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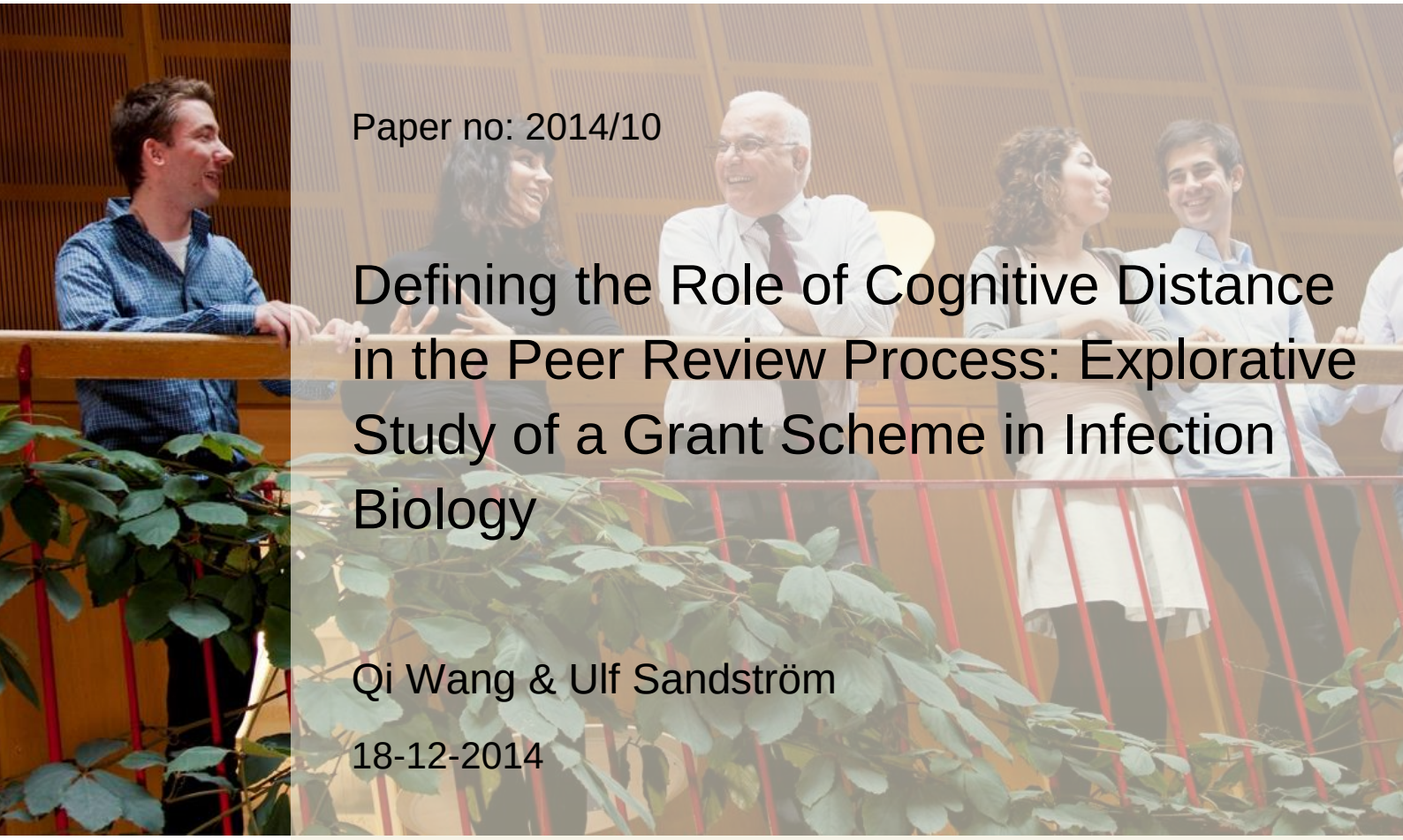

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Defining the Role of Cognitive Distance in the Peer Review Process:

Explorative Study of a Grant Scheme in Infection Biology

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Abstract
The aim of this paper is twofold: (1) to provide a methodology that can measure cognitive distance between researchers and (2) to explore the role of cognitive distance on the results of peer review processes. Citing references and the content of articles are used to represent their respective scientific knowledge bases. Based on the two different approaches—Author-Bibliographic Coupling analysis and Author-Topic analysis—we apply the methodology on a recent competition for grants from the Swedish Strategic Foundation. Results indicate that cognitive distances between applicants and reviewers might influence peer review results, but that the impact is to some extent at the unexpected end. The main contribution of this paper is the elaboration on the relevance of the concept of cognitive distance to the issue of research evaluation in general, and especially in relation to peer review as a model used in grant decisions.

Keyword: peer review, cognitive distance, cognitive bias

JEL Code: I2

1. Introduction

Peer review is intended to improve both the technical quality of projects in research and the credibility of the decision-making process. Nowadays it is taken for granted that peer review is fundamental to the institution of science and a symbol for the autonomy of science (Chubin & Hackett, 1990). Although peer review functions are put into action to enhance the quality of research and to prevent poor research from taking place, the procedures do not always function as expected. Bias in peer review is a crucial issue that has generated serious discussions over a period of years (Wesseley, 1998; Bornmann & Daniel, 2005; Bornmann, 2008; Bornmann, 2011). Any type of bias would be detrimental to the pursuit of excellent research at the different research fronts.

