The Significance and Impact of Winning an Academic Award: A Study of Early Career Academics

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ABSTRACT

Academic award plays an important role in an academic's career, particularly for early career academics. Previous studies have primarily focused on the impact of awards conferred to academics who have made outstanding contributions to a specific research field, such as the Nobel Prize. In contrast, this paper aims to investigate the effect of awards conferred to academics at an earlier career stage, who have the potential to make a great impact in the future. We devise a metric named Award Change Factor (ACF), to evaluate the change of a recipient's academic behavior after winning an academic award. Next, we propose a model to compare award recipients with academics who have similar performance before winning an academic award. In summary, we analyze the impact of an award on the recipients' academic impact and their teams from different perspectives. Experimental results show that most recipients do have improvements in both productivity and citations after winning an academic award, while there is no significant impact on publication quality. In addition, receipt of an academic award not only expands recipients' collaboration network, but also has a positive effect on their team size.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in collaborative and social computing**; • **Information systems** → *Information retrieval*; *Data mining*.

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JCDL '22, June 20–24, 2022, Cologne, Germany

ACM ISBN 978-1-4503-9345-4/22/06…$15.00
https://doi.org/10.1145/3529372.3530913

KEYWORDS

scholarly big data; academic award; academic performance; scientometrics

ACM Reference Format:
Jing Ren, Yajie Shi, Adrian Shatte, Xiangjie Kong, and Feng Xia. 2022. The Significance and Impact of Winning an Academic Award: A Study of Early Career Academics. In *The ACM/IEEE Joint Conference on Digital Libraries in 2022 (JCDL '22), June 20–24, 2022, Cologne, Germany*. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3529372.3530913

1 INTRODUCTION

The output of knowledge plays a crucial role in the long-term growth of the economy, but little is known about how knowledge is generated. It is difficult to justify what kind of award can most effectively stimulate the motivation of knowledge producers [3]. In academia, awards have been established as a measure to encourage scientific activities, with prominent awards being conferred to academics who have made outstanding achievements or have the potential to make further improvements in a specific research field. At present, numerous awards have been proposed in various scientific disciplines around the world, such as the Fields Medal in mathematics [1] and the Turing Award in computer science [39]. Due to the accessibility of big scholarly data [11, 27, 38], increasing focus has been placed on exploring how such scientific awards influence the performance and trajectory of the recipients' academic career from different perspectives [25, 43].

It is acknowledged that scholars have become the most important resource for scientific and technological progress, and economic development. While early career academics are at the beginning of their careers and may not have contributed a significant amount to the research field, their creativity levels are often at a peak during the start of their careers, so their output should be recognized in order to improve their scientific impact [34]. In their early career periods, awards can often play a key role in influencing an academic's career. Nowadays, many countries have introduced award programs for early career academics, such as the Waterman Award, the Presidential Young Scientists and Engineers Award in the United

States, the Federal Government Science and Technology Award for Young Scholars in Russia, and the Shanti Swarup Bhatnagar Medal in India. These awards aim to encourage increased scientific outputs in terms of both quality and quantity. Despite these awards are initiated for early career academics, it is still unclear what their impacts are in terms of improving academic performance of early career academics as they progress in their careers.

Existing works have primarily focused on studying the impact of awards and honors conferred to experienced academics who have achieved outstanding results in a specific scientific field of research (e.g. The Nobel Prize) [6, 16, 26]. In contrast, little attention has been given to the impact of awards set for encouraging early career academics who have the potential to make further improvements or achievements to the research field, which is the focus of this work. The main difference between these two kinds of analysis is that the recipients of the former award are generally older and more experienced in academia than the latter. Awards for early career academics are more likely to provide a motivation for increased performance and output of future scientific works, while awards for senior researchers constitute a reward for existing achievements. Therefore, the impact of these two kinds of awards on recipients should be analyzed separately to determine the impact on academics at different career stages.

With the modern advancement of communication technologies, academics tend to have more collaborators both nationally and internationally, thereby enlarging collaboration networks and their team size [47, 48]. Wuchty et al. [42] show that teamwork is a more efficient way to promote knowledge production when compared to individual work. Further, studies have shown that the achievements of teams tend to have higher impact and receive more attentions [20]. It is assumed that recipients of academic awards may also influence their peers and also increase their collaborations, thus resulting in a wider impact on the academic performance of their team members and collaborators. Therefore, it is also necessary to explore the influence of award recipients on their teams, such as the influence on increasing the number of collaborators and also the scientific impact of the recipients' collaboration network.

In this paper, we not only systematically evaluate how awards affect recipient's academic career in the near future, but also explore what recipients contribute to their teams. In addition, we also explore the impact of academic awards on different research fields, and the inter-relationship among these fields. To evaluate the impact of academics, we use two types of evaluation indicators: paper-based and citation-based indices. An analysis of these indicators can help to answer the following research questions:

RQ1. How do early career academic awards impact on recipients' scientific impact?

RQ2. Do early career academic awards improve the recipients' work performance?

RQ3. How do early career academic awards affect the recipients' teams and collaborations, in terms of team size and academic performance?

Contribution: To answer these questions, we execute a series of experiments to analyze how award influence an early career academic's career. We summarize the contributions of this paper as follows:

- By proposing Award Change Factor (ACF), we evaluate and analyze the effect of an award on the recipient's academic performance and influence.
- To measure the effect of award on recipients, we construct a control group which is composed of academics who have similar outputs and research performance with the recipients, but who have not received academic awards. Then, we explore how awards impact the recipients' academic career by comparing these two groups.
- We define an indicator to quantify the collaboration intensity (CI) between two scholars, thereby analyzing the team change of the recipients from the perspectives of team size and impact.
- Experimental results show that the proposed models can evaluate the influence of an award on recipients and their teams from different perspectives.

In the remainder of this paper, we first introduce the related works in Section 2, followed by the methodology in Section 3. Empirical applications are shown in Section 4. We conclude the paper and envision future directions in Section 5.

2 RELATED WORK

In this section, we will introduce existing research on analysis of academic awards and evaluation of scholarly impact, which are closely related to this work.

2.1 Analysis of Academic Awards

Previous research focused mainly on studying the performance and academic impact of Nobel Prize laureates. Jones and Weinberg [19] found that the number of major breakthroughs made by academics in their 30s declines gradually over time, but continues to increase in their 40s. Pan and Fortunato [32] put forward the AIF dynamic index to measure scholars' academic influence, and devise an evolution model to profile four Nobel Prize laureates' academic influence. Chan et al. explored whether awards breed further awards and what happens after a researcher receives the Nobel Prize in [5]. Later, they paid attention to the achievement of Nobel Prize life cycle of physics, chemistry, physiology and medicine recipients from 1901 to 2000, and find that Nobel Prize laureates with theoretical orientation would receive more awards than those with experience orientation, and their educational background seemed to shape their future cognition [9]. They also investigated the change of collaboration patterns and academic productivity in Nobel Laureate Teams after winning award [7, 8].

