How can I improve my scientific impact? The most influential factors in predicting the h-index

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Abstract
Evaluation of researchers’ output is vital for hiring committees and funding bodies, and it is usually measured via their scientific productivity, citations, or a combined metric such as h-index. Assessing young researchers is more critical because it takes a while to get citations and increment of h-index. Hence, predicting the h-index can help to discover the researchers’ scientific impact. In addition, identifying the influential factors to predict the scientific impact is helpful for researchers and their organizations seeking solutions to improve it. This study investigates the effect of author, paper and venue-specific features on the future h-index. For this purpose, we used machine learning methods to predict the h-index and feature analysis techniques to advance the understanding of feature impact. Utilizing the bibliometric data in Scopus, we defined and extracted two main groups of features. The first relates to prior scientific impact, and we name it ’prior impact-based features’ and includes the number of publications, received citations, and h-index. The second group is ‘non-impact-based features’ and contains the features related to author, co-authorship, paper, and venue characteristics. We explored their importance in predicting h-index for researchers in three different career phases. Also, we examine the temporal dimension of predicting performance for different feature categories to find out which features are more reliable for long- and short-term prediction. We referred to the gender of the authors to examine the role of this author’s characteristics in the prediction task. Our findings showed that gender has a very slight effect in predicting the h-index. We found that non-impact-based features are more robust predictors for younger scholars than seniors in the short term. Also, prior impact-based features lose their power to predict more than other features in the long-term.

Keywords: h-index prediction; feature importance; academic mobility; machine learning; open access publishing

1 Introduction
Predicting scientific impact helps to anticipate career trajectories of researchers and reveal mechanisms of the scientific process that influence future impact, which has always been a concern of individual researchers, universities, recruitment committees, and funding agencies. Also, it can reveal factors influencing the future outcome and propose path-ways to young researchers on how to improve future impact and their organizations for more support.

Scientific productivity and received citations are the basis for many evaluation metrics (e.g. h-index [1], g-index [2], hₛ-index [3]). The h-index is the most common metric which evaluates the scholars’ scientific impact since it measures researchers’
productivity and citation impact and has a leading role in hiring and funding decisions. Therefore, predicting this metric is crucial for these purposes. The current number of publications, received citations, and h-index (prior impact-based features) simplify the h-index prediction task because these features reflect the scholar’s impact. Since more senior scholars have a distinguished research profile, predicting their h-index is easier. Assessing the future impact is more pivotal for young scholars than seniors because prior impact-based features are less available for junior researchers as they have a shorter data history. Also, to identify rising stars, who have a lower research profile at the beginning of their career compared to other authors in the same career stage but may become prominent contributors in the future [4], we can not rely on prior impact-based features and need more reliable predictors in the long term. Although previous studies demonstrated high accuracy by employing prior impact-based features [5, 6, 7], they displayed a substantial decline in the performance of predicting the h-index in the distant future. We hypothesise that publication/citation-based features may be efficient short-term predictors, but there may be other feature categories that are more efficient in predicting long-term impact.

This study presents a comprehensive investigation of various features and feature sets in the h-index prediction task. We define features that previous studies have displayed their association with the productivity and received citations and examine their contribution to the future h-index of researchers. For this purpose, we employ a machine learning approach to predict the h-index for the next ten years and conduct extensive feature analysis. We implement the method for different feature combinations among three groups of junior, middle-level, and senior authors and compare their accuracy to see the extent of temporal stability.

Specifically, our contributions include:

1. **Feature impact analysis.** We advance the understanding of the impact of different feature categories on various h-index prediction tasks for researchers in different career phases and examine the reliability of these predictions.

2. **Temporal dimension of feature performance.** We investigate the temporal dimension of predictors to advance the understanding on feature performance depending on the time window considered for the future prediction, i.e. to understand which features/categories perform better for long- and short-term prediction regarding their seniority.

