Imperial College London

Department of Life Sciences

Silwood Park Campus

Quantifying the gender gap in UK STEM funding

Author: Xuan Wang

CID: 02150780

email: xuan.wang22@imperial.ac.uk

Supervisor:

Samraat Pawar

s.pawar@imperial.ac.uk

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Declaration

For this study, I utilised two primary datasets: one detailing staff numbers sourced from the Higher Education Statistics Agency (HESA) official website, and another containing information on UK funding projects within the Science, Technology, Engineering, and Mathematics (STEM) domain, obtained from the UK Research and Innovation (UKRI) website. I used the UKRI dataset shared by colleagues which can be assessed on Onedrive; For the analysis, I personally downloaded the HESA data from the official website. Regarding the coding, the machine learning-related code was provided by colleagues, which can be retrieved from the Github; Meanwhile, I personally generated the coding for the analysis part. Under the invaluable guidance of my supervisor, Samraat Pawar, I received direction on the entire coding and writing process, and insights on the types of results to showcase.

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Abstract

The advancement in Science, Technology, Engineering, and Mathematics (STEM) fields has profoundly transformed the global landscape. In response, the UK government has introduced numerous strategies to amplify funding in STEM, aiming to foster innovation and research. However, the equitable distribution of these benefits for different groups of people remains under scrutiny, which could directly affect the incentive of researchers and impact scientific innovation. My research looks into the gender disparities in STEM funding, employing a machine-learning methodology previously unexplored in this domain, thereby addressing this critical gap. I utilised a raw dataset comprising 107,760 projects for this research, where the projects were classified by topic analysis and ChatGPT. The findings were then compared and analysed among various institutions and categories. Though the result proved the existence of a gender disparity in STEM research funding, it displayed a decreasing trend in general. Among the various STEM fields, Agriculture, Forestry & Food Science exhibited the most pronounced gender bias. Interestingly, Electrical, Electronic & Computer Engineering stood out as an exception, with a higher funded ratio for females than males. The general pattern of gender disparity could be due to the previously accumulated advantage of males. To address this, a comprehensive approach to enhance the academic structure is necessary, encompassing aspects ranging from promoting diversity in university employment to revising the criteria for funding applications.

1 Introduction

1.1 Background

STEM - for Science, Technology, Engineering, Mathematics - has become necessary due to its power in solving global challenges such as climate change, resource availability, and human health [F. C. BELLOTTO TRIGO; M. MUSTRI]. As a traditional global problem to be discussed [García-Holgado et al. (2019a)], an increasing trend of research has also been done, studying the diversity gap in various aspects of the STEM area (employment, salary, etc.) to ensure the payoffs from STEM is beneficial worldwide. Nevertheless, it is still questionable whether these studies themselves are fair - according to the evidence provided by Handley et al. (2015), studies by males are usually less likely to judge gender discrimination than females. The results within a biased academic environment can be irrelevant, or even harmful, to women [Cislak et al. (2018)]. The equality for each gender in funding application would therefore be an important factor influencing the objectiveness of the research, which has a non-negligible impact on the incentive of qualified applicants to engage in the studies. Another important fact is that the disadvantage of females in the academic system could also lead to an accumulated bias, known as the "Mathew Effect", according to previous literature [Jebsen et al. (2020)]. The employment criteria for application can be an example since evidence shows that women are less favourable than men for granting a position at higher-ranking institutions, which would disadvantage females when submitting an application [Cruz-Castro et al. (2022)]. This inequality, therefore, causes an underrepresentation of females in the academic field, which further brings a more intense situation of gender discrimination.

As one of the top global corporate Research & Development investors [(WIPO)], a £39.8 billion R&D budget has been announced by the UK government for 2022-2025 to stimulate the power in science development [Department for Business (2022)]. On the other hand, the Engineering and Physical Sciences Research Council (EPSRC) data in 2016-2017 showed that £944m funding was awarded to male applicants while only £69m went to female applicants [Jebsen et al. (2020)]. An unequal opportunity for research funding would reduce the incentive and access to institutional resources [Cruz-Castro et al. (2022)]. Therefore, my study aims to determine whether there is a gender bias in the research funding in the UK, specifically in the STEM area.

1.2 Research aims and approaches

My study will use the data collected from the UK Research and Innovation (UKRI) from 2015 to 2022 to do the analysis. The study used a machine learning method, topic analysis, to the whole dataset and the results were classified using ChatGPT. The classified results were then analysed and compared among different subjects and universities.

1.2.1 Research questions

In this report, I will examine the overall pattern of gender proportion and then make a comparison across various categories and institutions. My primary focus will be to answer the following questions:

- From 2015 to 2022, how has the funding trend for each gender evolved? Is there a noticeable disparity?
- If a gender disparity exists, what could be the underlying cause?
- Is there any implication of the bias?