Apart from the Nobel Prize, Faria and McAdam [13] studied the career development of "experts" after their tenure in relevant departments, and the results show that there is a clear polarization between experts and other employees in terms of academic reputation and promotion prospects, which provides a new perspective for the study of academic productivity. Xia et al. [43] proposed the concept of Turing Number. Kong et al. [22] explored the collaboration patterns of Turing Award laureates. By analzing the evolution of the Turing Award collaboration network, the authors find that the laureates are more inclined to publish papers alone in the early stage of their career, but gradually increase attention towards collaboration as their career progresses. Besides, academics who are closer to laureates in the collaboration network are more likely to have higher academic impact. Borjas and Doran [2] compared the productivity of Fields medalists to that of similarly brilliant contenders. The authors find that the winners' productivity declines after the award year. Chan et al. [4] investigated whether receiving prestigious academic awards is associated with higher subsequent research productivity and status. The prize they studied are the John Bates Clark Medal and the Fellowship of the Econometric Society.

In [12], English discussed the correlation between prize and culture, including the age of awards, peculiarities of the award industry, and the global economy of cultural prestige. With the increasing attention on the study of awards such as medals, prizes and titles in economics, Frey and Gallus [14] reviewed how research on awards has advanced over the last couple of years, and provided several research points for future work. With the aim of understanding how the knowledge linkages among prizes and scientists' propensities for prizewinning relate to knowledge pathways between disciplines and stratification within disciplines, Ma and Uzzi [29] collected 3,000 different scientific prizes in diverse disciplines and the career histories of 10,455 prizewinners worldwide for over 100 years. By constructing prize network and social network of prizewinners, they identified the connections between prizes and prizewinners within and across disciplines, and explained the increasing concentration of scientific fame within a proportionately smaller and more tightly interconnected elite. Kim [21] introduced a book named Honours versus Money: The Economics of Awards. The main conclusion of this book is that awards are more effective than monetary incentives for motivating individuals.

The works introduced above all aimed to study awards conferred to academics who have made outstanding contributions to a specific field. Regarding the study of awards conferred to early career academics, Li et al. [24] studied alumni collaborations with Chang Jiang scholars as a research group and found that alumni faculty tend to collaborate less within intra-institution than non-alumni faculty. They only explored the impact of academic awards on the collaboration behavior of recipients. In this paper, we not only evaluate the impact of academic awards on recipients and their teams' academic influence, but also examine the interrelationship among different research fields.

2.2 Evaluation of Scholarly Impact

Assessing scholarly impact has been used to address many real-world issues like funding allocation, promotion decision, and award evaluation [30, 44]. It is acknowledged that citations are a widely used measure of scientific impact, but long-term prediction of citation number is very challenging and has become an emerging applied research topic [28, 31, 41]. The skewed distribution of citations tends to follow the power law or lognormal distribution [40].

Many researchers have studied some other easily-solved impact analysis and prediction problems. For example, Petersen et al. [33] conducted longitudinal analysis to measure the influence of the reputation of core authors on the citation rate of papers. Dong et al. [10] formulated and solved a classification problem by providing various characteristics such as publication subject, publisher and author institution to different classification models, so as to determine whether a paper will affect the $h-index$ of authors within a pre-defined time range. Recently, Kong et al. [23] predicted the academic success of scholars by analyzing different impact factors of scholars. They found that the author-centered and article-centered factors are most relevant to scholars' success in the future. Specifically, apart from some common measures like h-index and Journal Impact Factor (JIF), author-centered factors used in this paper also calculate the Q value of scholars and the effects of coauthors' research background on scholars' impact. Article-centered factors include some basic indicators like citation counts and the number of papers, and some heuristic indicators like the popular degree of article topic.

3 METHODOLOGY

In this section, we first introduce the proposed indicator Award Change Factor (ACF), which is used to evaluate the impact of awards on academics. Then, two models will be introduced, which can measure the effect of awards on academics and their teams.

3.1 Analysis of Academic Impact

To understand the impact of awards on academics, we propose ACF, which is used to evaluate changes in the impact made by academics after receiving an award.

3.1.1 Award Change Factor (ACF). Taking the number of papers published every year as an example, we qualitatively fit a piece-wise linear function according to the number of papers over time. As shown in Eq. 1, the origin point is the year of award.

$$f(x) = \begin{cases} b + m_1 t, & t \leq 0 \\ b + m_2 t, & t > 0 \end{cases} \tag{1}$$

where m_1 and m_2 are slopes of two fitted lines, showing productivity changes before and after the award. b is the bias. t denotes the time of winning the award, so $t < 0$ and $t > 0$ means before and after award, respectively. By fitting these three parameters for the production trajectory of academics, the function is fitted by the least square method. Based on this function, the ACF is defined as the difference between m_1 and m_2 , as shown in Eq. 2.

$$ACF = m_2 - m_1 \begin{cases} > 0, & Positive\ impact \\ < 0, & Negative\ impact \\ = 0, & No\ impact \end{cases} \tag{2}$$

when $ACF > 0$, we consider that the award has a positive effect on an academic.

3.2 Analysis of Effect on Awardees

In order to assess the effect of awards on academics, we need to build a control group for comparison. Then, we can explore the effect of awards on recipients by comparing the difference between the treatment group (recipients of awards) and the control group (academics who have similar performance with awardees but without awards). In this paper, we evaluate the effect of award on both academics themselves and their teams.

3.2.1 Construction of Control Group. Rosenbaum and Rubin [36] pioneered the propensity score matching method in 1983 to improve the estimation bias in randomized trials. Its basic idea is to find in a group of individuals who are similar to the participants in all relevant pre-treatment characteristics. In practical applications, the final propensity score of two groups of subjects is obtained by a designed model [35]. We will obtain the corresponding control group by comparing the propensity scores among academics.

The specific steps of the propensity score matching method are as follows:

Characteristics Selection: Here, the number of papers, fund papers, average citations, total citations, $H - index$ and journal impact factors (JIF) in the last five years before academics' awards are selected as control variables.

Model Building: Because there are only two cases in the research process, i.e., academics with award and without award, the binomial logistic regression model is selected to estimate the parameters of the relevant impact factors, and the coefficients of the model are obtained by the following equation:

$$ln\left(\frac{P(Award = 1|X)}{1 - P(Award = 1|X)}\right) = \alpha_0 + \alpha_1 X, \tag{3}$$

where $Award$ denotes virtual variables, and $P(Award = 1)$ is the propensity score value, denoting the probability of winning award. X is a vector representing the characteristic variables that affect academics' awards, including the number of papers, average citations, total citations, etc.

