). The metrics we borrow include: accuracy, precision (i.e. positive predictive value), recall (also known as sensitivity), F1 score (harmonic mean of precision and recall), and negative predictive value, as shown below. Here we use these metrics for each of the three sentiment estimation methods to measure their reliability in predicting proposals' funding worthiness based on review sentiments. High values on these metrics indicate that review sentiments can provide a reliable proxy of grant reviewer opinions on proposals funding worthiness.

$$\text{Accuracy} = (TP + TN)/(TP+TN+FN+FP)$$

$$\text{Precision} = TP/(TP+FP)$$

[4] Note that there were ties in the ranking (e.g., when two reviews have the same sentiment scores). All proposals that tie for the ranking position that sets the threshold between "relatively positive" and "relatively negative" are treated as "relatively positive".

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Recall = TP/(TP+FN)
F1 Score = (2×Precision×Recall)/(Precision+Recall)
Negative Predictive Value = TN/ (TN+FN)

To summarise our design, we use manual content analysis and two different SA algorithms on textual reviews to interpret reviewer opinions on individual subjects and overall proposals' funding worthiness. We test the reliability of review sentiment as a relatively new proxy of reviewer opinions by addressing three empirical questions using peer review reports and other data from two agencies: SFI and SNSF. The next section will explain the characteristics of our empirical datasets.

4. Empirical data characteristics

Our empirical dataset contained peer review reports from three funding programmes: two from SFI, Industry Fellowship (SFI:IF) and Investigators Programme (SFI:IvP), and one from SNSF (abbreviated as SNSF) that was also investigator-driven. The analysed documents for the three programmes included publicly accessible call documents and evaluation guidelines as well as confidential peer review reports, proposals' rankings and funding decisions. The three programmes had a similar review process where proposals were first evaluated by postal peer reviewers, the reviews synthesised to rank competing proposals, and then discussed in a panel. This panel makes funding recommendations for each proposal as awarded or rejected which the agency might follow or not. As a reminder, our study focuses on postal reviews to explore independent reviewer opinions.

All SFI and SNSF reviews were redacted by the agency (SFI) or during data curation (SNSF) to de-identify individuals, organisations, or specific research areas. Such redaction was

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irrelevant for the sentiment estimation by both humans and the SA algorithms, because it does not affect the key parts of a sentence that carry reviewers' judgments. Both agencies averaged the review scores from individual review sections and from multiple reviewers to obtain an overall score for each proposal. SFI and SNSF applied slightly different grading scales: 1-5 for SFI, 1-6 for SNSF. In both cases, higher scores indicate better quality. All SFI reviews were written in English. For SNSF reviews, we examined those written in the three languages: English (29% of the total), German (38%), and French (34%)[5].

The three programmes (SNSF, SFI:IF, SFI:IvP) differed in their organisational mandates, target applicants, and disciplinary areas. Furthermore, SFI applied standardised three-section structured review reports where each section represented one review subject (applicants, proposed research, and potential for impact). This allowed us to estimate sentiments at the level of individual review sections. By contrast, SNSF review reports covered seven subjects (scientific impact, originality, suitability of methods, feasibility, experience and past performance, specific abilities, and other comments) but did not always apply structured review reports. For the relatively small pool of SFI:IF proposals, only one comprehensive panel was organised by SFI each year to review proposals from different disciplines. We were provided with SFI:IF reviews from years 2014-2016 as three independent pools. For SFI:IvP and SNSF, different disciplinary panels were always organised in one year as independent competing pools. We were provided with the review reports from four different disciplinary panels of SFI:IvP in 2016 (all in STEM fields) and three panels of SNSF including Humanities and Social Sciences (see Table 3). SNSF review data comprised the funding decision for each

[5] We excluded from our dataset two SNSF reviews that were written in other languages not supported in the SA algorithms.

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proposal, their review texts, and scores from which we reconstructed the ranking by review scores (Table 1). By contrast, SFI data comprised funding decisions, review texts, and ranking by review scores, but not the scores themselves.

The sizes and funding rates of the competing pools were consistent within the same programmes but varied across programmes (see Table 3). Overall, 527 section-separated review reports from SFI and 125 from SNSF were shared to us and analysed, totalling to 2456 section-level reviews (527×3+125×7) coded by both manual analysers and algorithmic SA tools. The scale, proportion of our dataset in the pool, and composition of the reviews by programme, year, language, and disciplinary panel are presented in Table 3. The datasets shared by SFI and SNSF were randomly selected while the SFI sample was stratified by funding decisions: approximately 50% awarded and 50% declined.

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Programme	Year	No. of reviews	Proportion of dataset	Funding rate	Review Language	Disciplinary Panel
SFI:IvP	2016	261	35%	49%	English:100%	A) Communications, Engineering, Computer Science, Mathematics, and Geoscience; B) Materials and Chemistry; C) Life Sciences-Human Health; D) Life Sciences-Microbiology, Agriculture, Ecology, Biomarkers of Disease.
SFI:IF	2014-2016	266	46%	50%	English:100%	One comprehensive panel in each year.
SNSF	1998 or 2004[6]	125[7]	18%	71%	English:28.8% French: 33.6% German:37.6%	E) Humanities and Social Sciences; F) Mathematics, Natural and Engineering Sciences; G) Biology and Medicine.

Table 3. Overview of section-separated review samples analysed in this study.

Lastly, we conducted the algorithmic SA of the 9532 SNSF statement-level reviews and compared the result with the manual content analysis of the same dataset from a previous study (Reinhart, 2010). These statement-level reviews were manually coded segments of review texts from unstandardised SNSF review reports, so they did not overlap with section-level reviews. Coding was guided by a qualitative coding scheme containing 22 typical research evaluation subjects, such as "originality" or "methods" (Ibid.). On average, each review has 14.2 statements, and each statement represents a reviewer opinion on one specific subject. Most of the statements are short review segments (e.g., "*This is a small but competent team with a substantial record of achievement*"). We excluded those very short segments with fewer than three words, such as "his previous work", and fed the relatively complete 9532 reviews to the two SA algorithms.

[6] 1998: panels E and F; 2004: panel G.

[7] Unstandardised SNSF reviews (i.e. not section-separated) were excluded for some of our analyses.

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5. Results

First, we examine the descriptive statistics of the sentiment scores obtained from three different methods (manual coding, TextBlob, and VADER) for each of the three programmes (SFI:IF, SFI:IvP, and SNSF). Figure 1 shows the distribution of sentiment scores on section-level reviews—the box plots partition each distribution into quartiles. Review scores (dark red boxplots) were known for SNSF only. Overall, some general differences in the distribution of sentiment scores across the three methods can be observed. Manual coding results show greater variability from "most negative" all the way up to "most positive": This can be seen in the vertical span of the distribution (blue violins) and of their boxplots (i.e., the interquartile range). By contrast, the SA algorithmic results are always above the "neutral" mark, and TextBlob scores (green) show the least variability.

Review sentiments of different sections (within each programme and produced by the same method) can be compared to address reviewer opinions and disagreement with respect to individual subjects. For instance, reviewer opinions on "proposed research" are overall less positive and more variable than their opinions on "applicant" in the two SFI programmes. This is consistent with previous work where it was found that SNSF reviewers generally made more positive remarks about applicants (experiences, abilities) and more negative remarks about the properties of the projects (originality, methods) (Reinhart, 2010).