3. **Novel features.** We introduce and investigate the effect of non-impact-based features, namely gender and academic mobility, on the prediction task to reveal the influential factors on the scientific impact (prior impact-based features that implicitly or explicitly encode citation counts simplify the h-index prediction task dramatically by providing the model with data that directly influences the target metric (h-index)).

2 Related work

To identify the future scientific impact, some studies focus on predicting the citations’ count for a specific paper [8, 9, 10, 11, 12], others tried to predict the impact at the author level with the h-index [5, 6, 7, 13]. Among all models and methods presented in these studies to predict the h-index, those that took the number of prior
publications, received citations, or the current h-index (prior impact-based features) into consideration achieved the highest performance. Although prior impact-based features are the strongest predictors of future impact, sometimes we need to predict it using the other author, paper, and venue characteristics.

2.1 Features used for the prediction tasks

Many studies employed various properties of papers, venues, authors, and their co-authors to predict the scientific impact. [9] and [8] use time series methods and count of early citations to predict the number of citations in the long-term. [10] presented a citation time series approach to predict the citations for newly published papers. They used the paper’s topic (via keyword), author reputation, venue prestige, and temporal cues (e.g., increasing network centrality over time) to detect citation signals and convert them into signals for citation time series generation. [14] utilized some features and categorized them to author (regarding citations and publication), venue, social (co-author), and temporal (average citation increment of the author and co-authors within two years) features and examined their importance in predicting academic rising star. [5] and [6] used the number of current publications, citations, or h-index with other features to predict the future h-index and both presented models with $R^2 = 0.93$. [7] included related indicators to these features such as changes in citations and h-index over the last two years to the predictors’ list and demonstrated a model with a higher precision $R^2 = 0.97$. Further studies focused on other feature types rather than prior impact-based features to identify the influential factors on the scientific impact of researchers. For example, [15] investigated the relationship between some characteristics of the co-author network and the h-index. Their results showed the significance of co-authors’ productivity via collaborating with many authors and their impact on predicting the h-index.

[13] extracted two types of features, papers’ textual content and graph features (related to collaboration patterns), and found that graph features alone are stronger predictors. [16] studied the contribution of a publication to the author’s h-index and found that topical authority and publication venues are the most predictive features in the absence of citation-related features of prior publications. Otherwise, they reported citation count as the most decisive factor in predicting the future h-index. [5] reported the career age, number of high-quality papers, and number of publications in distinct journals as the most compelling feature after prior impact-based features. [10] found that some features, such as the author’s reputation more predictive than others. Therefore, they applied trainable weights to preserve the unequal contribution of different kinds of features.

2.2 Influential factors on scientific impact

In the following, we categorize the features affecting the scientific impacts into three groups: demographic, paper/venue, and co-author-based factors and report the previous related studies.

2.2.1 Demographic factors

Academic mobility: In the contemporary science, collaboration plays a significant role and international academic mobility affects the collaboration networks
which furthers more knowledge transmission among countries and scholars. Therefore, investigating its impact on science and scientists has been the focus of many studies. Our recent study ([17]) revealed the positive impact of international mobility on number of publications and received citations. However, mobile researchers do not perform necessarily better than those without mobility experience. [18] found that differences in research outputs between returnee PhD holders and those trained in their home country are field-specific and depend on their seniority. [19] reviewed the studies that investigated the effect of mobility on some scientific outcomes and found that most studies suggest a positive effect on mobility. But they reported some studies that demonstrated a negative effect mainly on productivity and citation impact and proposed a positive impact of mobility only under specific circumstances. [20] found that international collaboration before mobility has an essential role in high performance after mobility. The reputation of institutions is another influential factor they discovered in their study.

**Gender:** Gender differences in science and scientific impact have been the subject of many studies in various fields. A new study on the Breast Surgery Fellowship Faculty from [21] found no noticeable gender difference between assistant professors but a higher h-index for men professors than women. [22] studied the gender gap in social sciences and found the difference in all career phases, especially at full professor positions. In contrast, the results of the study by [23] demonstrated a higher h-index for men among academic ophthalmologists. Still, they found the same or more impact for women in the later career phases by controlling the range of publications. The results of the study by [24] indicated that although the h-index of men is higher than women for ecologists and evolutionary biologists, there is no gender difference in h-index once we control for publication rate.