Propensity Score Calculation: After getting the values of parameters α_0 and α_1, the propensity score of each researcher can be calculated:

$$E(Award = 1) = \frac{e^{\alpha_0+\alpha_1 X}}{1 + e^{\alpha_0+\alpha_1 X}} = \frac{1}{1 + e^{-\alpha_0-\alpha_1 X}} \tag{4}$$

Control Group Construction: According to the propensity score, the matching object, i.e. the control group, is selected as the object closest to treatment group. Academics in the treatment group are recorded as $S = 1$, while academics in the control group are recorded as $S = 0$. The difference between these two groups are defined as:

$$\begin{aligned} E(I) = E(P^1|S = 1, P(Award = 1|X)) \\ -E(P^0|S = 0, P(Award = 1|X)) \end{aligned} \tag{5}$$

Here, I refers to the effect of winning award on the research output of scholars. According to the propensity score, the control group and the treatment group are matched at 3 levels (high, medium, low) by considering the balance of propensity score among different levels.

Model Testing: We conduct a significance test for the two groups' characteristics. The matching model will be established when there is no significant difference between these two groups. T-test and standardized difference tests are used to adjust the equilibrium of stratified samples. It is concluded that there is no significant difference between the covariates at each level. In other words, it is reasonable to divide academics into three levels .

3.2.2 Effect Estimation on Scholars. Here we explore the effect of award on scholars by answering the following two questions.

Do academics who receive awards have higher academic influence than academics without award?

We construct a model to test it, as shown in Eq. 6:

$$AC_i = \alpha_1 L_i + \alpha_2 M_i + \alpha_3 H_i + \alpha_4 Award_i + \varepsilon_i, \tag{6}$$

where AC_i indicates the characteristics of academic i in the first five years after winning award (i.e. the number of papers, the number of fund papers, the number of citations, the average number of citations, $H - index$ and average journal impact factors). L_i, M_i, and H_i denote academics who have low, medium, and high probability of winning awards in the control group, while $Award_i$ represents whether academics in the treatment group received an award. α_1, α_2, and α_3 are the coefficients of low, medium and high probability academics in the control group respectively, while α_4 is the coefficient of academics in the treatment group. If $\alpha_4 > \alpha_3$, $\alpha_4 > \alpha_2$, $\alpha_4 > \alpha_1$, then it shows that academics with award have higher academic impact than those without award.

Do academics with higher probability of winning an award have higher academic impact than academics with lower probability?

We establish another model:

$$AC_i = \alpha_1 L_i + \alpha_2 M_i + \alpha_3 H_i + \sum_{i=1}^{3} \lambda_i S_i^{Award} + \varepsilon_i \tag{7}$$

where S_1^{Award}, S_2^{Award}, and S_3^{Award} represent the low, medium and high probability academics in the treatment group, and λ_i is coefficient. If $\lambda_1 < \lambda_2 < \lambda_3$, or $\alpha_1 < \alpha_2 < \alpha_3$, then academics who have higher probability of winning an award have higher academic influence after receiving the award. The completed algorithm for effect analysis is described in **Algorithm 1**.

Algorithm 1 Effect Analysis Algorithm

Input: Data in treatment group and control group.
Output: Evaluation results of effect model.

```
for Author in data do
    Calculate PropensityScore (PS) with Eq. 4.
end for
for Author in PS do
    Match recipients with the control group with Eq. 5.
    Calculate Layered Results (LR)
end for
Test the model with analysis of variance.
for Author in LR do
    Analyze the effect of award by comparing the treatment
    group and control group with Eq. 6.
    Analyze the difference of effect on scholars who have differ-
    ent levels of probabilities in winning award with Eq. 7.
end for
return Evaluation Results
```

3.2.3 Effect Estimation on Academics' Teams. Teams usually produce higher impact scientific work than individuals, because collaboration can improve work efficiency and reduce errors [46]. In order to evaluate the changes of team size and team influence before and after the award, we use the academic team identification algorithm based on the collaboration intensity to identify their team members.

Algorithm 2 Team identification Algorithm

Input: Collboration network $G = ((V, VWeight), (E, EWeight))$, team constraint coefficient ω;
Output: Academic team T.

for $Author$ in G **do**
  find the $NeighborsofAuthors$ from G
  for $NeighborsofAuthor$ in $NeighborsofAuthors$ **do**
    $CI = \frac{EWeight(Author, NeighborofAuthor)^2}{VWeight(Author)VWeight(NeighborofAuthor)}$
    $G.EWeight = CI$
    if $G.EWeight < \omega$ **then**
      remove $G.E$
    end if
  end for
end for
$NewNetwork = G$
for $Author$ in $NewNetwork$ **do**
  find the $NeighborsofAuthors$ from $NewNetwork$
  if $Edge$ between $NeighborsofAuthors$ is one-side **then**
    remove $NewNetwork.E$
  end if
  if $NeighborsofAuthors$ is $NULL$ **then**
    remove $NewNetwork.V$
  end if
end for
return $NewNetwork$

Collaboration Intensity (CI) is defined based on the coauthorship between two authors, which is calculated as:

$$CI_{ij} = \frac{(FQ_{ij}^{\Delta t})^2}{N_i^{\Delta t} \times N_j^{\Delta t}}, \tag{8}$$

where Δt indicates the interval of years measured, and $FQ_{ij}^{\Delta t}$ indicates the number of the author i and author j co-authored in the Δt year. $N_i^{\Delta t}$ and $N_j^{\Delta t}$ represent the publication number of author i and author j during the Δt year respectively. The higher the CI value, the closer the collaboration between two authors.

Hobbs et al. [18] showed that only 20% of the collaborators have strong relationships and 80% have weak ones. Therefore, we determine the threshold of team constraint coefficient to be 0.2. We identify teams by their partners in the last five years before the award and in the first five years after the award, so as to determine the team size of each academic. The completed algorithm for team identification process is described in **Algorithm 2**. In this paper, we only identify and compare the academic impact of awardees. The academic impact of teams are evaluated from the perspectives of the average number of citations, papers, and journal impact factors (JIF).

4 EMPIRICAL APPLICATION

In this section, the dataset used in this paper and data processing procedures are introduced first. Next, the academic impact indicators are explained in detail. Finally, we show the experimental results from different perspectives.

4.1 Data

4.1.1 Data source. First, we obtained the list of awardees from 1994 to 2015, consisting of 1717 academics in total. After removing academics sharing English names and retrieving the information of academics' papers through Web of Science (WoS), we obtained a final dataset of 1646 scholars and 403362 papers. The 267 subfields in WoS correspond to 13 research fields. In order to study the changes in the influence of awardees before and after the award, we set a limitation that scholars should have publications five years before and after the award. Finally, there are 1088 awardees with a total of 360876 papers in the treatment group. The number of academics' papers, fund papers, total citations, average citations, h-index and journal impact factors were analyzed. Considering that the research output of scholars are growing with the increase of years, it is inappropriate to consider all scholars in different years as one group, and the time interval of five years is supposed to be a suitable segmentation. Besides, considering that the publications 5 years after winning award will be used to evaluate the academic impact change, we select awardees from 2000 to 2011 as representative objects and divid them into two groups when exploring the effect on scholars: 381 in 2000-2005, and 597 in 2006-2011. Note that scholars between 2012 and 2015 are removed because some recipients lists cannot be accessed.