Furthermore, some SNSF review sections received on average a lower review score (dark red) than other sections (e.g., "originality" and "suitability of methods"). This indicates that reviewers might have a higher bar for grading on those subjects. Such differences across subjects are better captured by manual coded sentiments than the algorithmic results. In the

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appendix we also show that, similarly, disciplinary and language differences are captured better by manual coding than by algorithms (Appendix Figures A1, A2).

In the next sections (5.1 to 5.3) we examine the three research questions sequentially. Note that our results are reported at three levels of analysis: (1) the individual review sections; (2) the reviews as a whole aggregated from separated sections; and (3) the individual statements from not-section-separated reports. Our results for the three research questions are generally consistent across these three levels.

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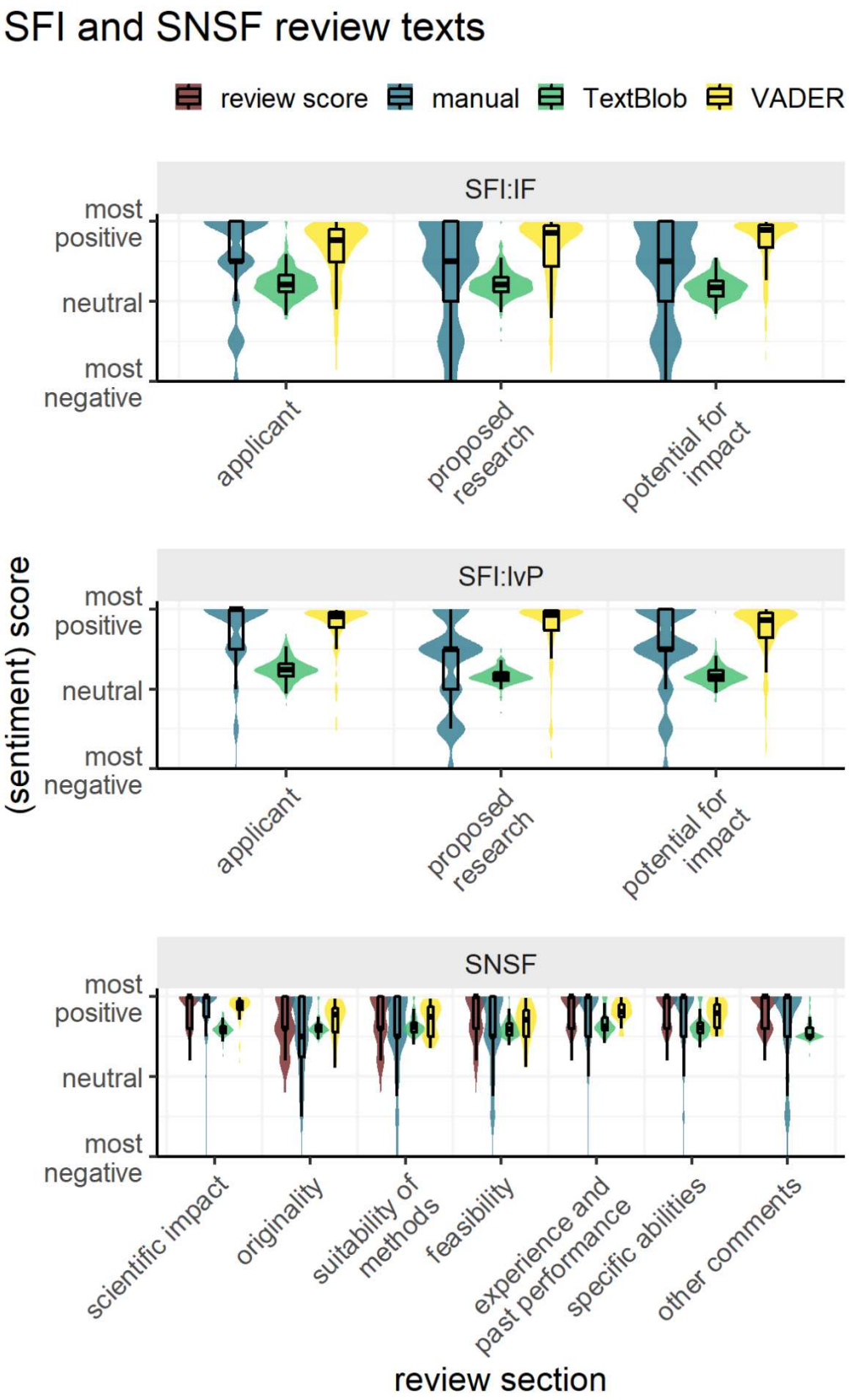

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Fig 1. Violin plots and boxplots showing the distribution and quartiles of section-level review scores and review sentiments obtained from the three methods (manual, TextBlob, VADER) for the three programmes (SFI:IF, SFI:IvP, SNSF).

5.1. Do review sentiment scores correlate with review scores?

We started by examining the correlation between SNSF review scores and sentiment scores in each of the six review sections[8]. Fig 2 shows regression lines between the scores assigned by reviewers (X axis) and the sentiment scores obtained from manual coding, TextBlob, and VADER (Y axis). Overall, manually coded sentiments (blue) correlate positively with review scores for all the sections, and some sections (e.g., feasibility) show stronger correlation than others (e.g., specific abilities). Both algorithmic SA results correlate poorly with review scores.

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[8] We excluded the seventh section "*other comments"* because many reviewers did not comment. In such cases, the overall review score was averaged from the six sections.

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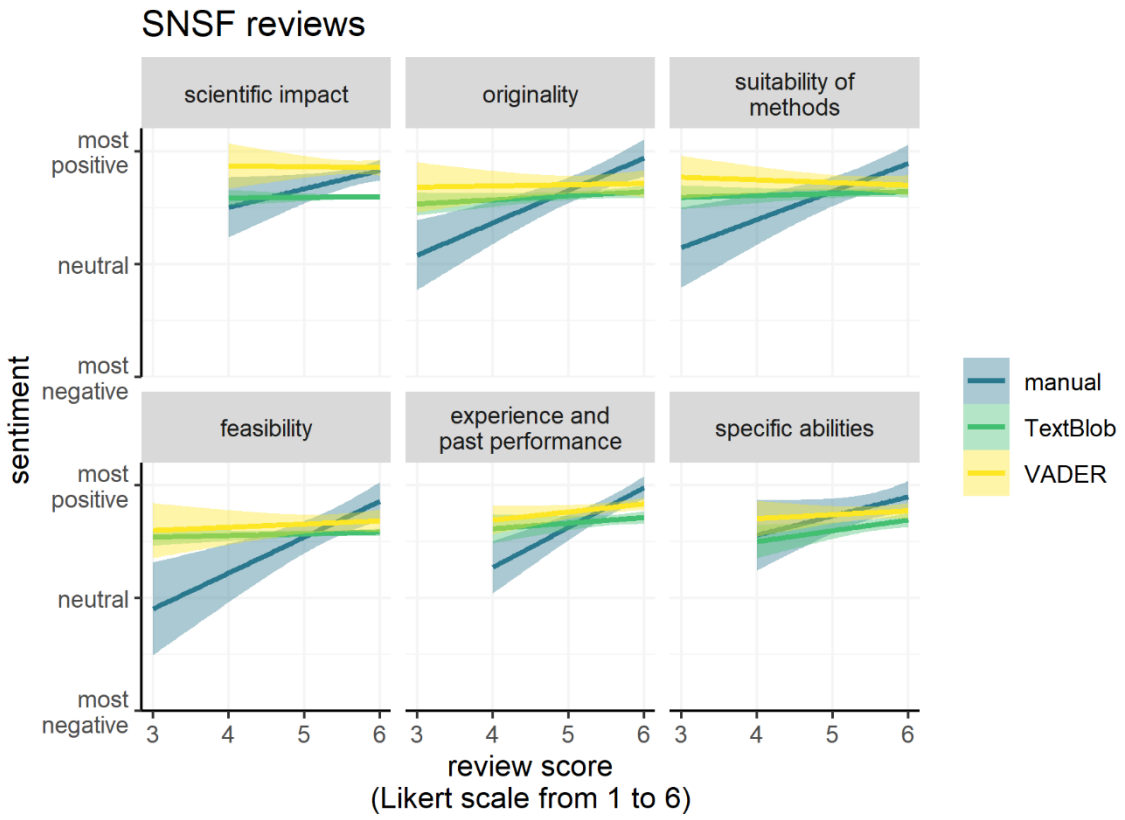