**Income level:** In many countries, governments are the main source of financial supports for scientific progress. [25] demonstrated the positive effect of economic development on scientific productivity in all scientific fields. [26] displayed a U-shape relationship between GDP per capita and received citations and found the citation impact correlates positively with the nation’s wealth after a certain GDP per capita level. However, their results showed that international collaboration is also crucial for higher citation impact among all countries.

### 2.2.2 Paper and venue factors

**Scientific field:** The average scholars’ h-index of researchers differs among fields, because productivity and the rate of citing vary from one to another [27, 28]. [29] showed the varying ranges of the h-index across fields and suggested a multiplicative correction to the h-index based on the scientific field to compare the scientists’ research impact from different areas.

**Journal quality:** Reputable journals increase the visibility of papers and the probability of receiving citations. [30] found that publishing in high-quality journals decreases the average time interval between the author’s future publications in those journals and has a cumulative citation advantage for the author.

**Open access:** Free access to publications in online form increases the probability of reading and citing papers. Various studies investigated the open access citation advantage (OACA) and most found a positive effect on received citations. [31] did
a systematic review about the OACA and reported that among 143 studies, 47.8% confirmed OACA, 37% found no OACA, and 24% found OACA for a subset of their sample. Also, the result of our recent study [32] showed substantially higher citations for preprint papers, making publications freely available.

2.2.3 Co-author factors

The number of the paper’s citations received reveals the scientific impact of all authors, and hence it can vary according to their collaboration pattern. [33] found a positive correlation between the number of co-authors and received citations. Also, the result of the study by [34] showed fewer citation scores for single-authored publications. [35] tried to predict highly cited papers via the centrality of their authors in the co-authorship network and found a positive correlation between highly cited publications and highly centralized authors.

[34] and [36] studied the citation impact of international co-authors and demonstrated a positive relation between international collaboration and received citations.

2.3 Prediction approaches

Many studies employed Machine learning regression and classification approaches to predict the scientific impact of publications and researchers [6, 13, 9, 11, 10, 7]. Most common methods in these studies were regression models such as Support Vector Regression (SVR), Gradient boosted regression trees (GBRT) or Gradient Boosting (GB), Gradient-boosting decision tree (GBDT), Extreme Gradient Boosting (XGBoost), Random Forest (RF), K-nearest neighbour (KNN), and Neural networks (NN). [14] introduced a classification method to detect the academic rising stars (who have a lower research profile at the beginning of their career compared to other authors in the same career stage but may become prominent contributors in the future) and found a better performance for KNN algorithm for small data-sets, but an relative stable results for GBDT, GB, RF, and RF with the change of dataset size. [11] examined the performance of different regression algorithms and reported the best performance for Backpropagation neural network. [7] examined SVR, RF, GBRT and XGBoost regression models for h-index prediction and obtained the best performance for XGBoost. The performance of methods for predicting the h-index in different ranges depends on applied features. By using prior impact-based features and regression models, [7], [5] and [6] presented models with \( R^2 > 0.90 \) for the first predicting year and decreased in the next predicting years. However, in these studies, the extent of contribution of different features in the prediction task is not indicated.

3 Data and methods

3.1 Describing the dataset

We used the in-house Scopus database maintained by the German Competence Centre for Bibliometrics (Scopus-KB), 2020 version, as the main resource of analyses and employed Scopus author Id to identify authors. We defined the career age of authors by the years between the first and last publication time and took authors who have started publishing from 1995 and used their publications until 2008 for
calculating the features’ value. To remove "not active authors" from the analyzed data, we included just those authors who matched the threshold of one publication per three years in their career age. It results in a final list of 2,945,881 authors.