Many possible flaws in the peer review process have been disclosed over the recent years. McCullough (1989) reported in a survey of principal investigators applying to the U.S. National Science Foundation (NSF) during 1985, based on 9,500 respondents, that two-fifths were unsatisfied with the assessment of their proposals. Among the reasons for dissatisfaction, 'reviewers or panelists are not expert in the field, poorly chosen, or poorly qualified' (McCullough, 1989). In a peer review process, reviewers are supposed to be experts in the field; however, the expertise and authority of reviewers are frequently being questioned. In fact, the guidelines for selecting reviewers in many journal editorial offices or research grant agencies are ambiguous. Occasionally project managers or editors select reviewers based on their experiences or personal relations (Caelleigh et al., 2001). If a reviewer is not an expert in the area under evaluation, the decision given might be unreliable or open for discussion.

Cognitive bias, also known as ‘cognitive particularism’ and ‘cognitive similarity’ (Travis & Collins, 1991), refers to a situation where scientists with a mainstream view of their respective fields could pose challenges to a fair review process of new and alternative research strategies. Moreover, cognitive bias is generated because of the existence of cognitive boundaries within and between scientific specialties and disciplines (Travis & Collins, 1991; Whitley, 2000). Due to the difficulties of measuring the cognitive distance between applicants and reviewers, cognitive bias in the peer review process is often ignored. However, this bias might have a substantial effect on interdisciplinary research proposals because that type of research is often located at the boundaries of traditional disciplines, causing difficulties in finding suitable reviewers.

To fill this gap, this paper discusses the role of cognitive distance in a peer review process by proposing an advanced measurement of cognitive distance between individual applicants and their reviewers and by evaluating to what extent cognitive distance impacts on peer review. The structure of this article is as follows. First, we provide background information and review of the concept of cognitive distance. Following that, we conceptualize the cognitive distance between applicants and reviewers. Next, we discuss and present a methodology based on Author-Bibliographic Coupling analysis and Author-Topic analysis. In the following section, we report the results. We conclude by discussing the results and the advantages and shortcomings of the proposed methodology.

2. Research Background

Few research works have investigated cognitive bias in peer review. A pivotal contribution by Mahoney (1977) found that ‘reviewers were strongly biased against manuscripts which reported results contrary to their theoretical perspective’. In other words, it implies that reviewers would likely support manuscripts similar to their own. Later, Travis and Collins (1991) first coined the terms ‘cognitive particularism’ or ‘cognitive cronyism/similarity’ to describe the different peer review situations. They believed that cognitive bias is caused by the ‘cognitive structure of science’ and that it ‘depends on the existence of cognitive boundaries within and between scientific specialties and disciplines’ (Travis & Collins, 1991). Moreover, they made direct observations within a grant-awarding committee of the British Science and Engineering Research Council. With this qualitative method, they were able to indicate the effects of cognitive cronyism/similarity on peer review results. Meanwhile, they operationalized ‘cognitive similarity’ into measures for the department status of applicants and reviewers and their social positions. However, no clear conclusions were drawn from their fieldwork because the authors neither mentioned how widespread cognitive cronyism is nor specified how damaging it might be to the peer review.

Based on Travis and Collins, Sandström (2009) developed a strategy for empirical investigation of cognitive bias. He introduced the concept of ‘cognitive distance’ in the peer review process, and proposed bibliographical coupling as a method to detect cognitive bias. The method was applied to a large grant scheme of the Swedish Research Council: the Linneaus Grants initiated in 2005. Preliminary conclusions based on mapping of applicants and their relations to reviewers indicated that groups who were not rewarded had fewer connections to reviewers than granted groups. At the same time, it could be shown that the non-rewarded groups exhibited better results in track records using relative citation scores. Another research by Sandström and colleagues (2010) indicated that ‘it was decisive to have a cognitive similarity in order to receive an excellent grant’. Out of three large calls for excellence grants, all groups that were granted had higher similarity compared to those not granted.

Full and detailed data on grant peer review are seldom disclosed due to secrecy and other policy issues. Two studies based on detailed data including bibliometric analysis have been published and both are

Swedish: Wennerås and Wold (1997) and a follow-up ten years later by Sandström and Hällsten (2008). These studies were made possible due to the Swedish principle of public access to official documents. But genders, conflict of interests, these studies did not investigate the issue of cognitive distance, although other possible biases were covered.

In short, former strategies for measuring cognitive bias have been based on the information concerning applicants and reviewers such as departments, co-authorships, and citing references; seldom have studies focused on the research content itself, however. In this study, we aim to use the term 'cognitive bias' to interpret the bias caused by heterogeneity of theoretical perspectives among individual researchers and to explore the role of cognitive bias in peer review. In doing so, a strategy that combines measuring research tradition and content is applied to obtain the cognitive distance between applicants and referees.