To address the first question, this report will assess the temporal trends of funding amount over time for each gender, and a two-sample t-test will be employed for evidence. The subsequent questions will be explored by comparing the trend among different classifications and universities, considering recent policies and previous literature.

2 Methods

My project aims to determine the proportion of males and females getting funded in the STEM area and conclude whether there is a gender bias in the research funding. The first step in our study is to apply topic analysis for the identification of the topic of each project; then, the classified data is used for the gender analysis among different subjects and UK universities. For the comparison, this report employed the ratio of funded females and males across time in various STEM categories and institutions. To account for all biases, including before the application stage, the ratio is calculated by dividing the funded males or females by the total number of staff in each classification for comparison.

2.1 Data acquisition and characteristics

This study uses a raw dataset of title abstracts with 107760 projects gathered from UKRI [F. C. BELLOTTO TRIGO; M. MUSTRI], merging with a UKRI dataset of the relevant information of the projects, including the leading institution, applicant name, start and end date of the project, etc. These data will be processed, classified and then analysed. For the analysis, I use the total number of staff in each university and classification to calculate the funding ratio, where the dataset of the entire staff is downloaded from the website of the Higher Education Statistics Agency (HESA). This includes the gender data of staff in each university and different fields. Since the HESA data is only available from 2015 to 2022, only the title abstract data within this period is used for our analysis.

2.2 Procedures

2.2.1 Data processing

The first step of our study is the pre-processing of the metadata. The raw dataset of the title abstracts is cleaned by several approaches, including the filtering of STEM funding bodies and the selection of valuable columns. The information in the clean UK data includes the project ID, funding body, the lead institution, the applicant's name, the date of the project, and the funding amount. In addition, the title abstracts are tokenised and filtered by dropping the rows where the number of tokens is smaller than 9, selecting only the data that provides meaningful information.

Having done the pre-processing of raw metadata, we apply Natural Language Processing (NLP), specifically topic analysis, to the clean data. Topic analysis is a machine-learning technique to identify topics by finding common themes in vast amounts of text [F. C. BELLOTTO TRIGO; M. MUSTRI]. Specifically, the Latent Dirichlet Analysis (LDA) was fitted on our clean data to find the underlying topic of each project in our dataset. As an example of topic analysis, LDA can detect the underlying topics in a collection of documents, and then determine how likely they belong to each topic by generating a likelihood distribution result [contributors (2023)]. We applied LDA models with 50 to 200 topics in 25 increments to the data, and calculated the perplexity value for each of the models with different numbers of topics to determine the best-fitted model. The model with 200 topics is finally selected due to its lowest perplexity value compared to the others.

2.2.2 Analysis

After implementing LDA on our dataset, we can obtain the conditional probability distribution of each project belonging to each of the 200 topics. I choose the topic with the highest probability as the corresponding topic for each project. The next step is the classification of the topics. By the results generated from LDA, we can have the keywords of each topic. To enhance efficiency, I employ the advanced machine-learning tool, ChatGPT, to sort the 200 topics into the following STEM categories depending on their keywords: Veterinary Science; Agriculture, Forestry & Food Science; General Engineering; Chemical Engineering; Mineral, Metallurgy & Materials Engineering; Civil Engineering; Electrical, Electronic & Computer Engineering; Mechanical, Aero & Production Engineering; IT, Systems Sciences & Computer Software Engineering; Earth, Marine & Environmental Sciences; Biosciences; Physics; Chemistry; Mathematics.

To determine the gender for each project, I applied a Python package - Gender Guessor, to the leading applicant of each project in the clean data to distinguish their gender based on their names. The output of this Python package includes Male, Female, Mostly male, Mostly female, Unknown and Androgynous. In this study, both "Male" and "Mostly male" outputs are classified as male, while "Female" and "Mostly female" are treated as female, and the other results are not considered due to the higher uncertainty and inaccuracy. The gender information is combined with the classification of each project and used for further analysis.

The research is structured into the following segments:

1. Tracking gender-based funding trends in each classification.

Despite the recent policy initiatives aimed at promoting STEM research by increasing funding, as discussed earlier, it's unclear if these measures will effectively boost innovation among female researchers. Therefore, the primary objective of this study is to identify the funding trend for each gender with every classification during the period 2015 - 2022 and ascertain if a gender disparity is evident. To ensure robustness, hypothesis testing is also incorporated. Since we are comparing the time series of two groups of results (male and female), a two-sample t-test is employed to determine if there is a significant difference between the mean of funding for males and females. The test is conducted against the hypothesis:

H0: The mean funding for males and females is identical;

H1: The mean funding for males and females differs.