4.1.2 Control group. In the process of selecting scholars for control group in 13 research fields, we set the following limitations in Web of Science: 1) Academic Age between 10 and 20 in 2005; 2) Having publications 5 years before and after 2005.

The construction method of control group we used in this paper is propensity score matching, which has been introduced in Section 3. To analyze the difference between the treatment group and control group, the analysis of variance (ANOVA) is used and we verify that there is no statistical difference between these two groups. During the experiments, the control group is composed of 863 scholars, and the treatment group consists of 1088 awardees. It should be noted that the sample size of the treatment group and the experiment group are so large that the ANOVA cannot be directly applied. Therefore, we classify the scholars into 50 groups, and the p value and F statistics are the average of these groups. The ANOVA results are shown in Table 1.

4.1.3 The award information. The award we studied in this paper is called "The National Science Fund for Distinguished Young Scholars", which is established for young academics in China. The fund supports young scholars under the age of 45 who have the capacity to independently choose research directions to carry out innovative research, aiming to promote the growth of young science and technology talents, absorb overseas talents, and cultivate a group of outstanding academic leaders who have entered the forefront of science and technology in the world. The National Science Fund for Distinguished Young Scholars sponsors about 160 outstanding young scholars each year. The research period is 4 years, which means that the researched project should be completed in 4 years.

4.1.4 Name disambiguity. To gain the complete and accurate publication records for each scholar, we need to ensure their actual identities and conduct name disambiguation to distinguish the duplicate names. Two main steps are applied in the process of author

Table 1: Results of the analysis of variance (ANOVA)

Parameter	Paper	Average Citation	H-index	JIF	Total Citation	Fund Paper
F statistic	0.126389	0.077558	0.099698	0.106219	0.090958	0.086704
P value	0.805638	0.828836	0.809730	0.791589	0.810849	0.811567

name disambiguation, namely separation and mergence. The motivation of this disambiguation method is used by [37]. Firstly, all scholars are seperated from each other, which means that we should regard each author (with the same name or not) in the records as a unique one. Secondly, we iteratively merge the scholars who have the same name and meet one of the following criteria: 1) Having been cited each other at least once; 2) Having at least one co-author; 3) Having at least one identical affiliation. The process of name disambiguation complete when no author pairs are able to be merged.

4.2 Academic Impact Indicators

In this part, we provide a collection of indicators that can evaluate an academic's scientific impact. Considering the diversities of academics' research fields, we classify features into two categories: paper-based and citation-based indicators.

4.2.1 Paper-based Indicators. For the paper-based factors mentioned here, we measured the relevant paper factors for each academic.

- **Author productivity:** The more papers an academic publishes, there is a higher chance that their total number of citations will be higher. Generally, the productivity of an academic can reflect the author's influence [45]. Here, the number of papers per year for authors are used to evaluate an academic's productivity.
- **Fund information:** Academics' funding information can be regarded as a recognition of their academic performance. If a paper notify its fund information in its content, then this paper is called 'fund paper'. Thus, the number of fund papers published by academics is also used as an indicator to evaluate an academic's scholarly impact.

4.2.2 Citation-based Indicators. Citation is the easiest feature to evaluate publications, but is not a comprehensive indicator that can be directly used to evaluate the impact of academics. Thus, we also utilise other citation-based metricss to evaluate academics' scholarly impact:

- **Citation:** The citations of academics can also characterize the impact of academics. Academics having published highly cited papers can reflect their status in their respective fields, because their papers can receive long-term attention in their fields. We calculate the average citation in the experiment.
- **H-index:** H-index is one of the most popular indices used in academia [17]. The h-index of an academic is defined as the number of papers with more than h citations. It not only guarantees the productivity of academics, but also takes account of the influence of papers published by academics. Specifically, an academic's h-index is h, if h of his/her n published papers are cited at least h times and the other $n-h$ papers are cited no more than h times.
- **Journal Impact Factor:** Journals intuitively have different levels of academic impact, and prestigious journals tend to attract the attention of more researchers (e.g. citation). Therefore, we also investigate the journal impact factor (JIF), which is a measure reflecting the average annual citations of a journal's recent articles [15]. It represents the relative importance of a journal in its field. WoS gives the value of JIF from 1997 to 2017. We obtained the JIF report from the official website of WoS.

Paper-based indicators are calculated according to the number of publications, while citation-based indicators are calculated from the perspective of the received citations of these publications. For paper-based indicators, it is apparent that the number of publications (i.e. author productivity) is higher than the number of fund papers. As for citation-based indicators, both h-index and journal impact factor are calculated based on the citations. Specifically, h-index could reflect a scholar's academic impact more comprehensive than citation, because it also requires the number of papers. On the other side, journal impact factor can reflect the research quality of a paper.

There is currently no formal definition for scientific impact and no commonly accepted standard for scientific impact evaluation up to now. Despite that these indicators have been used in numerous studies to verify that they have the capacity to reflect the scholar's academic impact to some extent, it should be noted that all these measures of academic influence has a common limitation, i.e., they are easily gamed by self-citation and mutual-citation.

4.3 Analysis of Academic Impact

Fig. 1 is the average value of each index in the five years before and after the award. The -4, -2, 0, 2 and 4 in x-axis represent the last four and two years before, when, and the first two and four years after the award, respectively. We can see that the average value of each index shows an increasing trend over time. For each index, the value in 2006-2011 is higher than that in 2000-2005. It can also be seen from the figure that besides the average citation and journal impact factor, the number of papers, fund papers and $h-index$ of scholars have increased significantly after receiving award.

In order to further explore the changes in the influence factors of awards, we select awardees between 2006 and 2011 as experimental objects. Fig. 2 shows the changes in the slope, which is obtained by fitting the index value before and after awards. Specifically, the value in the left line presents the slope of the fitted straight line for the 5 years before the award of each scholar, and the value in the right line represents the slope of the fitted straight line for the 5 years after the award. The "red line" indicates the decrease of the

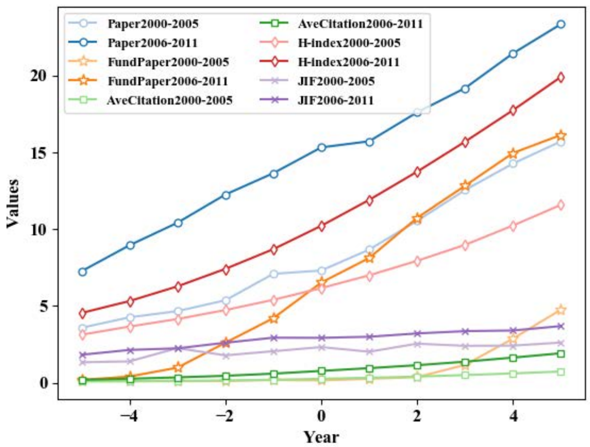


Figure 1: Average value of each index in 5 years before and after the award.

index after the award, and the "green line" indicates the increase of the index after the award.