3.2 Feature definitions

Table 1 shows variables used to estimate the future h-index of researchers. In this table, we mentioned the previous studies that employed any of the features for the prediction task. In the following, we list the novel features and explain how we calculated them:

- **gender**: We detected the gender status of authors by a combined name and image-based approach introduced by [37] which results in a binary variable. We acknowledge that the person’s gender can not be split into male and female, and if we consider the social dimensions, we have more gender identities.

- **mobility_score**: This feature indicates the frequency of movement between countries by tracking the authors’ affiliations over their publications. More details about calculating this feature are available in our previous study [17].

- **income_current_country**: This feature indicates the income levels of the affiliation country in the last publication. We used four income levels classified by the World Bank[1].

- **primary_author_proportion**: We defined the primary author as the first or corresponding author. We computed the value of this feature by dividing the number of publications in which the researcher is the primary author to all publications.

- **open_access_proportion**: We extracted the article’s access status from the Unpaywall dataset (a service that provides full-text articles from open access resources). An open-access article can be any form of gold, green, or bronze. We declare that we could match from 8,953,939 investigated papers only 5,476,852 (61%) with Unpaywall’s articles. To calculate the proportion of open access papers, we considered the number of detected as open access to the number of whole articles of the author.

- **main_field**: We identified the field of authors from the field of the journals in which they publish, and in Scopus are classified under four broad subject clusters[2]. The field with the most publications will be the main field of the author.

- **field_mobility**: This function indicates the number of unique fields the author has published during the entire academic age divided by the number of whole papers.

- **international_coauthors**: This feature specifies the number of international collaborators for all papers. To calculate it, first, we counted for each paper the number of co-authors who have a different country in the affiliation than the author, and then we summed these numbers among all publications.

To assess the quality of journals, we calculated the h-index of journals from 1995 to 2015. Because of different citation patterns among disciplines, journals’ h-index

[1]https://www.weforum.org/agenda/2020/08/world-bank-2020-classifications-low-high-income-countries/
[2]Subject Area
can have varying ranges for different disciplines, and it should be normalized. We applied the percentile rank approach inspired by [38] and computed the h-index’s rank among all journals inside its discipline. We used the classification system of Scopus to find the discipline of the journals. In this system, journals are classified into 27 subject categories [3]. In this percentile rank approach, each journal within a category has a rank between 0 (lowest h-index) to 100 (highest h-index). Journals with the same h-index have the same rank. If the journal belongs to more than one category, we used the weighted percentile ranking (wPR) ([39]). Based on this approach, wPR will be calculated using the formula:

$$wPR = \frac{PR_{sci1} \cdot n_{sci1} + PR_{sci2} \cdot n_{sci2} + \ldots + PR_{sci} \cdot n_{sci}}{n_{sci1} + n_{sci2} + \ldots + n_{sci}}$$

Whereby sci is the ith subject category that the journal belongs to and n_isci is the number of journals in this subject category, and PR_isci is PR of the journal in it. Journals with a percentile ranking higher than 50% are assumed to be high quality. Finally, we counted the proportion of the author’s publications in high-quality journals among all their publications for the variable high_quality_proportion.

### Table 1: Features used to train the machine learning models to predict the h-index

| Feature group   | Feature name                      | Description                                                                 | Studies |
|-----------------|-----------------------------------|-----------------------------------------------------------------------------|---------|
| demographic     | career_age                        | years since first publication                                               | [5]     |
|                 | gender                            | zero for females and one for males                                          |         |
|                 | mobility_score                    | number of changing the affiliation at the country level                     |         |
|                 | income_current_country            | income level of current affiliation country                                 |         |
| prior impact    | current_hindex                    | current h-index                                                             | [5, 6, 7]|
|                 | paper_per_year                    | number of total papers divided by age                                       | [5, 6, 7]|
|                 | citation_per_paper                | number of total citations among all papers until 2008 divided to the number of all papers | [5, 6, 7]|
| paper/venue     | primary_author_proportion          | proportion of papers being as primary author                               | [5]     |
|                 | open_access_proportion             | proportion of open access papers among all papers                          |         |
|                 | main_field                        | the scientific field with the highest amount of publications                |         |
|                 | high_quality_proportion           | proportion of publications in high quality journals among all papers        |         |
|                 | field_mobility                    | number of unique disciplines authors has published paper divided to the number of all papers |         |
| co-author       | max_h-index                       | maximum h-index of co-authors among all papers                              | [15]    |
|                 | coauthor_per_paper                | number of unique co-authors among all publications divided to the number of all papers | [7]     |
|                 | international_coauthors           | number of international coauthors among all papers                         |         |