This study uses a general significance level of 5% for the testing. If the p-value appears to be smaller than 5%, then it indicates that the result provides evidence for rejecting the null hypothesis; otherwise, there is probably a gender bias for the research funding over time.

2. Comparison of funding ratio for each gender in each classification and university.

The subsequent phase proceeds to the comparison, which aims to find the potential cause of the bias. I first compare the funding ratio among the different STEM categories to identify which area may be the primary contributor to the disparity. Secondly, to check the impact of institutions on each gender, I do the ratio comparison among universities. The ratio is computed for each gender by dividing the number of funded researchers within that gender by the total number of staff members of the same gender.

3 Results

As described above, the proportion of each gender getting funded will be displayed first; the following will show the detailed results comparing different classifications and universities across time. The calculated p-value of hypothesis testing will also be indicated.

3.1 Total funding across time

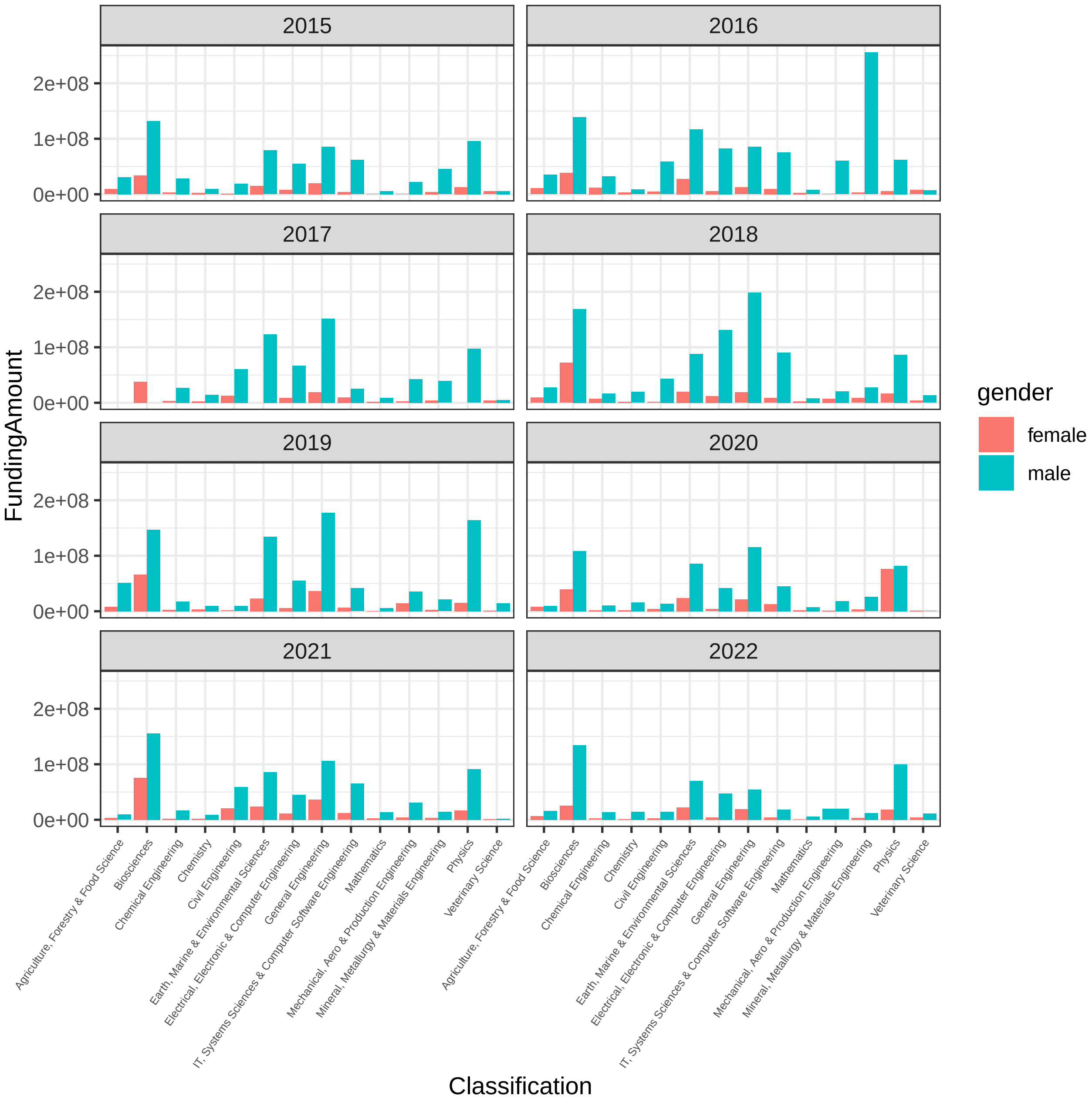


Figure 1: The plot shows the total research funding allocated to each gender during the period measured in GBP.