Before entering into the conceptualization of cognitive distance, it is necessary to distinguish between manuscript peer review and grant peer review. In the former case, it should be easier to find relevant reviewers—for example, based on the manuscript references—but in the latter case, this is not possible because panels in standing committees have to be organized over a longer period of time. This makes the process sensitive to differences between research trails in fields which may have several traditions. If there are many different trails, there cannot be representatives for all because the committee membership is limited to six or seven members. Consequently, there is much more room for cognitive bias in the panel- or committee-organized peer review. It should be said that it is possible to combine peer review approaches, as is the case in the NSF and in many other national research councils. The Swedish Research Council has worked for decades on the basis of nationally organized committees, but lately there seems to be a change towards more of international and mail peer review in combination with standing committees.

3. Conceptualization of Applicant-Reviewer Cognitive Distance

A vague concept could lead to misunderstandings, thus it is necessary to define precisely what we consider as cognitive distance between individual researchers. Cognition refers to a series of mental activities, including proprioception, perception, sense making, categorization, inference, value judgments, emotions, and feelings, which all build on each other' (Nooteboom et al., 2007). Hence, to measure the individual cognition seems an almost unmanageable task. However, when individuals are labeled as researchers, the cognitions laid bare by their scientific work are our only concern. Nooteboom and colleagues (2007) stated that cognitive differences between individuals are the result of their respective knowledge bases. Here, we aim to take his conceptual work a bit further. In several papers by Nooteboom and others (Nooteboom, 1999, 2000; Nooteboom et al., 2007) cognitive differences at the company level have been analyzed by utilizing patent data as a proxy for companies' knowledge base—that is, when two companies have (one or more) patents in the same category, it indicates a smaller cognitive distance between the two companies (Wuyts et al., 2005; Cantner et al., 2010; Dangelico et al., 2010).

For a researcher, the knowledge base might be the result of diverse sources, such as educational background, books or articles read, and research programmes implemented. Here, considering data availability and quality, we use a researcher's citing references as an indicator of his/her research trail. The reason is that the citing papers are used to develop a researcher's own articles, then the research work of an individual researcher would be highly related to the citing papers. Thus, we infer that the more references shared by the different authors, the smaller the cognitive distance between the two researchers.

In addition to research trail, research content itself could reflect a researcher's cognition directly. Researchers demonstrate how they understand, analyze, and interpret different problems through their research outcomes such as journal publications, proceedings papers, reports, books, and patents. Thus, we could obtain the cognitive distance between researchers by measuring and comparing their research contents. Considering the efficiency of calculation, we use text from titles and abstracts obtained from the Thomson Reuters database Web of Science (WoS), instead of full text of papers. Accordingly, we assume that aggregating titles and abstracts from all of a researcher's publications would approximately represent this researcher's cognition. Figure 1 summarizes the relations between research trail and research content.

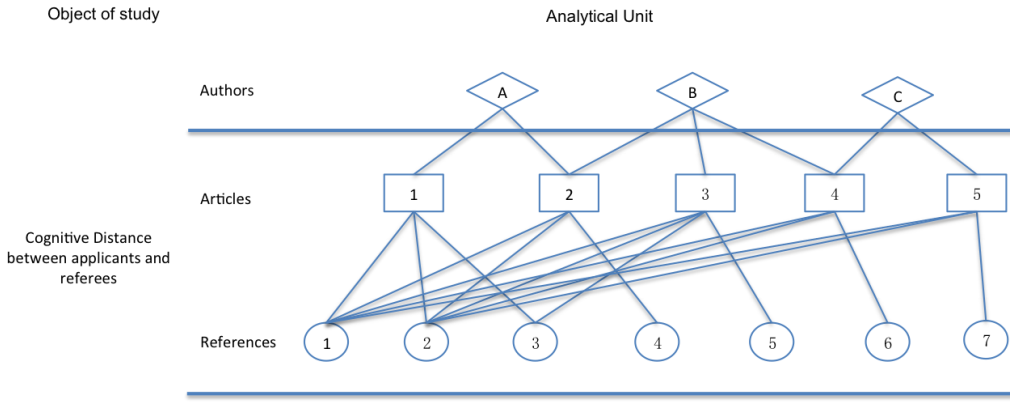

Figure 1. Scheme of operationalization of cognitive distance

4. Operationalization of cognitive distance

The proposed method for measuring the cognitive distance between applicants and reviewers can be subdivided into two perspectives: the first is Author-Bibliographic Coupling analysis (ABC), and the second is the Author-Topic analysis (A-T) .

4.1 Author Bibliographic Coupling Analysis

Author-Bibliographic Coupling analysis (Zhao & Strotmann, 2008; Zhao & Strotmann, 2008; Sandström, 2008; Ma, 2012), which is an extension of the concept of bibliographic coupling (Kessler, 1963), can be used to measure the knowledge similarity between researchers, to construct the intellectual structure of research areas, and even to represent the knowledge absorption, diffusion, flow of the research area, and so forth (Glänzel & Czerwon, 1996; Boyack, Klavans & Börner, 2005).