Fig 2. Linear regression to compare SNSF section-level review scores and sentiment scores produced by three methods.

Confidence interval: 95%.

To examine these correlations more closely, we then calculated the Spearman rank correlation coefficients between the SNSF review scores and sentiment scores (RQ1), and between the sentiment scores produced by the different methods (RQ2). The correlation coefficients were calculated for section-level reviews and whole reviews (sections aggregated) respectively. The correlation results on the two levels are largely consistent, and Table 4 shows the whole review level results.

In Table 4, there is a positive and significant correlation for manual coding to review scores. The correlation is also positive for TextBlob, although the effect is only significant for SNSF Panel F. There is no significant correlation for VADER. These results indicate that manually

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coded sentiment scores were generally similar to the actual review scores; the two algorithmic SA results were less so.

	Review scores	
	SNSF Panel E	*SNSF Panel F*
Manual	0.654***	0.333**
TextBlob	0.22	0.319*
VADER	n.a.[9]	0.128

Table 4 Spearman rank correlation coefficient between SNSF (section-separated) review scores and sentiment scores produced by three methods (* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$).

For SFI data the review scores were not available for our study, but the resulting rankings of proposals were. Thus, we compared the similarity between the two types of the proposals' rankings: actual ranking by review scores and the ranking by sentiment scores produced by different methods. Table 5 shows the Spearman rank correlation coefficients and significance levels for SFI's seven pools. The results generally show the positive correlation across all the pools and all the methods. Manual coding can produce more similar rankings to the proposals' actual rankings than the two algorithms, which is consistent with our finding from the SNSF data.

	SFI:IvP Panel A	SFI:IvP Panel B	SFI:IvP Panel C	SFI:IvP Panel D	SFI:IF Panel 2014	SFI:IF Panel 2015	SFI:IF Panel 2016
Manual	0.753***	0.877***	0.902***	0.94***	0.358	0.844***	0.888***
TextBlob	0.427	0.691**	0.518*	0.631**	0.197	0.666**	0.318
VADER	0.392	0.686**	0.546*	0.516*	0.447*	0.57**	0.637***

Table 5 Spearman rank correlation coefficient between SFI proposals' ranking by review scores and ranking by sentiment scores produced by three methods (* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$).

[9] SNSF reviews are in different languages, and only English is supported by VADER. This particularly affects SNSF Panel E (Humanities and Social Sciences) where only 3 out of 61 reviews were written in English. For this reason, we omitted VADER results for SNSF Panel E.

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5.2. Do algorithmic SA results correlate with manually coded sentiment scores?

We turn to compare the performance of the two algorithmic SA to the manual coding as a benchmark. Fig 3 plots the regression lines and confidence interval between the sentiment scores from algorithmic SA results (Y axis) and the manually coded sentiment scores (X axis). VADER correlates with the benchmark more strongly than TextBlob. Furthermore, both VADER and TextBlob values sit above the ‘‘neutral’’ mark on the Y axis, which indicates that neither SA algorithm could detect negative reviews as identified by manually coding. This suggests that the SA algorithms are not as reliable as the benchmark to measure individual absolute review sentiments. One reason could be that even the most negative reviews were often written in rather restrained or neutral language. In such cases, algorithms are far less reliable than human coders in detecting the key negative messages out of long, more complicated comments. A fully negative review is very rare in our dataset. Appendix Figure A3 shows the correlation between the two SA algorithms and manual benchmark for groups of different programmes and different review sections. The results are largely consistent with the overall result as shown in Fig 3.

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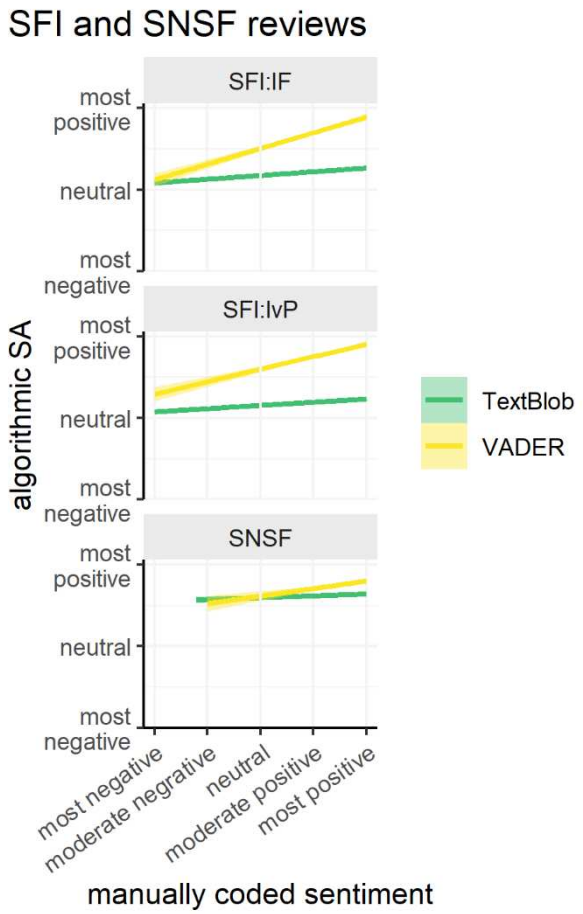

Fig 3. Linear regression between manually coded sentiments and algorithmic SA for three programmes. Confidence interval: 95%.

We also tested the Spearman correlation coefficients between each of the two algorithms and the manual coding, for each programme and their different units of analysis: SNSF review statements (N=9532), SNSF section-separated reviews (N=125), and SFI section-level reviews (N=527). Overall, the two SA algorithmic results correlate positively and significantly with the manual coding. However, the correlation coefficients are not high, especially for SNSF review statements. Interestingly, VADER results are more similar to manual coding than TextBlob (Table 6), but we found earlier (Tables 4 and 5) that TextBlob results are more similar to actual review scores. The reason for this variability in the relative performance of TextBlob and

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VADER can be attributed to measurement noise because VADER results are from English reviews only.