From this result, a great gender gap is seen. The graph indicates that the gender gap in recent years is smaller compared to the first three years when the funding amount for females almost cannot be seen compared to males. The Biosciences field has the greatest amount of funding for females across time, except in 2020, when the gender gap in Physics is the smallest. Despite an emerging trend towards bridging the gender gap, the progress is subtle, and the overall scenario remains concerning.

For the robustness of our result, a two-sample t-test is conducted for the number of funded males and females in different years. According to the result of the two-sample t-test, the t-statistic, representing the difference between the mean of the two data groups, is approximately 8.40; the p-value is 6.918e-14, much smaller than a significance level of 0.05. This result provides strong evidence to reject the null hypothesis, indicating a significant difference between the mean of research funding allocated to males and females from 2015 to 2022.

3.2 Temporal trends comparison

This subsection will display the comparison results for the temporal trends across the various STEM categories and institutions. The proportion of males and females getting funded will be shown in a time-series form. At the same time, I will show the ranking of the degree of bias across time to find the source of the disparity.

3.2.1 Comparison among classifications

As displayed in Figures 2 and 3, the results show a great gender gap in the research funding of Biosciences, where the gap almost persists; though the extent of gender bias overall is the greatest in Agriculture, Forestry & Food Science, the disparity has been considered diminished in the latest years. By contrast, there are several categories where the proportion of both genders is nearly the same over time, including General Engineering, Civil Engineering, and IT, Systems Sciences & Computer Software Engineering. In most classifications, there is an encouraging trend indicating a reduction in the gap between males and females. An exception would be Chemistry, where the gender gap increased over time. An interesting observation is that in the field of Electrical, Electronic & Computer Engineering, the proportion of funded females even exceeded that of males in recent years.