Taking individual researchers as the study target, we have grouped the publications and references of each researcher. The relations among author, publication and citing references that are shown in Figure 2 can be represented by the following Table 1. As mentioned above, we did not exclude the duplicated publications in our dataset; thus publications 2 and 4 appear more than once in Table 1.

Table 1. Represent bibliographic information shown in Figure 1

Author	*Publication*	*Reference*
A	Publication 1	Ref 1; Ref 2; Ref 3
	Publication 2	Ref 1; Ref 2; Ref 4
B	Publication 2	Ref 1; Ref 2; Ref 4
	Publication 3	Ref 1; Ref 2; Ref 3; Ref 5
	Publication 4	Ref 1; Ref 2; Ref 6

Furthermore, we could create an author–reference matrix for Author-Bibliographic Coupling analysis, which is shown in Table 2. It displays the cited times of each reference by individual researchers. Taking authors A and B as an example, they have published 2 and 3 documents, respectively, and one of the documents is their cooperative work. We added the references cited by the collaborative paper by both authors.

Table 2. The Author–Reference matrix

Reference	*Author A*	*Author B*
Reference 1	2	3
Reference 2	2	3
Reference 3	1	1
Reference 4	1	1
Reference 5	0	1
Reference 6	0	1

With the author-reference matrix as an input, the Salton's cosine (Salton & McGill, 1983) was used to measure the similarity between applicant *a* and referee *b*. The formula is as follows,

$$cos(a,b) = \frac{\sum c_{ai}c_{bi}}{\sqrt{\sum c_{ai}^2}\sqrt{\sum c_{bi}^2}}.$$

Using this function, we obtain the similarity that is in the interval between 0 and 1. Then, the cognitive distance based on author bibliographic coupling can be calculated by

$$cog\_distance_{biblio} = 1 - cos(a,b)_{biblio}.$$

Obviously the smaller the cognitive distance is, the more similar their research would be. Furthermore, when the distance between an applicant and a referee is 1, it indicates that they have 0 references in common in their previous research. In other words, they differ in their research traditions, trails, or paths. On the contrary, if the cognitive distance is 0, it implies that all of the references are the same on both sides (applicant and reviewer). That might be a result of intense collaboration and jointly published papers.

There are several reasons for applying the author-bibliographic coupling method to test the cognitive similarity instead of other similar approaches, such as direct citation analysis and co-citation analysis. First, there is a time lag in the co-citation analysis (Hopcroft et al., 2004; Shibata et al., 2009), which implies the fact that a certain time interval is required for conducting co-citation analysis. In comparison, Author-Bibliographic Coupling is more sensitive to recent publications. Meanwhile, although direct citation could avoid the time effect, its accuracy in assessing the similarity is inferior to the bibliographic-coupling method (Ahlgren & Colliander, 2009).

4.2 Author-Topic Model

To measure the cognitive distance between applicants and reviewers regarding their cognitive content, we apply an author-topic model (Rosen-Zvi et al., 2004), which is an extension of the *Latent Dirichlet Allocation* method (Blei et al., 2003), by including information about authors into the model. It presents the multinomial distribution of each author over topics. The advantage of this model is that it uses 'a topic-based representation in order to model both the content of documents and the interests of authors' (Rosen-Zvi et al., 2004).

Here we used the text data from titles and abstracts of publications to represent research content, and furthermore applied the Author-Topic model to obtain the distribution of individual researchers over multiple topics. However, identifying an appropriate number of topics is one limitation inherent in this model. Generally, there are two ways to solve the problem: one is training parameter by minimizing the complexity of a sample data; another is to use the rule of thumb to approximately estimate the number of topics. In this case, we chose the latter and expected to identify 40 research topics based on experience. Although based on an arbitrary decision, we emphasize that the number of topics does not have considerable impact on the actual analysis. We calculated the similarity using the Salton's cosine (Salton & McGill, 1983) based on the author-topic matrix—that is, the same way as above. Finally, cognitive distance based on the Author-Topic analysis can be obtained by the following formula:

$$cog\_distance_{topic} = 1 - cos(a, b)_{topic}.$$

Likewise, cognitive distance obtained by the Author-Topic analysis is in the interval between 0 and 1. If an applicant and a referee have a small cognitive distance obtained by the author-topic model, it indicates that they are quite similar in the terms used in the title and abstract. On the other hand, if the cognitive distance is large, it implies that they differ in their use of research terms.