3.3 Applied methods for the prediction task

We tackled the h-index prediction as a regression problem comparable to previous studies [5, 16, 11, 6, 7]. We tried four machine learning methods (SVR, RF, GB, and XGBoost) and found XGBoost, the best method regarding the performance as it has been proved in the study by [7]. Therefore, we selected this approach for the prediction task. XGBoost is a scalable end-to-end tree boosting system introduced by [40]. It is an efficient implementation of Gradient boosting in terms of speed and is appropriate to solve the problems using minimal amount of resources. We used k-fold cross validation procedure to evaluate the models and fixed the k to 10. We used the mean absolute percentage error (MAPE) to assess the model performance, which

[3] Subject Area Classifications
measures error as a percentage. This performance metric enables us to compare our results with those from state-of-the-art [5, 41, 7, 6].

3.3.1 Temporal dimension of feature performance

Prior studies regarded varying time frames to estimate the future h-index [41, 5, 7] and examined several years from one to five-year and [41] for five-year and ten-year time frames. The prediction performance declined as the prediction time frame increased in all studies. We considered the h-index as our target from one to ten years in the future (h-index from 2009 to 2018). It enables us to measure the extent of predicting performance in the future. We defined different feature combinations based on the attributes of the author, paper, venue, and coauthors to see which feature categories are better for short/long-term prediction. Table 2 shows the different combination sets utilized to train the model.

3.3.2 Feature impact analysis

To calculate the importance of features, we employed permutation feature importance, which measures the decrease in the model performance if a feature value is shuffled randomly [42]. A higher score for a specific feature indicates its larger effect on the prediction model. To compare the feature importance across authors with different career development, we divided the authors into three into three groups:

- Junior: researchers with the career age less than 5 years (first publication between 2005 and 2008)
- Mid-level: researchers with the career age between 5 and 9 years (first publication between 2000 and 2004)
- Senior: researchers with the career age more than ten years (first publication between 1995 and 1999)

4 Results

4.1 Correlation results

To examine the affecting factors on the h-index, we first provided the correlation between features introduced in table 1 and future h-index. Table 3 presents the Pearson correlation coefficient between the features (except for field which is...
Table 3: Pearson correlation coefficient between the features and h-index in the future for three different years.

| Feature                      | 2009 | 2014 | 2018 |
|------------------------------|------|------|------|
| career_age                   | 0.46 | 0.39 | 0.36 |
| gender                       | 0.07 | 0.06 | 0.06 |
| mobility_score               | 0.48 | 0.48 | 0.47 |
| income_current_country       | 0.17 | 0.15 | 0.13 |
| current_h-index              | 0.99 | 0.94 | 0.89 |
| paper_per_year               | 0.77 | 0.75 | 0.76 |
| citation_per_paper           | 0.16 | 0.13 | 0.12 |
| primary_author_proportion    | 0.01 | 0.03 | 0.04 |
| open_access_proportion       | 0.09 | 0.10 | 0.09 |
| high_quality_papers_proportion | 0.85 | 0.83 | 0.80 |
| field_mobility               | -0.46 | -0.48 | -0.47 |
| max_coauthor_h-index         | 0.58 | 0.57 | 0.55 |
| coauthor_per_paper           | -0.02 | -0.003 | 0.002 |
| international_coauthors      | 0.23 | 0.29 | 0.30 |

categorical variable) and h-index in 2009, 2014, and 2018. The stronger correlation coefficient between the future h-index and number of papers (paper_per_year) than the number of citations (citation_per_paper) reveals that productivity has a more significant impact than received citations on the h-index. Among non-impact-based features, the quality of the journal in which the paper has been published has the highest correlation with the h-index. The negative value for field_mobility suggests that authors who published in several scientific fields have a lower h-index than those who publish in a specific field.