In order to further explore the impact of award time on academic impact, we analyzed the distribution of ACF. Fig. 3 shows the distribution of how 5 academic impact indicators change after winning awards, and the change of the two groups are similar. It can be seen that the change range of the ACF based on the paper index is relatively large. Specifically, and the change range of ACF_{Paper} is between -30 and 30. However, the change range of ACF based on the citation index is small. Specifically, $ACF_{AveCitation}$ is between -1.5 and 3.5, $ACF_{H-index}$ is between -4 and 6, and ACF_{JIF} is between -6.5 and 6.5. It can be further observed that the parameters in 2006-2011 have a wider range of changes than the parameters in 2000-2005, that is, the changes in parameters in 2000-2005 are more concentrated.

Fig. 4 shows the average distribution of each index, in which the height of rectangular bar reflects the centralized trend of parameter variables. We notice that the average value of $ACF_{FundPaper}$ is the highest in both groups. For recipients in 2000-2005, ACF_{Paper} ranks the second in the number of awards, while $ACF_{H-index}$ ranks the second in 2006-2011, and the gap between the two groups is the biggest. From Fig. 4, it can be seen that the average citation and h-index change factors in 2006-2011 are higher than those in 2000-2005. However, ACF_{Paper} and ACF_{JIF} in 2006-2011 are lower than those in 2000-2005, which shows that the citation-based indicators have a greater impact on scholars. In addition, the ACF_{JIF} of two groups' journal influence factor is negative, which shows that the level of papers published after receiving award has not changed significantly.

4.4 Analysis of Effect Evaluation Function

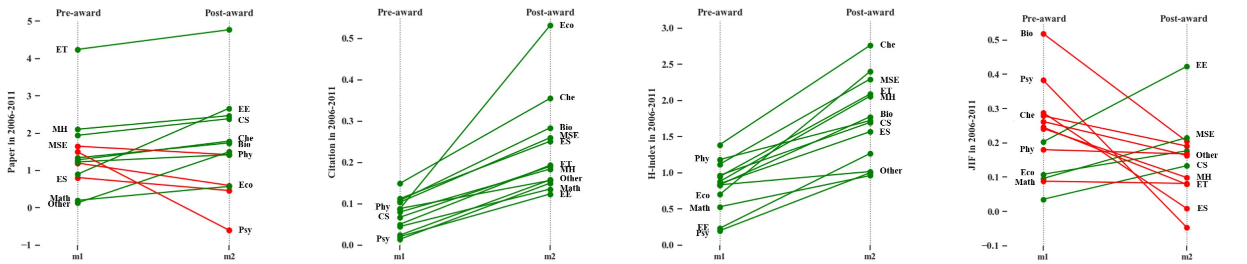
4.4.1 Propensity score after logistic regression. In order to explore the relationship between academic impact after award and a scholar's result, this research chooses the number of papers, fund papers, citations, average citations, h-index and average JIF in the first five years after winning an award as academic impact indicators. Logistic regression was used to analyze the data. The results are shown in Table 2. The coefficient in the second row is the p-value of the indicator, if the value of p is less than 0.01, then it means this indicator has significant relationship on the award result, and otherwise there is no significant relationship. The symbol of the regression coefficient (the first row) refers to the positive or negative relationship on the award result. Therefore, we can conclude from this table that the number of papers, average citations, and total citations have positive relationships on the award results, while journal impact factors have negative relationship on the award results. The number of fund papers and h-index have no significant relationship on the award results.

Through the results of the regression model, we can get the probability of all academics winning award, and then stratify the academics by using the propensity score. The treatment group consists of academics with award, and the control group consists of academics without award. By comparing the equilibrium of probability values between layers and groups, scholars are divided into three layers. The specific layer criteria are shown in Table 3.

4.4.2 The effect of awards on academics. According to the propensity scoring method, 1088 academics with award and 863 academics without awards were stratified according to the standard of Table 3. They were equally divided into three groups according to the probability of winning an award. The specific results are shown in Table 4. The indices of high probability recipients are obviously higher than those of low and medium probability recipients, and the indices of medium probability recipients are also higher than those of low probability recipients. In addition, compared with the low, medium, and high probability academics in the control group, the low, medium, and high probability academics in the treatment group have higher values of indices. Through the above analysis, it can be seen that the value of each index in the treatment group is obviously higher than that of the control group.

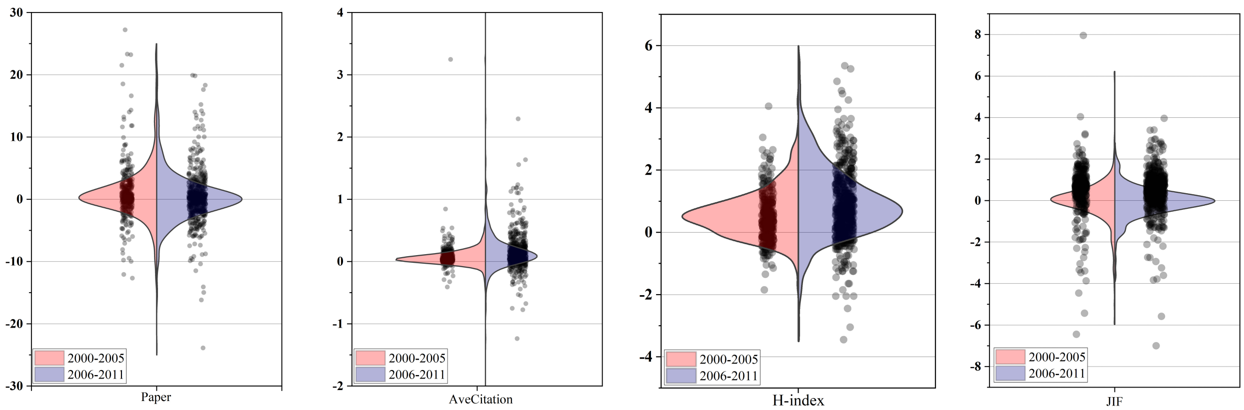
In order to study whether the academic influence of the academics with award is higher than that of the academics without award, we carry out the regression analysis by using Eq. (6). The results are shown in Table 5. It can be seen that the coefficients of low and medium probability academics in the control group are significantly lower than those in the treatment group, but the coefficients of high probability academics in the control group are slightly higher than those of academics in the treatment group. That is, α_4 is significant in statistical sense and $\alpha_4 > \alpha_2$, $\alpha_4 > \alpha_1$, $\alpha_4 < \alpha_3$. The results show that compared with the middle and low probability academics in the control group, the impact factors of the academics in the treatment group are higher, which indicates that awards do have positive effect on academics in the treatment group from the perspective of scholarly influence. However, when analyzing the influence of the treatment group as a whole, the advantage is not obvious when compared with the academics in the control group who have a high probability of winning an award.

Furthermore, we study whether high probability academics in the treatment group have higher scholarly influence than the low probability academics in the control group. Eq. (7) is used as the model for analysis, and the results are shown in Table 6. It can be



(a) Paper (b) Average Citation (c) H-index (d) Journal Impact Factor

Figure 2: Slope changes based on paper and citation indicators in 2000-2011.