4.3 Short Summary on Methodology

We propose a combined method to measure cognitive distance where both the references and the content of individual researcher and reviewer are considered. Previous research on this problem has paid little attention to the latter aspect, that is, research content; solely references were used (Sandström, 2009; Sugimoto et al., 2013). In our view, references could reflect research traditions/trails of an individual researcher. Furthermore, with the Author-Topic analysis, we could obtain cognitive distances in their research content itself. Studies in computer science have applied topic models to match submissions with referees (Mimno & McCallum, 2007; Daud, 2012). However, the drawback of this kind of technique is that it is difficult to detect the researcher's attitude on specific theoretical perspectives. Different schools probably differ in perspectives, interpretations, and research methods/paradigms to the same research question. For instance, in the case of classical economics, new classical economics, Keynesian economics, and the like, they all have the same focus in economics research but are extremely far from each other. Thus, it is quite important to have insight into a researcher's tradition/trail in order to be able to correctly classify the content of a paper Because cognitive distances obtained by Author-Topic analysis and Author-Bibliographic Coupling, respectively, have different implications, we did not provide an integrated algorithm. Figure 2 summarizes the methods we proposed.

In addition, the strength of our method is that collaborative relations are adequately addressed. Obviously, collaboration is an important way to achieve cognitive similarity and absorptive capacity (Nooteboom, 2000; Hautala, 2011). The more collaborative work among researchers, the more similar their cognitive relations will be. In our measurement, if two researchers have active collaborations, the cognitive distance between them would be shorter than if they are only refereeing to the same references. If the distance is short without collaboration then we can infer that they are competitors at a specific research front.

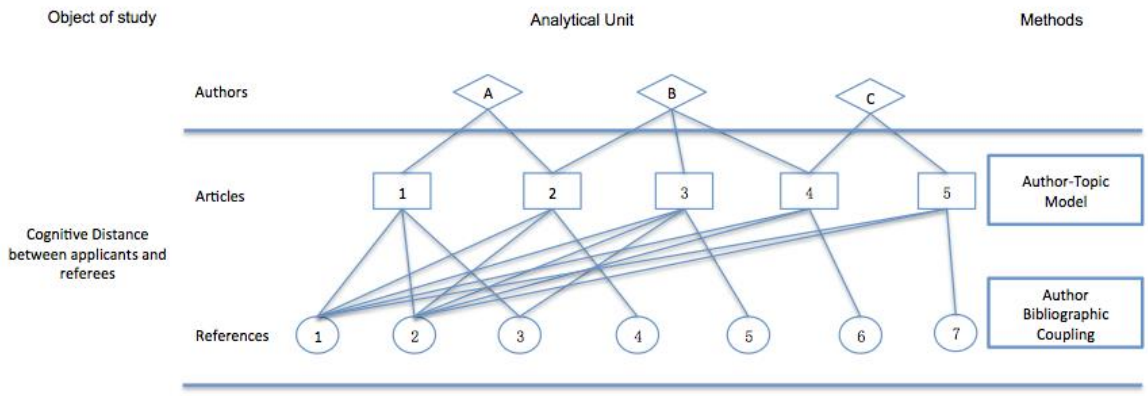

Figure 2. Summary of the proposed methodology

5. Case and Data

The case used in this paper was initiated by the Swedish Foundation for Strategic Research (SSF). The full name of the scheme is 'Molecular mechanisms in the interplay between microorganisms/parasites and their host (man, domestic animals, plans and forest trees) in relation to disease'. In 2013, SSF decided to invest 225 million Swedish kronor on projects that would 'result in new knowledge that may be used in finding cures for malaria or cholera or in the development of new antibiotics, diagnostic tests or vaccines' (SSF, 2013). Projects were organized as framework grants aiming at stimulating individual researchers, from both academic and industrial fields, to collaborate to conduct 'excellent' research.

The foundation received 57 research proposals, from 57 main applicants with 136 co-applicants. To select the projects with potential value, SSF used a two-stage peer review approach. In the first round, fourteen referees involved had a diversity of backgrounds both from university and from the pharmaceutical industry. Referees were Swedish or Swedish permanent residents. Notable is that some of the referees in the first round have no publications, they were relevance persons from industry with none or very few recent academic merits, leading to difficulties in measuring cognitive distance.

Twenty-eight out of 57 applications advanced to the next stage. Unlike the previous round, nine international referees (non-Swedish) were selected (by whom the referees were selected was not disclosed by the foundation). Nine proposals were granted. A single-blind sort of 'peer review' was applied in both rounds, which implies that referees could review the resumes of applicants, including the information on educational background, professional experiences, publications, and the like. It should also be pointed out that all the referees were probably involved in the review of each application. However, it is not clear whether referees could discuss or exchange views among themselves during the review process. It is still unclear whether referees had an actual meeting in the same location.

Data on publications were collected from the WoS database, using the following document types: *Article*, *Letters*, *Proceedings Papers*, and *Reviews*. Names of applicants and referees were used to search and retrieve publications. This might have led to the obtainment of redundant publications due to duplicate names (homonyms). To make the data accurate, we refined data automatically based on all possible information, such as sources, organizations, and countries. But due to collaborations among applicants and even between referees and applicants, there are a few duplicate publications in our dataset. These duplicates were not removed. Finally, the total number of publications (not unique)

obtained was around 8,000. According to regulations of SSF, every referee is likely to be involved in each application's review process. With this refined dataset, we measured the cognitive distance between the main applicants and each referee, and then used the minimum distance for each relation to represent the cognitive distance between an applicant and his/her possible referees.