4.2 Temporal dimension of feature performance

Before we show the result of the analyses, we make some comparisons between the performance of our model and previous works. [7] have already compared their performance with [41], [6] and [5] and presented the best performance among all these studies. They excluded the authors with an h-index less than four from the investigated data. They achieved the minimum MAPE of 0.063 for the first prediction year by employing more prior impact-based features. By applying this condition to investigated authors, we could reach the minimum MAPE of 0.068. Instead, two-thirds of the authors will be discarded in our analyses. Because of losing too much data, particularly from young scholars, we didn’t apply this condition and implemented our models with all authors, despite reducing the performance.

Figure 1 shows the performance of the XGBoost model implemented for different combination sets and researchers from three career stages over ten years of prediction. In this figure, the lower MAPE for combinations including prior impact-based features indicates the higher performance for these sets, but losing the performance with the passing years for these combinations is more than other sets. To display the rate of losing performance we calculated the slope for MAPEs over ten years using this equation:

\[
Slope = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sum(x - \bar{x})^2}
\]

where \(x\) is the year in the range of 2009 to 2018, \(y\) the MAPE in the related year, and \(\bar{x}\) and \(\bar{y}\) are their averages. To compare the prediction efficiency between
different career stages, we implemented the prediction model for authors from three
career stages and presented the performance (MAPE) in Figure 1. Figure 1(b)
displays the Slope for MAPE reported in figure 1 (a) from the first to the tenth
year for each combination. We generally observe a higher slope (which means more
loss in performance) for combinations with prior impact-based features than other
combinations among researchers in any career stage. This indicates that non prior
impact-based features are more stable predictors in long term.

4.3 Feature impact

Table 4 demonstrates the permutation importance of features for the combination
set 4 (all features included) for researchers from different career stages and in three
prediction years (first (2009), fifth (2014) and tenth years (2008) in the future).
If we compare the MAPE for three groups and consider MAPE under 0.25 as an
acceptable performance [43], it is only for seniors achievable in the long-term (more
than the next five years). Among all features, \textit{paper per year} and current h-index are
the best predictors, although for different career phases are different. It suggests that
prior impact-based features in the earlier career stage have a varying pattern and
can not estimate the h-index in the long term. But for seniors, they are more stable
to predetermine the future h-index. Comparing the MAPE for these three groups
of researchers indicates that to anticipate the future h-index with the presented
features, the time frame in which we analyse the author’s data plays a key role.

Table 4: Performance (MAPE) and permutation importance in predicting h-index
for three prediction years implemented for three groups of researchers (in early,
middle and late stages). The score function to compute the importance is MAPE.
For this model, all features are included (combination set 4 in Table 2).