(a) Paper (b) Average Citation (c) H-index (d) Journal Impact Factor

Figure 3: Distribution trend of each ACF.

Table 2: Results of logistic regression model

Parameter	Paper	Fund Paper	Average Citation	Total Citation	H-index	JIF
Regression coefficient	0.018784	-0.02054	0.008918	0.01899	-0.00024	-0.02273
P value	5.49E-13	0.501361	0.002908	0.003587	0.08347	0.000114

Table 3: Classification criteria for academics based on propensity score values

Group	Variable	Description
Treatment group	Low w/ Award	$P(Award = 1 \vert X \leq 0.5076)$ and a low probability recipient.
	Med w/ Award	$0.5076 < P(Award = 1 \vert X) \leq 0.6358$ and a medium probability recipient.
	High w/ Award	$P(Award = 1 \vert X) > 0.6358$ and a high probability recipient.
Control group	Low w/o Award	$P(Award = 0 \vert X \leq 0.5076)$ and a low probability academic without award.
	Med w/o Award	$0.5076 < P(Award = 0 \vert X) \leq 0.6358$ and a medium probability academic without award.
	High w/o Award	$P(Award = 0 \vert X) > 0.6358$ and a high probability academic without award.

seen from the table that for the treatment group, the coefficient of high probability academics is obviously higher than that of medium and low probability academics, and the coefficient of medium probability academics is higher than that of low probability academics,

Table 4: Feature statistics for scholars based on propensity score values

Group	Variable	Number	Paper	Fund Paper	Average Citation	Total Citation	H-index	JIF
Treatment group	Low w/ Award	363	9.14	0.58	4.78	47.39	6.76	2.06
	Med w/ Award	362	29.45	1.96	13.50	282.58	23.79	7.28
	High w/ Award	363	96.10	2.29	15.30	995.65	59.00	15.23
Control group	Low w/o Award	288	3.22	0.24	2.11	9.53	1.72	0.91
	Med w/o Award	287	14.64	0.73	8.00	61.45	8.09	4.03
	High w/o Award	288	46.77	2.49	14.87	499.98	38.74	9.56

Table 5: Comparative results of the regression model between treatment group and control group

Parameter	Paper	Fund Paper	Average Citation	Total Citation	H-index	JIF
Low w/o Award	-18.5752	-3.6068	-0.7600	-191.1200	-13.8393	-5.1092
Med w/o Award	-7.41611	-0.5086	-0.2723	-139.4912	-7.5023	0.7719
High w/o Award	24.58560	4.9404	1.4380	289.9915	22.5678	7.5348
Award	23.1595	3.6835	0.6010	241.3185	14.3147	3.9967
Adj-R2	0.0935	0.0267	0.0777	0.0410	0.1375	0.0882
F value	68.0758	18.8143	55.7509	28.7551	104.6244	63.9020
P value	7.33E-42	4.98E-12	1.43E-34	3.44E-18	8.50E-63	2.09E-39

Table 6: Correlation between the probability of obtaining award and academics' performance

Parameter	Paper	Fund Paper	Average Citation	Total Citation	H-index	JIF
Low w/o Award	-24.9728	-4.6291	-17.8034	-0.9288	-257.6942	-6.2333
Med w/o Award	-13.8137	-1.5308	-11.4664	-0.4410	-206.0654	-0.3522
High w/o Award	18.1884	3.9182	18.6037	1.2693	223.4173	6.4106
Low w/ Award	-19.0765	-3.4863	-12.9146	-0.6002	-220.2174	-3.5610
Med w/ Award	0.9457	1.7032	3.9935	0.7672	10.7492	5.1198
High w/ Award	66.8807	9.5557	39.0922	1.1090	717.0836	6.9344
Adj-R2	0.3468	0.0802	0.3677	0.1306	0.1445	0.1627
F value	208.0859	35.0261	227.8354	59.5775	66.8561	76.7984
P value	5.06E-178	2.13E-34	9.95E-192	7.28E-58	1.34E-64	1.23E-73

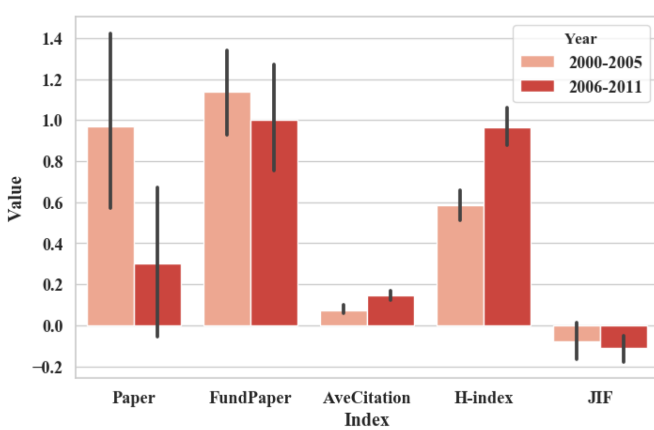


Figure 4: Average value of ACF of each index in five years before and after awards.

namely $\lambda_1 < \lambda_2 < \lambda_3$. This shows that the higher the probability of winning award is, the higher the output and influence of academics is. For the control group, there are similar cases of parameters (i.e. $\alpha_1 < \alpha_2 < \alpha_3$). In addition to the total number of citations of high probability academics, the number of academics in the treatment group at all levels is higher than that of those in control group correspondingly (i.e. $\lambda_1 > \alpha_1$, $\lambda_2 > \alpha_2$ and $\lambda_3 > \alpha_3$), which shows that the academics who have received an award do have higher scholarly influence than those without award, and further confirms the previous problem.

In summary, we can find that compared with the academics without award, the academics with award generally have higher research output and scholarly influence. At the same time, among the academics with award, the higher the probability of winning an award is, the higher the scholarly influence of academics is. On the whole, the experimental results show that the acquisition of an award has a certain positive effect on recipients.

Table 7: Team impact change of recipients before and after awards.

Parameter	Citation		Paper		JIF	
	Pre-award	Post-award	Pre-award	Post-award	Pre-award	Post-award
Mean	5.2376	8.5189	51.1546	91.3930	2.8616	3.9039
Max	75.5	50.1395	211.0	383.0	8.6148	9.2021
Min	0.0588	0.0513	1.0	1.0	0.23667	0.6787
Std	6.1600	6.8328	35.5963	58.1843	1.4460	1.6654

4.5 Impact on Recipient's Team

The influence of 234 teams before and after winning award is calculated, as shown in Table 7. It can be seen that the average citation number of recipients before award is 5.2376, which increases to 8.5189 after award, while the average number of papers before award is 51.1546 and 91.3930 after award. The value of JIF before award is 2.8616, and increased to 3.9039 after award. It can be concluded that the influence of their teams after award is stronger than that before award.