	Manual		
	SNSF review statements	*SNSF section-separated reviews*	*SFI section-separated reviews*
VADER	0.3***	0.586***	0.558***
TextBlob	0.195***	0.209*	0.63***

Table 6 Spearman correlation coefficient between manually coded sentiments and two algorithmic SA results of two agencies' reviews (* $p \leq 0.05$; *** $p \leq 0.001$).

To sum up, the correlation between the manual coding as a benchmark and the two SA algorithms respectively are generally positive and significant, but the correlations are not strong. Furthermore, SA algorithms show an important shortcoming: While they usually can tell a relatively negative review from a relatively positive one, they systematically fail to detect absolute negative reviews - instead, they interpret even the most negative reviews as being at least "neutral". This is a first hint that the usefulness of dictionary-based SA algorithms for measuring scientific reviews is limited to very specific tasks. For example, TextBlob and VADER are not useful to accurately estimate the absolute sentiment of specific reviews, but they can be of help when comparing the relative sentiments between groups of reviews. We will test this for the two funding decision groups in the next section.

5.3. Can review sentiments predict funding decisions?

We explore the link between review sentiments and funding decisions of proposals by first looking at the distribution of sentiment scores for awarded and rejected proposals for the three different programmes. Overall, manual coding results in Fig 4 agree with our expectation: Review sentiment is more positive for awarded proposals. However, only small

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differences between the two groups are shown by VADER; almost no noticeable difference is captured by TextBlob.

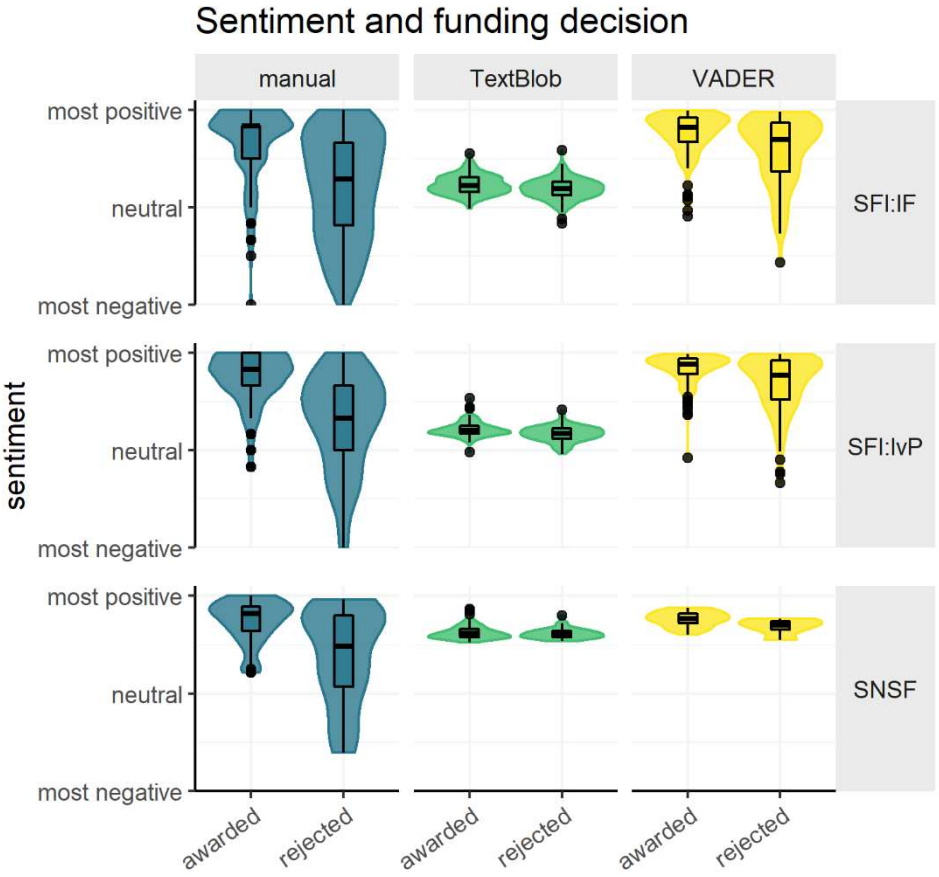

Fig 4. Review Sentiments under different groups of funding decisions for the three programmes.

To explore this research question further, we examine the four prediction scenarios from the confusion matrix (TP: true positive, TN: true negative, FP: false positive, and FN: false negative) introduced in the research design. For each proposal, we averaged the overall sentiment score of all the reviews it received. Table 7 tallies the four scenarios in each of the three programmes (aggregated from multiple pools in different years or disciplines) as well the five metrics to measure the performance of the prediction model.

SFI: IF, N= 22+20+30=72 (sum of three pools)

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Manual	Positive sentiment	Negative sentiment	TextBlob	Positive sentiment	Negative sentiment	VADER	Positive sentiment	Negative sentiment
Funded	TP 30	FN 6	Funded	TP 25	FN 11	Funded	TP 26	FN 10
Rejected	FP 9	TN 27	Rejected	FP 11	TN 25	Rejected	FP 10	TN 26

	Manual	TextBlob	VADER
Accuracy = (TP + TN)/(TP+TN+FN+FP)	79.17%	69.44%	72.22%
Precision = TP/(TP+FP)	76.92%	69.44%	72.22%
Recall = TP/(TP+FN)	83.33%	69.44%	72.22%
F1 Score = (2×Precision×Recall)/(Precision+Recall)	80.00%	69.44%	72.22%
Negative Predictive Value = TN/ (TN+FN)	81.82%	69.44%	72.22%

SFI: IvP, N= 20+14+16+16=66 (sum of four pools)

Manual	Positive sentiment	Negative sentiment	TextBlob	Positive sentiment	Negative sentiment	VADER	Positive sentiment	Negative sentiment
Funded	TP 29	FN 4	Funded	TP 27	FN 6	Funded	TP 25	FN 8
Rejected	FP 6	TN 27	Rejected	FP 7	TN 26	Rejected	FP 8	TN 25

	Manual	TextBlob	VADER
Accuracy = (TP + TN)/(TP+TN+FN+FP)	84.85%	80.30%	75.76%
Precision = TP/(TP+FP)	82.86%	79.41%	75.76%
Recall = TP/(TP+FN)	87.88%	81.82%	75.76%
F1 Score = (2×Precision×Recall)/(Precision+Recall)	85.29%	80.60%	75.76%
Negative Predictive Value = TN/ (TN+FN)	87.10%	81.25%	75.76%

SNSF, N= 64+61=125 (sum of two pools)

Manual	Positive sentiment	Negative sentiment	TextBlob	Positive sentiment	Negative sentiment	VADER	Positive sentiment	Negative sentiment
Funded	TP 74	FN 15	Funded	TP 67	FN 22	Funded	n.a.[10]	n.a.
Rejected	FP 17	TN 19	Rejected	FP 23	TN 13	Rejected	n.a.	n.a.

	Manual	TextBlob	VADER
Accuracy = (TP + TN)/(TP+TN+FN+FP)	74.40%	64.00%	n.a.
Precision = TP/(TP+FP)	81.32%	74.44%	n.a.
Recall = TP/(TP+FN)	83.15%	75.28%	n.a.
F1 Score = (2×Precision×Recall)/(Precision+Recall)	82.22%	74.86%	n.a.
Negative Predictive Value = TN/ (TN+FN)	55.88%	37.14%	n.a.