| Career stage | Prediction year | Feature: | 2009 | 2014 | 2018 | 2009 | 2014 | 2018 | 2009 | 2014 | 2018 |
|--------------|----------------|----------|------|------|------|------|------|------|------|------|------|
|              |                | career_age | 0.031 | 0.049 | 0.056 | 0.004 | 0.009 | 0.011 | 0.0004 | 0.002 | 0.0028 |
|              |                | gender | 0 | 0.0006 | 0.001 | 0 | 0.0004 | 0.001 | 0.0001 | 0.0009 | 0.0015 |
|              |                | mobility_score | 0.0003 | 0.003 | 0.006 | 0.0005 | 0.006 | 0.009 | 0.001 | 0.005 | 0.01 |
|              |                | income_current | 0.002 | 0.004 | 0.004 | 0.0005 | 0.0004 | 0.0002 | 0.0001 | 0.0004 | 0.0007 |
|              |                | current_h_index | 0.23 | 0.024 | 0.005 | 0.76 | 0.37 | 0.114 | 1.65 | 1.24 | 1.04 |
|              |                | paper_per_year | 0.26 | 0.77 | 0.97 | 0.26 | 0.95 | 1.40 | 0.19 | 0.80 | 1.22 |
|              |                | citation_per_paper | 0.039 | 0.032 | 0.030 | 0.029 | 0.034 | 0.035 | 0.016 | 0.019 | 0.018 |
|              |                | primary_author_proportion | 0.002 | 0.02 | 0.041 | 0.001 | 0.018 | 0.032 | 0.0002 | 0.007 | 0.014 |
|              |                | open_access_proportion | 0.004 | 0.01 | 0.02 | 0.002 | 0.007 | 0.01 | 0.001 | 0.008 | 0.012 |
|              |                | main_field | 0.001 | 0.01 | 0.014 | 0.001 | 0.008 | 0.014 | 0.0007 | 0.005 | 0.007 |
|              |                | high_quality_papers_proportion | 0.016 | 0.036 | 0.045 | 0.009 | 0.026 | 0.028 | 0.0036 | 0.012 | 0.013 |
|              |                | field_mobility | 0.006 | 0.008 | 0.013 | 0.004 | 0.012 | 0.017 | 0.0021 | 0.011 | 0.017 |
|              |                | max_coauthor_h_index | 0.002 | 0.007 | 0.009 | 0.001 | 0.006 | 0.007 | 0.0006 | 0.005 | 0.005 |
|              |                | coauthor_per_paper | 0.002 | 0.007 | 0.012 | 0.001 | 0.007 | 0.012 | 0.0004 | 0.004 | 0.006 |
|              |                | international_coauthors | 0.002 | 0.009 | 0.0162 | 0.009 | 0.025 | 0.028 | 0.013 | 0.077 | 0.118 |
|              |                | MAPE of the model | 0.15 | 0.46 | 0.7 | 0.10 | 0.26 | 0.39 | 0.06 | 0.15 | 0.21 |

Table 5 presents the feature importance for the combination set 5 (non-impact-
based features). The variety of fields that authors publish is the most determining
factor in predicting the h-index. Considering the negative correlation between these
two variables, we can conclude that mobility between fields impacts the future h-
index negatively. Comparing MAPE between different groups in Table 5, we observe
a better performance in short-term for junior and mid-level researchers. It can mean
that to predict the h-index is better not to include all history of data and consider
only the latest part.

The lowest importance score for gender compared to other features reveals that
this demographic characteristic doesn’t determine the h-index in the future.
Figure 1: Comparison of performance (a) and the slope (b) over ten years for different feature sets trained with the XGB regression method and implemented for three groups of researchers (junior, mid-level, and senior). The performance metric is MAPE. The dark blue columns in (b) show the sets, including prior impact-based features.

5 Limitations
In this study, we considered just journal papers and not conference papers, and it causes bias issues, especially for disciplines in which authors publish their studies.
Table 5: Performance (MAPE) and permutation importance in predicting h-index for three prediction years implemented for three groups of researchers (in early, middle and late stages). The score function to compute the importance is MAPE. For this model, just Non-impact based features are included (combination set 9 in Table 2).