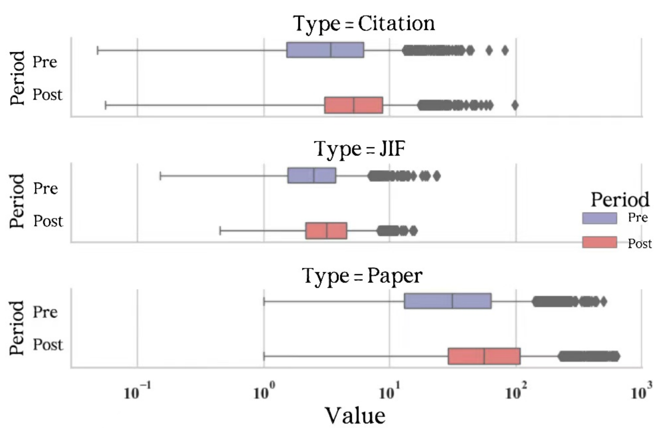


Figure 5: Logarithmic box figure of team impact change before and after awards.

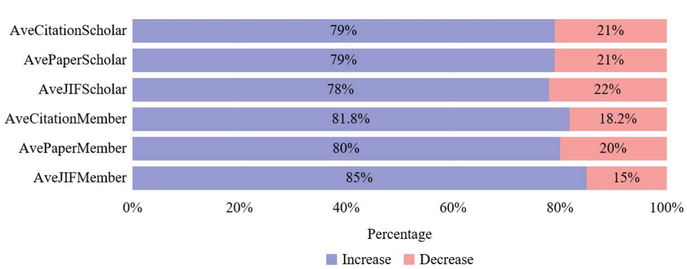


Figure 6: Proportion of academics with increased and decreased impacts before and after awards.

In order to explore the change rule of team influence before and after winning the award more intuitively, the logarithmic box chart in Fig. 5 shows the change of team influence factors. Compared with before the award, the number of papers, citations and the value of JIF have been improved after receiving an award. Among them, the difference of JIF is small, while citation and paper have a larger range of values, and the change of JIF before and after award is more obvious. This shows that the influence of most teams have increased after award, but there are also many abnormal data points. It can be seen that some teams do not show obvious improvement in their influence.

Furthermore, we examine that the citation, the number of papers and the proportion of JIF increase after award. The proportion of academics whose parameters increase or decrease before and after winning the award is shown in Fig. 6. For 234 recipients, we selected 368 team members who stayed in the same team before and after award. 79% of award recipients and 81.8% of their team members increased in terms of average citations of each paper. The average number of papers for both academic groups are similar (79% for recipients and 80% for team members). From the perspective of publication quality, which is reflected by the value of journal impact factors here, 78% recipients and 85% team members make progress after winning an award. In summary, the receipt of an award has a positive impact on most recipients and their collaborators.

5 CONCLUSION

In this paper, we studied the impact of scholarly awards on recipients, and their teams from different perspectives. Particularly, we focused on an award that was established for early career academics to study its impact on academic performance. Experiments show that most scientific indicators, such as paper and citation count, increase after awards for both recipients and their teams. However, we found that academics who have a high probability of winning awards but who have not yet received an award perform even better than award recipients in terms of both paper-based and citation-based indicators. This means that awards are not the only motivation to encourage academics' research.

This study illustrates that the receipt of an award will impact the recipients' academic impact, while demonstrating the various impact of awards on academic performance. While this study only considered the case of one type of awards, the proposed model can be applied or extended for analyzing other academic awards. This will be explored in the future work.

REFERENCES

[1] M Barany. 2018. The Fields Medal should return to its roots. *Nature* 553, 7688 (2018), 271–273.

[2] George J Borjas and Kirk B Doran. 2015. Prizes and productivity how winning the fields medal affects scientific output. *Journal of human resources* 50, 3 (2015),