Table 7 Confusion matrices for each of the three programmes (aggregated from pools). The observed funding rate in the samples of each programme is used as a threshold to set binary classifications (relatively positive or negative sentiment).

[10] VADER were only applied to English written reviews, so the SNSF pools do not have complete VADER score-based ranking.

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Table 7 shows the confusion matrix for each of the three programmes as well as the five standard metrics that measure the performance of our prediction model. Overall, the accuracy of the three methods in predicting proposals' funding decisions ranges from moderate to high. Manual coding still performs the best in all scenarios on all the metrics whilst the two algorithms are not far behind. The values of the five metrics are often close to each other, which flags the overall reliability of our prediction model. Even though the two algorithms did not perform well in detecting the individual absolute review sentiments as compared to manual coding, they are fairly reliable in predicting the proposals' relative positions either above or below the funding lines, especially for the two SFI programmes[11].

Across different programmes, predictions were most accurate for SFI:IvP, then SFI:IF, and the least for SNSF. A significant difference that may affect the predictions among the programmes is their funding rates; the smallest is SFI:IvP (17% on average in original pools) with much bigger rates for SFI:IF (73%) and SNSF (72%). The funding rate is exogenously imposed, as it depends on the organizational objectives and budget availability and is thus beyond the consideration of peer reviewers. However, the funding rate plays an important role for the agency in setting the threshold between awardable and rejectable proposals, and for us to classify the two groups of proposals as either "relatively positive" or "relatively negative". For instance, in a large pool with a low success rate (which is often the case), grants will only be awarded to a small number of proposals even if many of them are outstanding.

[11] TextBlob predictions appear to be relatively poorer for SNSF reviews than for SFI reviews especially with respect to the negative predictive value. For SNSF reviews, TextBlob is only moderately better than randomly correct predictions.

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In our case, due to the generally high quality of proposals as perceived from the reviewers' comments skewing towards "most positive" in Fig 1, (absolute) negative reviews were rare across the three programmes and could explicitly lead to bottom ranking of the proposals. However, the negative reviews in SFI:IvP have higher reliability to predict rejection decisions than the other two programmes, as seen by its 87% negative predictive value (by manual coding), the highest indicator among all. Because SFI:IvP's small funding rate signals that the majority of the proposals would get rejected, negatively reviewed proposals could be more easily excluded from the pool to reduce the workload in the decision-making process. But with a high funding rate, the majority would be funded, so the rejection decision became the minority, and it was uncertain how the rejection decision was made. As in our SNSF case, several rejected proposals actually received quite high grades and positive comments (what we call false positive, or FP cases), which resulted in the lowest negative predictive value among all the programmes. Here, the rejection decision made by funders could be based upon some other considerations than reviewer opinions.

We took a closer look at some specific false prediction cases and found different underlying reasons. For instance, in SFI:IvP Panel A where both TextBlob and VADER had low accurate prediction, we found the false predictions of the two SA algorithms could be attributed to outliers: Their estimated sentiments were not as positive as manual coders assigned for some awarded proposals (resulting in false negatives); and not as negative for some rejected proposals (resulting in false positive). In both situations, the algorithms performed less accurately than manual coders when dealing with very long or very short reviews. For very short reviews where one or a few key words represent reviewer opinions, misinterpretation

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of these words would skew the overall message. For example, for this comment "*The PI is a leader in the field of (redacted)*", both TextBlob and VADER interpret it as "neutral" (sentiment score = 0) because the sum of the weights of these words is zero. By contrast, manual coders interpreted the comment as "moderate positive", because being recognised as a "leader" in an academic field is a compliment. For very long comments where reviewers wrote rich technical details and diverse considerations, manual coders attempted to identify the most summative signals such as the sentences after a term of "*in summary*" or "*to conclude*" and then to interpret reviewers' key judgmental opinions from the summative sentences. The SA algorithms still worked by valency attribution of individual words, which would likely misinterpret reviewers' overall opinions expressed in the long and complex texts.

We notice that another factor for the false prediction cases could be the incomplete pool that this study examined, as shown by the proportion of the dataset in Table 3. The unshared or excluded reviews might have had variant opinions from the included reviews and thus have led to a different funding result.

Furthermore, we analysed the link between sentiments, obtained from manual coding and TextBlob, and funding decisions of the 9532 SNSF statement-level reviews[12]. Fig 5 shows that the manual results detect more positive sentiments for awarded proposals than rejected ones whereas no difference is noticeable for TextBlob. This further supports the higher reliability

[12] Note that statements are nested by review texts. The classification of statements in "relatively positive" and "relatively negative" requires further assumptions that make it impossible to directly compare our results for RQ3 between section- and statement- levels. For these reasons, our replication of RQ3 at the statement level only relies on a plot to show the distribution of sentiment scores for awarded and rejected proposals (Figure 5).

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of the manual coding in predicting funding decisions than TextBlob at the review statement level.

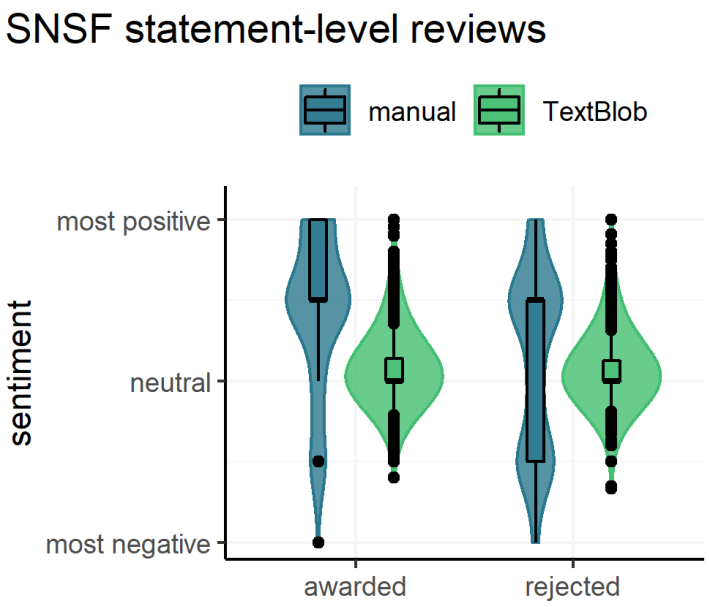

Fig 5. Violin plots and boxplots showing manually coded and TextBlob sentiments of SNSF statement-level reviews under different groups of funding decisions.

Lastly, we analysed the funding prediction of the reviews on the 21 specific topics Reinhart (2010) identified and found that for almost all the topics (except "*previous affiliation*") the average sentiment scores were significantly higher for awarded proposals than rejected ones. That said, the statement-level reviews are less reliable in this funding prediction analysis than section-level reviews, because the number and weight of statements in each review depend on reviewers' epistemic and writing styles. In this sense, section-level reviews act as the results of reviewers having been guided to organise their otherwise freeform statements into summative signals for the next stage actors (panellists and decision makers).