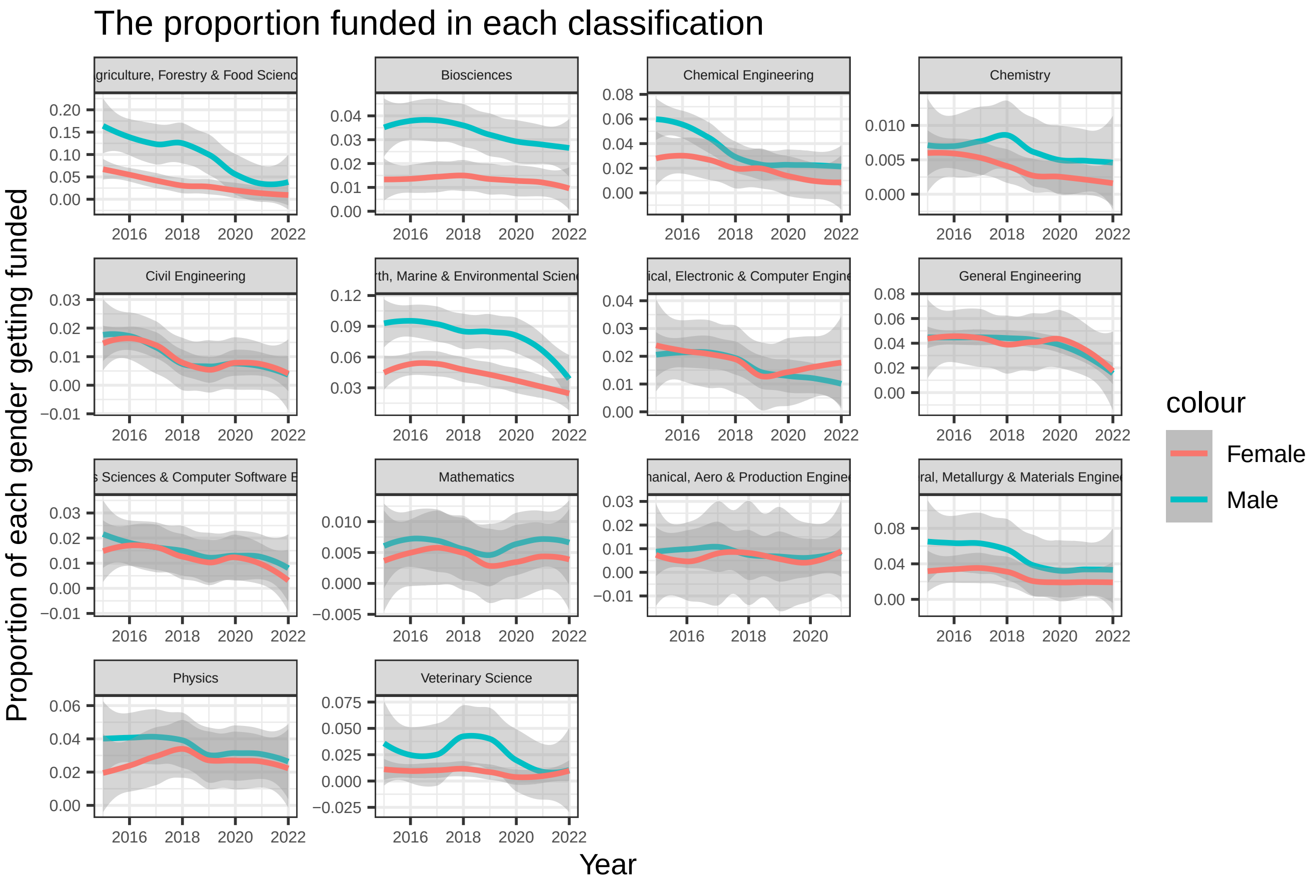


Figure 2: This figure shows the general trend of funded proportion in each classification across time. In this result, the proportion of each gender is used, calculated by dividing the funded males or females by the total number of HESA staff in each gender. The grey area represents the 0.95 confidence interval - a narrower band usually indicates a more precise result.