728–758.
[3] Erin A Cech. 2013. How Economics Shapes Science. *Contemporary Sociology* 42, 3 (2013), 424.
[4] Ho Fai Chan, Bruno S Frey, Jana Gallus, and Benno Torgler. 2014. Academic honors and performance. *Labour Economics* 31 (2014), 188–204.
[5] Ho Fai Chan, Laura Gleeson, and Benno Torgler. 2014. Awards before and after the Nobel Prize: A Matthew effect and/or a ticket to one's own funeral? *Research Evaluation* 23, 3 (2014), 210–220.
[6] Ho F Chan, Franklin G Mixon, and Benno Torgler. 2018. Relation of early career performance and recognition to the probability of winning the Nobel Prize in economics. *Scientometrics* 114, 3 (2018), 1069–1086.
[7] Ho Fai Chan, Ali Sina Önder, and Benno Torgler. 2015. Do Nobel laureates change their patterns of collaboration following prize reception? *Scientometrics* 105, 3 (2015), 2215–2235.
[8] Ho Fai Chan, Ali Sina Önder, and Benno Torgler. 2016. The first cut is the deepest: repeated interactions of coauthorship and academic productivity in Nobel laureate teams. *Scientometrics* 106, 2 (2016), 509–524.
[9] Ho Fai Chan and Benno Torgler. 2015. The implications of educational and methodological background for the career success of Nobel laureates: an investigation of major awards. *Scientometrics* 102, 1 (2015), 847–863.
[10] Yuxiao Dong, Reid A Johnson, and Nitesh V Chawla. 2015. Will this paper increase your h-index?: Scientific impact prediction. In *Proceedings of the eighth ACM international conference on web search and data mining*. ACM, 149–158.
[11] Amna Dridi, Mohamed Medhat Gaber, R Muhammad Atif Azad, and Jagdev Bhogal. 2021. Scholarly data mining: A systematic review of its applications. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 11, 2 (2021), e1395.
[12] James F English. 2014. The economics of cultural awards. In *Handbook of the Economics of Art and Culture*. Vol. 2. Elsevier, 119–143.
[13] João Ricardo Faria and Peter McAdam. 2015. Academic productivity before and after tenure: the case of the 'specialist'. *Oxford Economic Papers* 67, 2 (2015), 291–309.
[14] Bruno S Frey and Jana Gallus. 2017. Towards an economics of awards. *Journal of Economic Surveys* 31, 1 (2017), 190–200.
[15] Eugene Garfield. 2006. The history and meaning of the journal impact factor. *Jama* 295, 1 (2006), 90–93.
[16] Nils Hansson, Giacomo Padrini, Friedrich H Moll, Thorsten Halling, and Carsten Timmermann. 2021. Why so few Nobel Prizes for cancer researchers? An analysis of Nobel Prize nominations for German physicians with a focus on Ernst von Leyden and Karl Heinrich Bauer. *Journal of Cancer Research and Clinical Oncology* (2021), 1–7.
[17] Jorge E Hirsch. 2005. An index to quantify an individual's scientific research output. *Proceedings of the National academy of Sciences* 102, 46 (2005), 16569–16572.
[18] Mitchell Hobbs, Stephen Owen, and Livia Gerber. 2017. Liquid love? Dating apps, sex, relationships and the digital transformation of intimacy. *Journal of Sociology* 53, 2 (2017), 271–284.
[19] Benjamin F Jones and Bruce A Weinberg. 2011. Age dynamics in scientific creativity. *Proceedings of the National Academy of Sciences* 108, 47 (2011), 18910–18914.
[20] Benjamin F Jones, Stefan Wuchty, and Brian Uzzi. 2008. Multi-university research teams: Shifting impact, geography, and stratification in science. *Science* 322, 5905 (2008), 1259–1262.
[21] Jerry W. Kim. 2019. Honours versus Money: The Economics of Awards. *Contemporary Sociology* 48, 4 (2019), 421–423.
[22] Xiangjie Kong, Yajie Shi, Wei Wang, Kai Ma, Liangtian Wan, and Feng Xia. 2019. The evolution of turing award collaboration network: Bibliometric-level and network-level metrics. *IEEE Transactions on Computational Social Systems* 6, 6 (2019), 1318–1328.
[23] Xiangjie Kong, Jun Zhang, Da Zhang, Yi Bu, Ying Ding, and Feng Xia. 2020. The Gene of Scientific Success. *ACM Transactions on Knowledge Discovery from Data (TKDD)* 14, 4 (2020), 1–19.
[24] Feng Li, Yajun Miao, and Chenchen Yang. 2015. How do alumni faculty behave in research collaboration? An analysis of Chang Jiang Scholars in China. *Research Policy* 44, 2 (2015), 438–450.
[25] Jichao Li, Yian Yin, Santo Fortunato, and Dashun Wang. 2020. Scientific elite revisited: patterns of productivity, collaboration, authorship and impact. *Journal of the Royal Society Interface* 17, 165 (2020), 20200135.
[26] Guoqiang Liang, Haiyan Hou, Ying Ding, and Zhigang Hu. 2020. Knowledge recency to the birth of Nobel Prize-winning articles: Gender, career stage, and country. *Journal of Informetrics* 14, 3 (2020), 101053.
[27] Jiaying Liu, Jing Ren, Wenqing Zheng, Lianhua Chi, Ivan Lee, and Feng Xia. 2020. Web of scholars: A scholar knowledge graph. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2153–2156.
[28] Anqi Ma, Yu Liu, Xiujuan Xu, and Tao Dong. 2021. A deep-learning based citation count prediction model with paper metadata semantic features. *Scientometrics* (2021), 1–21.
[29] Yifang Ma and Brian Uzzi. 2018. Scientific prize network predicts who pushes the boundaries of science. *Proceedings of the National Academy of Sciences* 115, 50 (2018), 12608–12615.
[30] Saurav Manchanda and George Karypis. 2021. Evaluating Scholarly Impact: Towards Content-Aware Bibliometrics. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 6041–6053.
[31] Mojtaba Nayyeri, Gokce Muge Cil, Sahar Vahdati, Francesco Osborne, Mahfuzur Rahman, Simone Angioni, Angelo Salatino, Diego Reforgiato Recupero, Nadezhda Vassilyeva, Enrico Motta, et al. 2021. Trans4E: Link prediction on scholarly knowledge graphs. *Neurocomputing* 461 (2021), 530–542.
[32] Raj Kumar Pan and Santo Fortunato. 2014. Author Impact Factor: tracking the dynamics of individual scientific impact. *Scientific Reports* 4 (2014), 4880.
[33] Alexander Michael Petersen, Santo Fortunato, Raj K Pan, Kimmo Kaski, Orion Penner, Armando Rungi, Massimo Riccaboni, H Eugene Stanley, and Fabio Pammolli. 2014. Reputation and impact in academic careers. *Proceedings of the National Academy of Sciences* 111, 43 (2014), 15316–15321.
[34] Jing Ren, Lei Wang, Kailai Wang, Shuo Yu, Mingliang Hou, Ivan Lee, Xiangjie Kong, and Feng Xia. 2019. API: An Index for Quantifying a Scholar's Academic Potential. *IEEE Access* 7 (2019), 178675–178684.
[35] Jing Ren, Feng Xia, Xiangtai Chen, Jiaying Liu, Mingliang Hou, Ahsan Shehzad, Nargiz Sultanova, and Xiangjie Kong. 2021. Matching Algorithms: Fundamentals, Applications and Challenges. *IEEE Transactions on Emerging Topics in Computational Intelligence* 5, 3 (2021), 332–350.
[36] Paul R Rosenbaum and Donald B Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* 70, 1 (1983), 41–55.
[37] Roberta Sinatra, Dashun Wang, Pierre Deville, Chaoming Song, and Albert-László Barabási. 2016. Quantifying the evolution of individual scientific impact. *Science* 354, 6312 (2016).
[38] Jie Tang. 2016. AMiner: Toward understanding big scholar data. In *Proceedings of the ninth ACM international conference on web search and data mining*. 467–467.
[39] Moshe Y Vardi. 2017. Would Turing have won the Turing award? *Commun. ACM* 60, 11 (2017), 7–7.
[40] Ludo Waltman. 2016. A review of the literature on citation impact indicators. *Journal of informetrics* 10, 2 (2016), 365–391.
[41] Dashun Wang, Chaoming Song, and Albert-László Barabási. 2013. Quantifying long-term scientific impact. *Science* 342, 6154 (2013), 127–132.
[42] Stefan Wuchty, Benjamin F Jones, and Brian Uzzi. 2007. The increasing dominance of teams in production of knowledge. *Science* 316, 5827 (2007), 1036–1039.
[43] Feng Xia, Jiaying Liu, Jing Ren, Wei Wang, and Xiangjie Kong. 2020. Turing number: how far are you to AM Turing award? *ACM SIGWEB Newsletter* Autumn (2020), 1–8.
[44] Feng Xia, Wei Wang, Teshome Megersa Bekele, and Huan Liu. 2017. Big scholarly data: A survey. *IEEE Transactions on Big Data* 3, 1 (2017), 18–35.
[45] Rui Yan, Congrui Huang, Jie Tang, Yan Zhang, and Xiaoming Li. 2012. To better stand on the shoulder of giants. In *Proceedings of the 12th ACM/IEEE-CS joint conference on Digital Libraries*. ACM, 51–60.
[46] Shuo Yu, Feng Xia, and Huan Liu. 2019. Academic team formulation based on Liebig's barrel: Discovery of anticask effect. *IEEE Transactions on Computational Social Systems* 6, 5 (2019), 1083–1094.
[47] Shuo Yu, Feng Xia, Chen Zhang, Haoran Wei, Kathleen Keogh, and Honglong Chen. 2021. Familiarity-based Collaborative Team Recognition in Academic Social Networks. *IEEE Transactions on Computational Social Systems* (2021). https://doi.org/10.1109/TCSS.2021.3129054
[48] Xiaokang Zhou, Wei Liang, I Kevin, Kai Wang, Runhe Huang, and Qun Jin. 2021. Academic influence aware and multidimensional network analysis for research collaboration navigation based on scholarly big data. *IEEE Transactions on Emerging Topics in Computing* 9, 1 (2021), 246–257.