6. Result

6.1 Result from First-Round Peer Review

In the first review stage, there were 57 main applicants, of which two had no publications in WoS. Fourteen referees were involved in the review session. About half, 28 out of 57, of applicants were forwarded to the next peer review round. Figure 3 shows the results. The horizontal axis represents the cognitive distance measured by A-T analysis, whereas the vertical axis shows results based on ABC analysis. Each dot represents an application, and the red color represents those applications that were forwarded to the second round, whereas the blue color is for the failed applications.

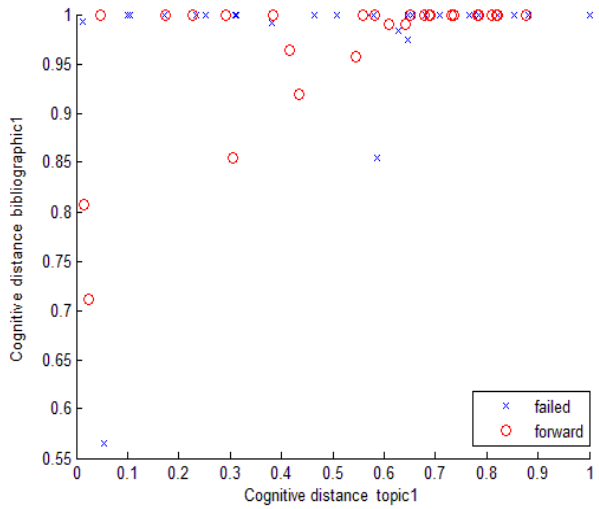

Figure. 3 Cognitive distances between applicants and reviewers in the first round

First, as shown from the vertical axis (measured by the ABC analysis) in the above figure, most applicants have large cognitive distances to reviewers, concentrated in the interval from 0.95 to 1. Long distances obtained by ABC analysis indicate that applicants and referees rarely use the same references.

Second, cognitive distances obtained by the A-T analysis were scattered from 0 to 1, and clearly there are only a few applicants with extremely short (0–0.2) or long (0.8–1) cognitive distances to their reviewers. Based on this result, we can infer that some of reviewers have few publications in their reviewed research areas. Therefore, it is difficult to ascertain whether or not the reviewers are experts in the field; the credibility of the procedure for (*peer*) review in this case could be doubted.

6.2 More Tests on First Round Peer Review

As mentioned above, the reviewers involved in the first round were all from Sweden, and they were from many sectors of society. Thus, there might be a small country problem, which implies 'personal relations and politics might dominate the scene and objective impartial evaluation is not possible' (Pouris, 2007). In this case, other factors rather than the applications themselves could play an important role in the review process. Therefore, we investigate whether bibliographic indicators, such

as the number of publications, journal impact factors, and positions, could have affected the review results. We used a regression model to determine what factors could be involved. In this section, we should emphasize that data from all applicants including both principal investigators and co-applicants were used.

Because the dependent variable is whether applications entered to the second review round, which is binary and not continuous, a logistic model is used. We divided the independent variables into two categories:

- Individual level variables: independent variables on the individual level include three variables. The first one is fractionalized papers (*Frac P*), which indicates the number of publications of each applicant. The second is Top1%, which measures the share of citations above the 99th percentile (*Top1%*). The last one is Vitality, which is the 'freshness 'of references they used (*Vitality*).
- Journal level variables: normalized journal citation score (*NJCS*) to the field.

Included are two control variables regarding the identities of applicants: gender, valuing 1 if the applicants are female, and scientific position, valuing 1 if the applicants are professors.

Table 3. Logit regression in first round selection

Variable Name	*Coef.*	*S.E.*
Frac P	0.0730	0.0579
NJCS	1.558**	0.642
Top1%	20.34**	8.406
Vitality	3.237	2.117
Gender	-0.223	0.403
Prof	0.484	0.436
Constant	-5.873**	2.312

*** p<0.01, ** p<0.05, * p<0.1

Table 3 reports the results of logistic regression, investigating the impact of bibliographic indicators on first round review results. First, *NJCS* and *Top1%* are significant and positive, indicating that the more articles published in good journals, the more possible it was that they could move forward to the next review round. Obviously, the quality of the journal has a strong impact on the review results. However, *Frac P* and *Vitality* are not significant. It seems that reviewers did not consider the number of publications of individual applicants. *Vitality* was used as an indicator of research novelty, which is not significant in the model; thus, it is not an influential factor in peer review (at least, not in this specific case under these specific circumstances).

In brief, we found that the review results were influenced by the previous research outcomes of applicants. Furthermore, reviewers tend to pay attention to journal impact factors, a measure that is easy to use as a proxy indicator for research quality. However, it is dangerous to use journal impact as a procedure in evaluation at the individual level. According to Seglen (1992; 1994; 1997), although articles are published in journals with relatively high expected citation rates, it does not necessarily imply that the articles themselves are good quality.

6.3 Result from Second Round Peer Review

Half of the applications entered into the second peer review round, and nine out of these finally were granted funding support. As in the first round, we measured the cognitive distances between each application and the new group of reviewers in the second round. Figure 4 shows the result. Compared

with the results of the first review round, a certain pattern can be observed between cognitive distances and final results.