The three research questions, examined as whole, present an interesting puzzle. The manually coded sentiments are shown to positively correlate with both review scores or

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rankings (RQ1) and funding decisions (RQ3), as we expected. However, results from the SA algorithms paint a somewhat different picture: TextBlob and VADER sentiments correlate poorly with review scores or rankings, while they do correlate with the funding decisions.

We believe there are two plausible reasons. First, manual coders are better at detecting sentiment: They understand review nuances and can easily pick up cues from very long or very short reviews; whereas SA algorithms like TextBlob and VADER analyse individual words ignoring their contexts and with several constraints. Thus, it is not surprising that manually coded sentiment correlates more strongly with review scores or rankings than the SA algorithms: TextBlob and VADER are just less accurate.

Second, the result might be due to the different measurement scales we used for the different research questions. When correlating sentiment with scores or rankings, we considered sentiment as an ordinal variable. However, we then dichotomised the ordinal scale to treat sentiment as a binary classifier to predict funding decisions (awarded or rejected). Thus, the lack of correlation between algorithmically measured sentiments and scores or rankings might signal that SA can produce binary classifications well but can not produce equally well finer-grained rankings. Take for example a set of reviews that fall into two groups, those that are relatively positive and those that are relatively negative. If there are large differences in the sentiment between the two groups but only subtle differences within each group, then sentiments would allow for good binary classifications but relatively poorer rankings. Our results from the SA algorithms suggest this might be the situation.

6. Discussion

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This study contributes to the literature in several ways. Methodologically, it contributes empirical evidence on the calibration and triangulation of different proxies of reviewer opinions by using different analytic methods and datasets. First, we compared two SA algorithms with similar working principles on the same data to check their reliability. Second, we benchmarked SA algorithms with the manual coding as an independently established form of measurement. Third, we tested and calibrated the sentiment analysis/interpretation results with related and supplementary data, such as review scores (when available), rankings and funding results of proposals. All these data constitute different measurements by different actors (peer reviewers, panellists, and decision-makers) of the same subject, proposals' (perceived) funding worthiness.

Our study is the first, to our knowledge, to compare algorithmic and manual coding of peer review data. Reviews from different disciplines, agencies, and national contexts in our dataset strengthened the generalisability of our methods as well as the findings. We find that the two SA algorithms (TextBlob and VADER) perform better in detecting proposals' relative worthiness than individual absolute review sentiments. The two simple algorithmic tools that we applied worked quickly and almost as accurately (69-82% accuracy in most of our cases) as manual coders (74-87% accuracy) to detect proposals positioned either above or below the funding line, especially for programmes with low funding rates. This informs a cost-benefit analysis to decide whether to apply algorithmic SA tools. The cost of lower accuracy compared to manual analysis can be weighed against the benefit of using algorithms to process large datasets quickly. If the cost, 5-10% loss in accuracy, for instance, is tolerable by uses, then SA algorithms can be of use in some specific situations, e.g., to quickly classify binary groups of

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"relative positives" and "relative negatives". While more advanced SA methods have been developed (such as BERT, see Devlin, Chang, et al. 2019), it is not clear yet how these would perform with peer review reports especially for the data with heavy information redaction (for anonymity in our case). The exploration of other SA methods suggests some potential venues for future research.

Our findings support the reliability of using review sentiment to predict proposals' funding decisions, especially for manual analysis method and for prorgammes with low funding rates. The funding rate is shown to play an important role in agencies' decision-making (Roebber, & Schultz, 2011; Van den Besselaar, Sandström, & Schiffbaenker, 2018) and are often beyond peer reviewers' considerations. We find that a small funding rate in a pool of generally high-quality applications (such as in our SFI:IvP case) signals intensified competition and leads to more accurate predictions of review sentiments than other programmes with higher funding rates. Especially, negative reviews can predict rejection decisions in an intensive competing pool with high accuracy. This finding supports the study of Van den Besselaar, Sandström, and Schiffbaenker (2018) on the ERC programme (also with a low funding rate) where they found negative comments had a stronger effect on funding decisions than positive ones.

Our study provides potential to explore at least three understudied subjects in the peer review literature. The first is the dependency between a reviewer's grading and commenting behaviors. This can be studied by the correlation between review scores and review sentiments as we did in RQ1. Strong correlation can be expected if a reviewer gives a score first and then normalises the comments around the score, or the other way around. In this sense, either of the two proxies (score and sentiment) can be considered as an alternative

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proxy of the other to represent reviewer opinions. Weak correlation, as we found out, does not necessarily indicate the unreliability of sentiment estimation methods but may indicate heterogeneity between a reviewer's grading and commenting behaviors.

The second understudied subject is "grading heterogeneity" (Morgan, 2014) and "commenting heterogeneity" between different peers that have been found in our datasets: The former refers to reviewers of the same proposal with similar opinions but different grades; the latter with different opinions but the same grades. These cases resonate with the literature on interpersonal differences in the understanding of a grading language and of evaluation criteria (Abdoul, Perrey, et al., 2012; Lee, Sugimoto, et al., 2013). Research suggests that these differences can skew the outcome of the proposals evaluations (Feliciani, Moorthy, et al., 2020).

Third, such "grading heterogeneity" and "commenting heterogeneity" can also be explored between peers and panellists from different review stages. A generally accurate prediction of postal peer review sentiments in proposals' funding decisions, across different programmes in our datasets, argues that the panellists and decision-makers followed most of the peer reviewer opinions on proposals' funding worthiness. Only a small proportion of proposals that received "relatively positive" reviews from peer experts were not approved by either panellists who synthesised and discussed the peer reviews or decision makers who may have other (administrative or policy) considerations. Our study suggests the potential to research (dis)agreement between peers and later stage panellists by measuring not only review scores but also review sentiments especially on specific review subjects (Bethencourt, Luo, & Feliciani, 2021). With both sentiment and scores as available research data, we can scrutinise

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some of the findings of previous research that measure inter-reviewer reliability by using review scores only (e.g., Pina, Buljan, et al., 2021). Compounding review score data and review sentiment data, especially for individual evaluation subjects, can mitigate the risk of finding false agreement and further support research on inter-reviewer reliability by considering reviewers' grading heterogeneity and commenting heterogeneity on different subjects.

Our study also has several limitations. First, many of the differences between the two funding agencies that may have influenced the review data were not addressed in the study, such as the year, country, language of the data resources, reviewer identities (domestic or international) as well as many other contextual differences between the two agencies. Second, we only applied simple tools for both the SA and statistical analyses. Third, even though the scale of our analysed datasets (2456 section-level reviews and 9532 statement-level reviews) is quite large especially for manual analysis, the incomplete pools (less than 50%) this study examined may affect our testing of the reliability of the three methods. Thus, the results from the samples may not generalize to the complete pools. For instance, the difference in funding rates between our sample and the original pool is important to classify the "relative positive" and "relative negative" reviews and to calculate the performance of the prediction model. The behavior of binary classifiers based on SA with different funding rates is untested in this study and deserves further studies with more complete datasets.