| Career stage | Prediction year | Junior | Mid-level | Senior |
|--------------|-----------------|--------|-----------|--------|
|              | 2009 | 2014 | 2018 | 2009 | 2014 | 2018 | 2009 | 2014 | 2018 |
| Feature:     |      |      |      |      |      |      |      |      |      |
|              |      |      |      |      |      |      |      |      |      |
| career_age   | 0.003 | 0.006 | 0.009 | 0.003 | 0.006 | 0.002 | 0.006 | 0.0001 | -0.0023 |
| gender       | 0.0004 | 0.0006 | 0.001 | 0.001 | 0.0018 | 0.0017 | 0.0004 | 0.001 | 0.001 |
| mobility_score| 0.001 | 0.009 | 0.017 | 0.005 | 0.018 | 0.028 | 0.016 | 0.030 | 0.044 |
| income_current_country | 0.012 | 0.007 | 0.005 | 0.014 | 0.005 | 0.002 | 0.014 | 0.006 | 0.003 |
| primary_author_proportion | 0.017 | 0.03 | 0.031 | 0.011 | 0.023 | 0.032 | 0.019 | 0.11 | 0.16 |
| open_access_proportion | 0.079 | 0.14 | 0.16 | 0.128 | 0.245 | 0.296 | 0.11 | 0.21 | 0.22 |
| main_field | 0.021 | 0.042 | 0.061 | 0.026 | 0.030 | 0.039 | 0.029 | 0.028 | 0.028 |
| high_quality_papers_proportion | 0.077 | 0.118 | 0.145 | 0.120 | 0.143 | 0.167 | 0.151 | 0.183 | 0.224 |
| field_mobility | 0.216 | 0.377 | 0.459 | 0.38 | 0.574 | 0.681 | 0.47 | 0.61 | 0.70 |
| max_coauthor_per_paper | 0.024 | 0.032 | 0.033 | 0.05 | 0.044 | 0.041 | 0.097 | 0.084 | 0.075 |
| coauthor_per_paper | 0.086 | 0.077 | 0.095 | 0.077 | 0.095 | 0.1 | 0.053 | 0.058 | 0.057 |
| international_coauthors | 0.0146 | 0.0236 | 0.0330 | 0.038 | 0.066 | 0.082 | 0.061 | 0.169 | 0.22 |
| MAPE of the model | 0.25 | 0.53 | 0.78 | 0.29 | 0.38 | 0.51 | 0.32 | 0.35 | 0.37 |
| Sample size | 564,812 | 1,063,600 | 1,354,233 |

mainly as conference proceedings papers. Another limitation is not complete data in computing the features. For example, to obtain the proportion of open access publications, we identify the access form of articles in 2019 on Unpaywall. Many journals have changed their business model to open access or close access. We can not be sure about the accessibility of papers at the time of publishing and two years time windows that we considered to calculate the number of received citations. Also, we measure the mobility feature similar to our previous paper [17] and the mentioned limitations in that paper exist for this feature too.

6 Conclusion and discussion

In this study, we examined the impact of different feature categories on predicting the h-index for authors in different career stages. We compared the accuracy of the presented models implemented for researchers at junior, mid-level, and senior levels. We found that predicting the authors' future impact in later career phases via prior impact-based features is much more reliable, and other descriptive features are required to assess the younger researchers' future impact.

Also, we verified the extent of predicting power in the future distance for different feature combinations. We found that prior impact-based features are the best predictors in the short term and they lose their predictive power in the long term more than other features.

We introduced some novel author and paper/venue-specific features to estimate the author’s h-index and analysed their impact on the prediction tasks. The results showed that the prediction model based on non-impact-based features has a higher accuracy for less experienced researchers in a short time. The results relating to importance analyses revealed the contribution of each feature on scientific impact.

We found a positive moderate correlation coefficient between authors’ international mobility and their future h-index. With accounting for other factors and a low proportion of mobile researchers (about 19%), this author's feature is not so effective for predicting h-index. We found a very weak correlation between gender and h-index and, the lowest importance in predicting h-index among all features.
Also, the results display the importance of focusing on a study’s field for a better scientific impact. The results suggest that paper/venue-specific features have the more impact on the future h-index than author’s demographic and co-authorship characteristics.

The performances of proposed models indicate that still more features that don’t depend on the history of publications and citations are required to forecast the feature h-index of young researchers. For example, the textual content of papers examined by [13] and topic authority by [41] can be applied together with introduced features in this study to improve the performance.

**Declarations**

**Competing interests**
The authors declare that they have no competing interests.

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**Availability of data and materials**
The dataset analysed during the current study is available in the [Git repository](#).

**Author’s contributions**
Stefan Dietzte supervised this study, and Philipp Mayr was the project leader that supported it financially. Material preparation, data collection, Methodology, analysis, Validation, and Visualization were performed by Fakhri Momeni. Fakhri Momeni wrote the first draft of the manuscript and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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