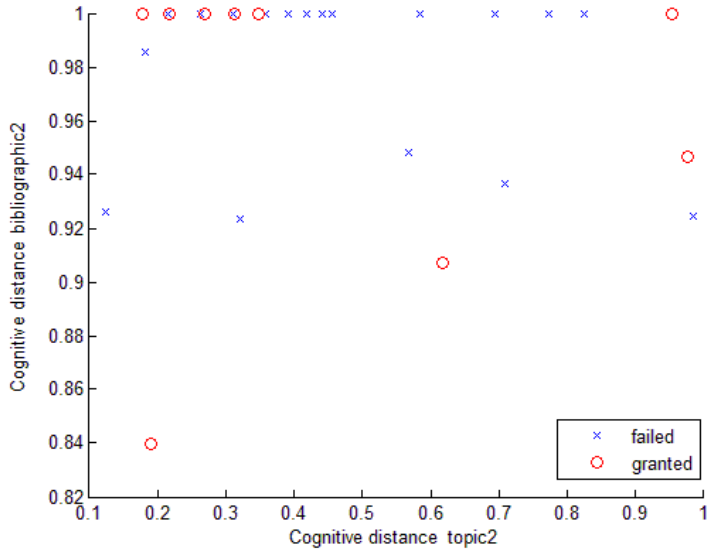

Figure. 4 Cognitive distances between applicants and reviewers in second round

Cognitive distances measured by ABC analysis were still quite large, like the results in the first round, mostly concentrated between 0.95 and 1. On the other hand, cognitive distances obtained by the A-T analysis were scattered from 0 to 1, and clearly there are only a few applicants with extremely short or long cognitive distance to their reviewers.

Unlike the results from the first round, it can be seen that 6 of 9 winners have relatively short cognitive distances (A-T analysis) with their reviewers, while 2 of 9 winners have high levels of cognitive distances (ABC analysis). Applicants located in the middle of the range had a small probability of success: only one application was granted. This result, on one hand, is consistent with statements from previous research that reviewers are predicted to be more likely to support applicants within short cognitive distances. On the other hand, our results show that reviewers also support applicants who have a long cognitive distance to the reviewers. In other words, results from the second round show that reviewers are likely to support applicants whose cognitive distance is either short or long, and that the applications in between have difficulties getting approval.

To summarize, in the first round, the impact counted as societal relevance and journal quality had a strong impact on the review results, but cognitive distance did not have a strong influence on the results. However, in the second round, an influence from the cognitive distance factor can be observed. The applicants with short or long cognitive distances had higher probabilities of getting granted.

7. Discussion

This paper focuses on exploring the role of cognitive distance in the peer review process and measuring cognitive distances between applicants and referees. One motivation behind our work is lack of theoretical and empirical research on cognitive distance and peer review. The evidence here shows that there was the neglect of consideration about the cognitive distance when the SSF selected referees for reviewing the research proposals. In peer review procedures, academic status plays an

important role. However, in the normal sense, cognitive bias in the peer review process is not taken into consideration by those who are in charge for selecting reviewers.

First, cognitive distances obtained by ABC analysis in both peer review rounds were all quite large. Because most of the reviewers in the first review round were from the practical-industrial field, they did not have many publications. They were probably not active in the same time frame as the applicants. Furthermore, the number of publications and cited half-life of *infectious diseases* is 7,253 and 5.2, which indicates that the rapid renewal speed of this area. Thus, there might be very little overlap of the references used by reviewers and applicants (see Figure 5). This could be one explanation as to why cognitive distances measured by ABC analysis became quite long.

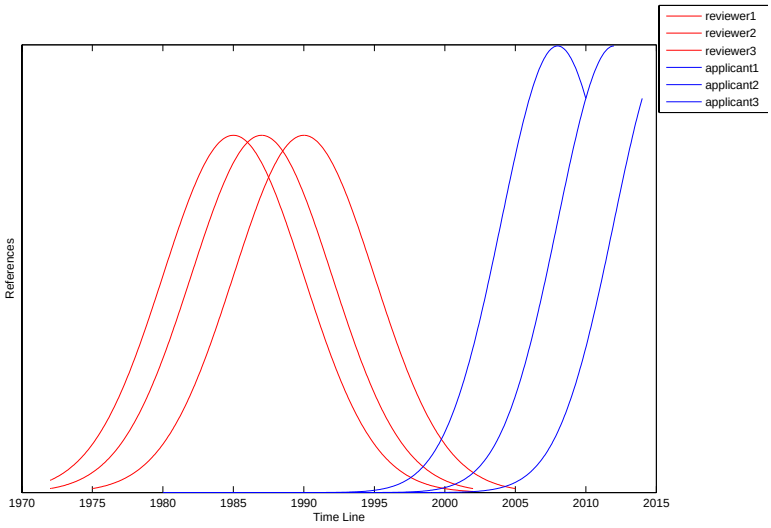

Figure 5. References used by reviewers and applicants.