7. Conclusion

We consider this study as an early exploratory academic work with some potential methodological and practical insights. The grant review process is important and complex but

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understudied. Data are not widely available, which inhibits research (Lee, & Moher, 2017; Squazzoni, Brezis, et al., 2017; Shankar, Luo, & Ma, 2020). Comparative empirical research across systems has been especially difficult. Simulation research on peer review has been a promising approach where the lack of empirical data is hindering progress (Roebber, & Schultz, 2011; Feliciani, Luo, et al., 2019). Automated methods for supporting journal peer review have been suggested as far back as the 1980s (Garfield, 1987). For the pre-peer review screening stage, a trained machine-learning system could quickly check formatting, language, and expression of submissions; the results accurately predicted the "accepted" or "rejected" review outcomes (Checco, Bracciale, et al., 2021). The National Natural Science Foundation of China uses automated tools to reduce the load on the selection of review panels (Cyranoski, 2019). But these tools have not been formally adopted (Brezis, & Biroukou, 2020) in any widespread manner, and we do not intend to suggest that they should be.

However, we believe in the potential benefits of combining qualitative research and algorithmic tools (such as computational simulations) for peer review research. As our results demonstrated, even simple algorithmic SA tools have the potential to provide a quick addition to the existing toolkit of quantitative, qualitative, and modelling approaches to study peer review further. Far more research is needed before making any concrete policy recommendations for the use of automated tools for practice. In peer review practice, human analysers and decision-makers can never be replaced but potentially can be informed and supported by automated tools that have been trained, tested, and calibrated to work reliably under specific conditions and for specific situations.

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Future research can further explore ways to test and calibrate the reliability and generalisability of our empirical findings with more complete and broader data from agencies with different funding strategies and review processes. With sentiments as another supplementary proxy of reviewer opinions beyond numeric scores, inter-reviewer reliability between different subjects, between independent peer reviewers of the same proposals, and between postal and panel reviewers, can be quickly reported to funding agencies. Consequently, sentiment as supplementary data has the potential to help improve the validity and transparency of grant peer review systems. Of course, the costs (to conduct textual analysis), risks (e.g., algorithms' lower accuracy than humans) and challenges (e.g., applicants may not trust sentiment analysis at all) would have to be addressed in future studies and practical pilots if possible.

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Author contributions

Junwen Luo: Conceptualization, Investigation, Formal analysis, Data Curation, Writing - Original Draft, Writing - Review & Editing.

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Thomas Feliciani: Conceptualization, Investigation, Writing - Review & Editing, Formal analysis, Visualization.

Martin Reinhart: Conceptualization, Writing - Review & Editing, Investigation, Data curation (SNSF data).

Judith Hartstein: Conceptualization, Writing - Review & Editing, Investigation, Data curation (SNSF data).

Vineeth Das: Investigation, Data curation (SFI and SNSF data).

Olalere Alabi: Investigation, Data curation (SFI data).

Kalpana Shankar: Conceptualization, Investigation, Writing - Review & Editing, Project administration.

Competing interests

The authors have no competing interests. The two funding agencies, SFI and SNSF, did not influence the research design, analyses, or the writing of this article.

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Data availability

We are not allowed to share the review data due to our research agreement with the two funding agencies, but our scripts for data analysis are available on GitHub at https://github.com/thomasfeliciani/SFI-and-SNSF-review-sentiment.

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Appendix

Figures A1 and A2 show the overall distribution (in violin plots) and the quartiles (in boxplots) of the review scores and sentiment scores of SNSF reviews under two disciplinary panels (A1) and three review languages (A2).

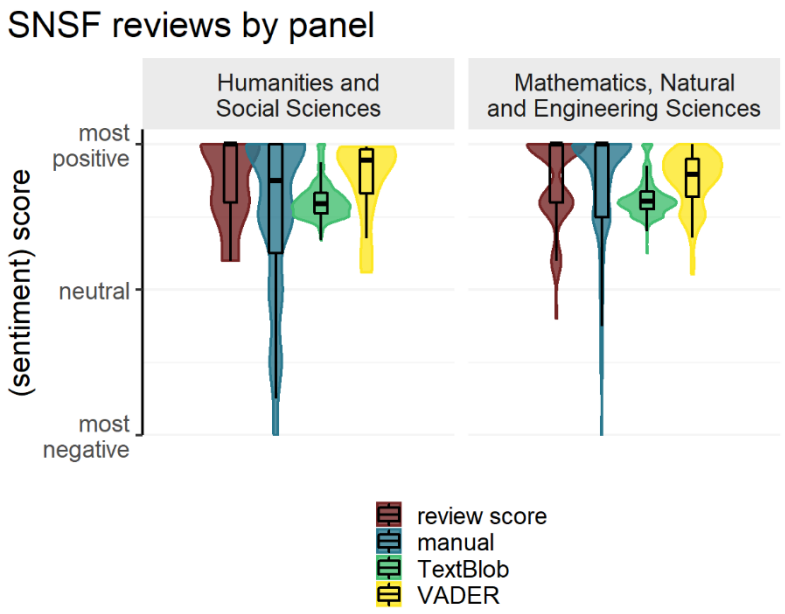

Fig A1 Violin plots and boxplots showing the distribution and quartiles of the SNSF review scores and sentiments as measured by three methods under the two disciplinary panels.

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Fig A1 involved 60 reviews from Humanities and Social Sciences panel and 65 reviews from Mathematics, Natural and Engineering Sciences panel. Note that for Biology and Medicine Panel, none of the reviews are section-separated, so we only include this panel for statement-level analysis.

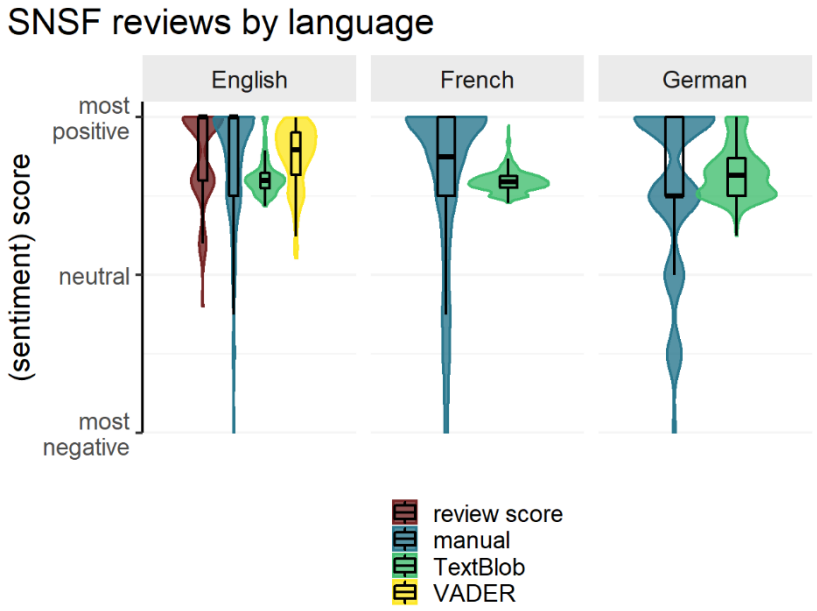

Fig A2 Violin plots and boxplots showing the distribution and quartiles of the SNSF review scores and sentiments of reviews written in three different languages.

Figure A2 involved 36 English reviews, 47 German reviews, and 42 French ones. Note that review scores and VADER scores were only available for SNSF reviews written in English.