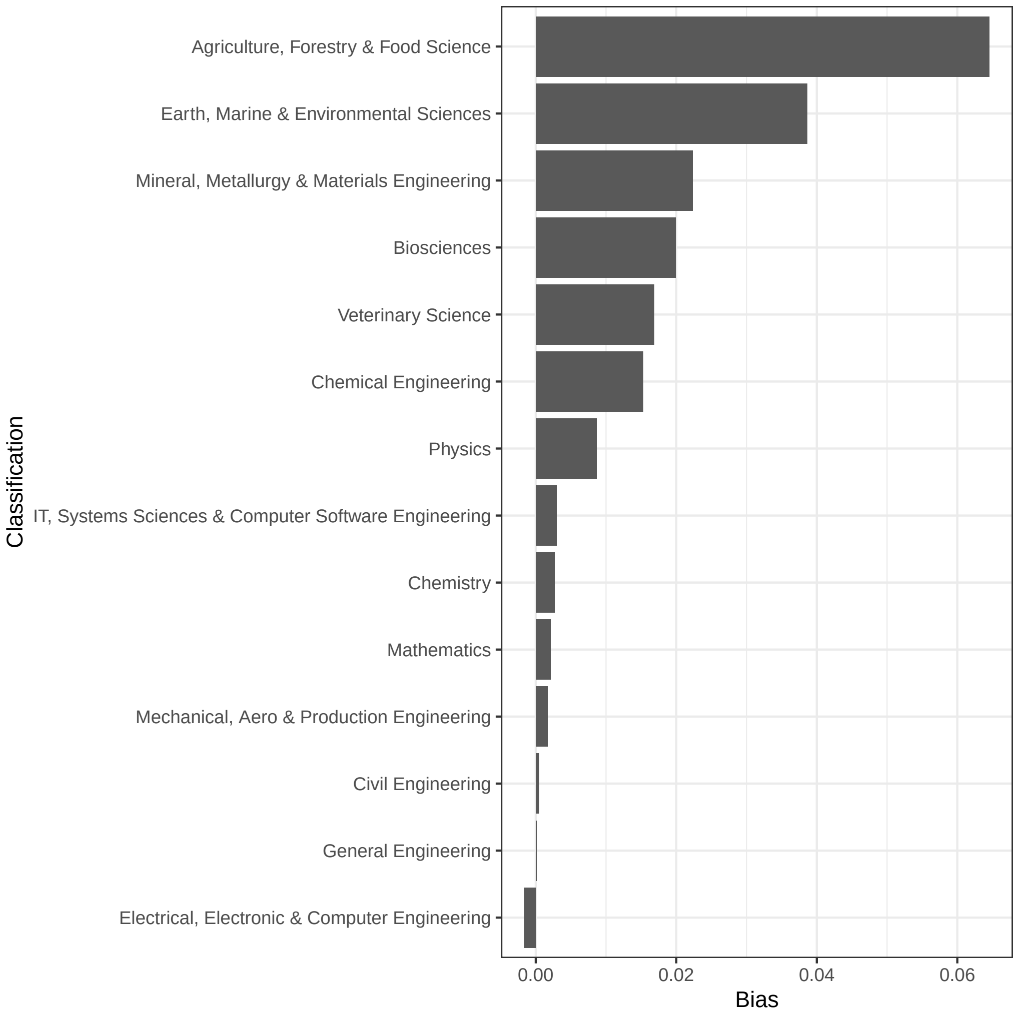


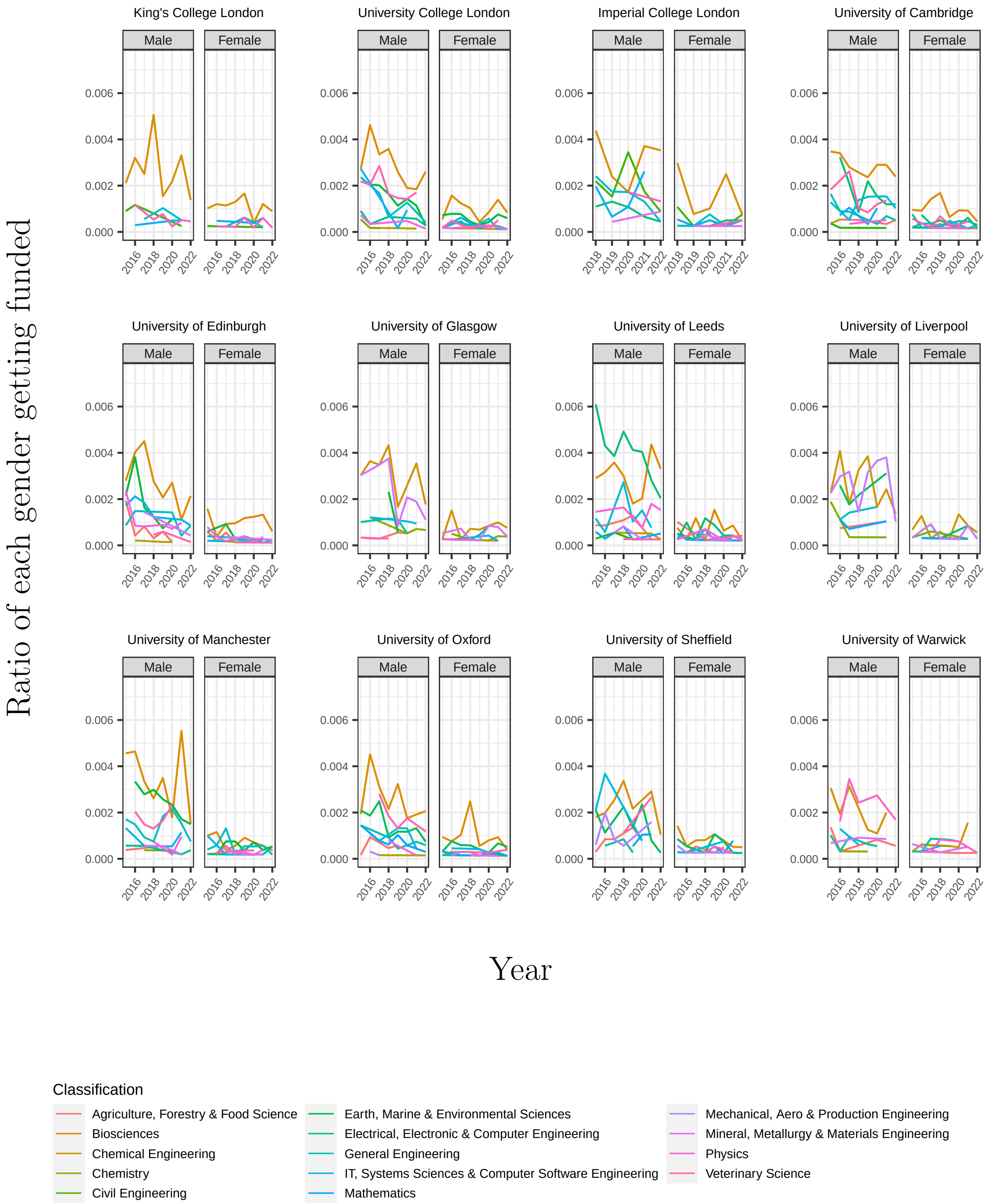
Figure 3: This figure shows the ranking of the extent of gender bias in each classification across time. For the bias degree, I calculated the total number of funded males or females from 2015 to 2022, divided by the total number of HESA staff in the corresponding gender during the period. Then, the difference of the ratios for males and females is conducted and is reordered depending on the degree of biases - the upper represents the classification with greater gender bias.

3.2.2 Comparison among universities

As one of the primary criteria of the research application, university ranking would be an important factor that may affect funding fairness. The ratio of funded researchers in different universities is displayed in Figures 4 and 5, where each colour represents a classification, and the scales for each subplot were set to be the same; only the universities with sufficient funding data are selected for the comparison.

From the results shown, gender differences can be observed in all the universities we are studying. Among these universities, our results suggest that the gender gap at King's College London and the University of Warwick is comparatively smaller. In contrast, the gap in the other universities shows a baptism pattern with a larger gender gap. The gap is the largest for the results in the University of Liverpool and the University of Manchester compared to other institutions. We may conclude that the institution's ranking might potentially affect gender equality in STEM research funding. Additionally, a sad observation is that from this comparison result, there is no signal of an improving trend of reducing the gap. Though the ratio of funded males in recent years is decreasing, the reduction is also seen for females.