Furthermore, our results to some extent complement the previous research on the role of cognitive bias. Previous research (Mahoney, 1977; Travis & Collins, 1991; Sandström, 2009; Sandström, 2010) focused on exploring the influence of cognitive similarity to the results of peer review, but ignored the impact caused by extremely low similarity of research cognition. Our results from the second review stage show that reviewers are likely to support the applicants who hold either short or long distances with them, which implies reviewers are more likely to approve applications which they are familiar, and, actually, the same applies for applications with which they are relatively unfamiliar. One reason for this could be that reviewers might be less strict in the evaluation of unfamiliar applications for which they are not experts. It is undeniable that further research both theoretical and practical is still required to explain this phenomenon.

From the perspective of knowledge management, Nooteboom and colleagues (1999, 2000 2007) have proposed and empirically confirmed that inverted U-shaped relations exist between cognitive distance and absorptive capacity. This implies that a too small or a too large cognitive distance has a negative effect on knowledge absorption. Therefore, there is an ‘optimal cognitive distance’ in a learning process. Borrowing the concept of ‘optimal cognitive distance’ into a peer review process, we assume that in order to avoid cognitive bias, reviewers should have optimal cognitive distances with applicants. Fundamentally, the reason for this proposition is that short or long cognitive distances may cause the type of cognitive biases, which is summarized in Figure 6.

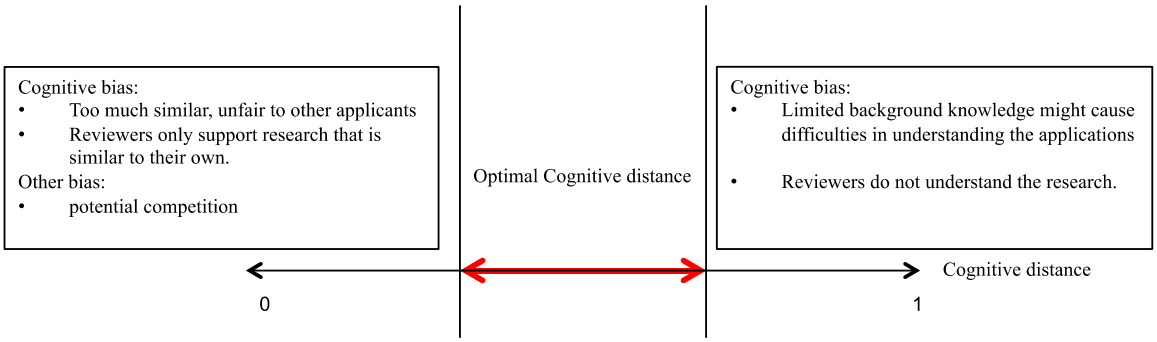

Figure 6. An optimal cognitive distance in peer review

As we motioned above, current research in the area of computer science focuses on selecting reviewers conducting (very) similar research to the applicants or contributors. Many algorithms, based not only on references but also on research content, are applied to calculate the research similarity. However, the research community of computer scientists has ignored the bias caused by cognitive similarity. Hence, to avoid cognitive bias in the peer review process, we would like to suggest that funding agencies should avoid selecting the reviewers whose cognitive distance with their applicants is either too large or too small.

In addition, it is also necessary to discuss the limitations with the specific case in our study. As mentioned by Bornmann (2008; 2011), there are two fundamental problems making generalization of the findings from research on peer review difficult. First, it is difficult to judge whether the applicants who receive unfavorable review results are negatively evaluated due to the potential bias, like cognitive bias, or due to their 'insufficient quality of the proposals or manuscripts' (Bornmann, 2008; see also Daniel, 2004). Another limitation is that due to data access problems, lack of data makes the empirical research on fairness in the peer review process, such as research on cognitive bias, quite difficult. Our case study has the same problem because we have no information regarding the research proposals themselves. As a result, an assumption for this research is that all proposals should have the similar research quality or that the track record of applicants should count as the quality indicator. Only Wennerås and Wold (1997) and, later, Sandström and Hällsten (2008) have used a data set that could apply such indicators. Meanwhile, lack of information of research proposals may cause another problem. There are cases when a researcher starts a new research trail (line) with a proposal to the research council. Obviously, in those cases the researcher does not have any papers in that trail and there will be no connection to reviewers with a specific bias for such a trail, although the trail will be opened by the researcher. However, due to the limited data, it is difficult to make further studies regarding this issue.

8. Conclusion

The paper explores the issue of cognitive bias in the peer review process. A major part of the paper is an elaboration of the concept of cognitive distance in relation to the peer review processes. We show the connection between the concept of cognitive distance in the context of peer review and the research design, including the use of the Author-Topic analysis. Third, we illustrate a novel perspective to select reviewers, especially for the managers of research funding agencies, who have large effects on cognitive development (Braun, 1998). However, this paper was analyzed based on a relatively small number of cases, thus causing the statistical significance problem. Therefore, more empirical tests on the relations of cognitive distance and peer review are required before there is ground for a new policy in these matters.

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