Figure A3 shows the linear regression between manually coded sentiment and the two SA algorithms for all review sections for each of the three programmes (A: SNSF, B: SFI:IvP, C: SFI:IF). Together with Fig 3, Fig A3 shows that VADER correlated more strongly than TextBlob across all the programmes and almost all the review sections.

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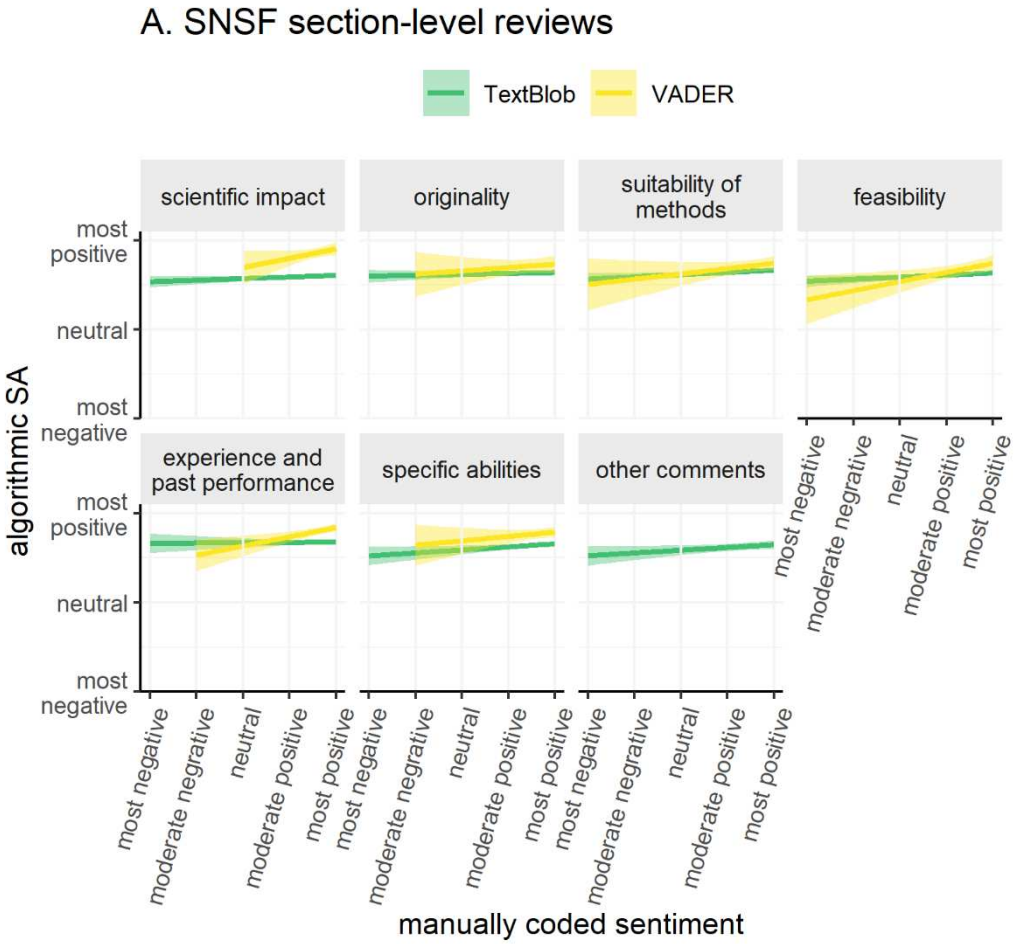

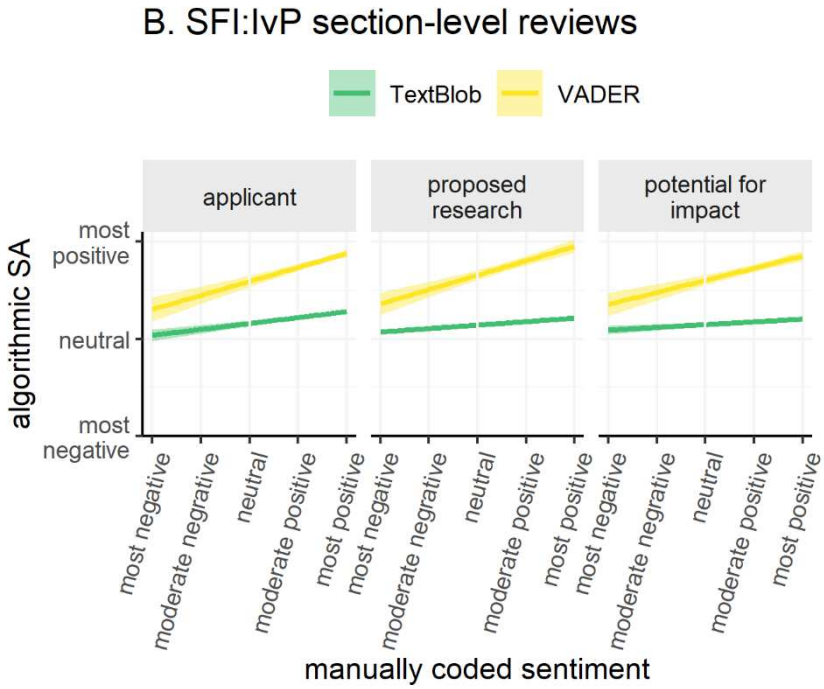

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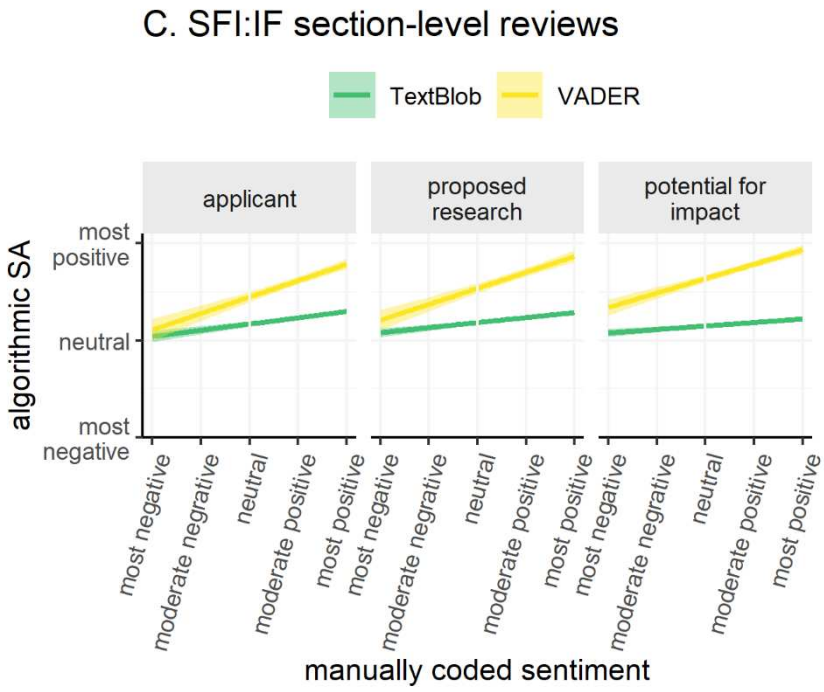

Fig A3. Linear regression between manually coded sentiment and algorithmic SA for section-level reviews for three programmes. Confidence interval: 95%.

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