Figure 4: This figure shows the comparison among different universities. The results of 65 universities were generated in my study; however, only 12 of them were selected. The reason is that some of the universities have little funding data, therefore only the universities with the most number of results displayed are selected for analysis.



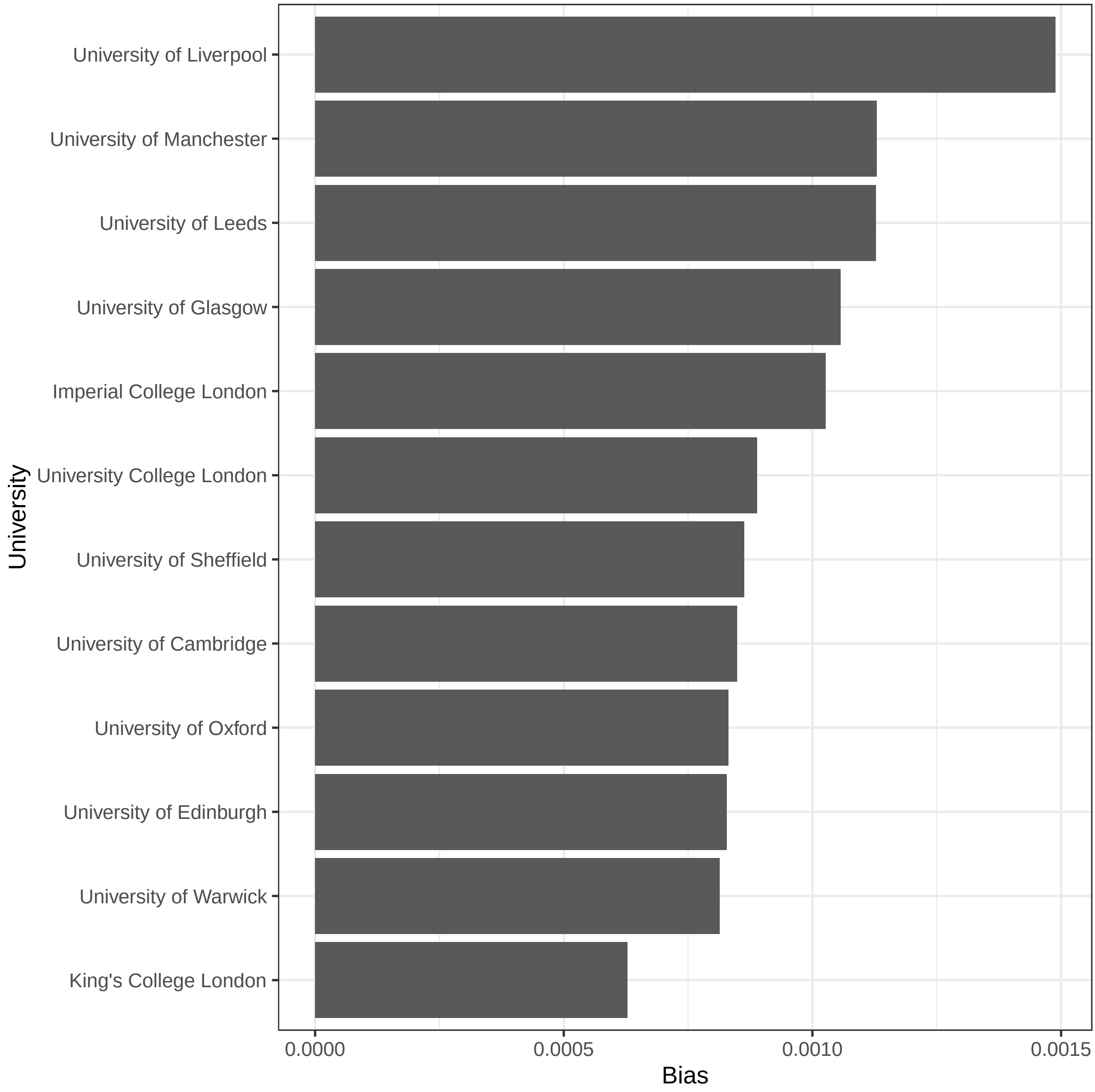


Figure 5: Similar to the previous comparison across various classifications, this figure shows the ranking of the extent of gender bias in universities. For each university, the total number of funded males or females in all classifications during the period 2015 2022 is summed up, and divided by the total number of HESA male or female staff in the corresponding university. The results are then used to calculate the degree of bias by finding the ratio for males minus the ratio for females in each university.

4 Discussion

This study's results have indicated a gender gap in the general trend of research funding in the STEM field in the UK. A positive sign is that the gap is being reduced to some extent, possibly due to the increasing attention paid to the diversity of research funding. Nevertheless, the positive impact is not apparent, and inequality is still observed. On the official website of UKRI, a commitment to gender equality is published, establishing the equality plan from 2022 to 2026. This includes ensuring the transparency and monitoring of the gender data, providing support to UK female leaders, targeting to address gender inequality in the recruitment process, etc. [Research and Innovation (2022)] However, to the best of our knowledge, there isn't any plan specifically for the fairness of research funding for different genders currently, which may be the potential reason leading to our result that the bias exists in the funding amount for males and females. This reveals that despite the government's announcement of increasing the funding for STEM subjects, different genders do not have equal access to the resources.

Having done the data analysis of the funding amount of each gender, I compared the trend among the classifications in the STEM field and among different universities. In a few classifications, mainly the engineering disciplines, the difference between genders is comparatively smaller; a trend of reducing the gap is observed in most other classifications, except Chemistry, where the difference is more significant than the previous value in 2015. A report by the Royal Society of Chemistry in 2018 indicates that the relative proportion of female chemists between undergraduate study and reaching senior positions in academia has dropped by 35 percentage points [of Chemistry (2018)]. The funding structure would be one of the leading causes of this phenomenon, where arbitrary funding criteria are mentioned; another cause is the lack of transparency in the recruitment and promotion process [of Chemistry (2018)]. Though some actions were taken to mitigate the gender gap [RSC (2023)], the gap was minorly reduced initially and persisted after 2018.

While the comparison among universities confirms the presence of gender bias across all the studied institutions, a minor difference is still observed. In the universities with higher ranks, the gender gap tends to be comparatively more minor in general. This could point to a concerning situation for female researchers - According to previous studies, females are usually less likely to be granted a position in institutions with higher ranking compared to males [Fox (2020)]. Consequently, even if higher-ranked institutions offer advantages to their female staff, the barriers to entry for these institutions might prevent many women from enjoying these benefits. This underscores potential inequities in resource distribution and possible biases in admission criteria.

4.1 Implications and Recommendations

In conclusion, our results revealed a significant gender bias in STEM research funding within the UK.While there is a decreasing trend of the gap, the academic framework continues to pose challenges for females. The internal link between the research funding and the ranking of their institution could pose additional hurdles for female researchers. This could be regarded as a systematic bias in the reviewing criteria, which benefits male applicants due to previous accumulative advantage [Tannenbaum (2019)]. The inequality not only causes a reduction in the female researcher's incentive to deliver innovative studies contributing to science, but would also be a factor influencing the career life of female researchers [Jebsen et al. (2022)]. The number of research fundings, as an important role affecting the promotion of academic careers, would directly impact the retention and progression of female researchers [Jebsen et al. (2022)], forming a vicious circle harmful to female researchers' situation. To break the cycle, having a systematic improvement for gender equality is necessary, which could include establishing a diversity focus group that keeps an eye on the diversity of each institution's employment and ensures that the recruitment process for universities is fair and offers equal opportunity to various groups of people [Sardelis et al. (2017)]. At the same time, this focus group should also be responsible for revising the funding application criteria, ensuring that the criteria could minimise the impact of accumulated advantage.

4.2 Limitations

In this study, we conducted the trend comparison using the ratio of each gender getting funded, where the HESA staff data is used for the calculation. We assumed that the HESA staff number in each classification and university is the total number of researchers in these areas. In addition, another caveat that is worth noticing is that this study only considered females and males as the genders. All the other genders are not listed in consideration, while these are also worth more attention. Though this study mainly focuses on female researchers, it can be a broad indication of the situation of most minority groups [Jebsen et al. (2022)]. Lastly, the gender determination for each project relies on the name of the primary applicant, which could introduce some inaccuracy.

4.3 Future Work

In this research, I have conducted the university-wide comparison and also showed the difference among disciplines based on the total number of HESA staff to consider the bias in all stages. Nevertheless, to check the existing problem in the current diversity system, it would also be beneficial to study the ratio based on the total number of applications so that we can find the proportion of bias caused during different stages, including the bias in the review stage and the step before application. In addition, this study only learned about the gender gap in STEM research funding. According to previous research, the fact is that there may also be a lot of other biases that may exist in the research funding, including racial or nationality bias, ethnicity bias, risk aversion bias, etc. [Wojick and Michaels (2015)] All the diversity should be as important as each other [Formanowicz et al. (2018)], and bias in any aspect would lead to direct impact on the science innovation and career life of individuals. As such, further studies should be conducted on other elements of discrimination to heighten awareness.

5 Data and Code Availability

In my study, the HESA staff data is sourced from the official HESA website, including staff number under various institutions and categories over time. The project information from UKRI can be assessed from Onedrive. The coding part is available on Github, including the machine-learning related part and the analysis part.

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