# Written Evidence Submitted by Dr Yang Hu, Professor Monideepa Tarafdar, Jabir Alshehabi Al-Ani, Irina Rets, Shenggang Hu, Nicole Denier, Karen D. Hughes, Alla Konnikov and Lei Ding

## (DIV0095)

# Gendered STEM Workforce in the United Kingdom: The Role of Gender Bias in Job Advertising

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## FUNDING

This work is supported by the Economic and Social Research Council (ESRC ES/T012382/1) and the Social Sciences and Humanities Research Council (SSHRC 2003-2019-0003) under the scheme of the Canada-UK Artificial Intelligence Initiative. The project title is ‘BIAS: Responsible AI for Labour Market Equality’.

## RECOMMENDED CITATION

Hu, Y., Tarafdar, M., Al-Ani, J. A., Rets, I., Hu, S., Denier, D., Hughes, K. D., Konnikov, A., & Ding, L. (2022). *Gendered STEM workforce in the United Kingdom: The role of gender bias in job advertising*. BIAS project evidence submission to the ‘Diversity in STEM’ inquiry, Science and Technology Committee, House of Commons, UK Parliament.

# Contents

# EXECUTIVE SUMMARY

This report presents new evidence on gender (in)equality in STEM from the UKRI-funded interdisciplinary project ‘BIAS: Responsible artificial intelligence (AI) for labour market equality’.

First, we provide up-to-date evidence on the state of gender (in)equality in the science, technology, engineering, and mathematics (STEM) workforce in the United Kingdom (UK). Analysing data from the Office for National Statistics (ONS) Quarterly Labour Force Survey between 2018 and 2020, we describe the state of gender segregation across STEM industries (i.e. industrial sectors of economic activities such as education and healthcare) and occupations (i.e. specific roles within industrial sectors such as managerial and associate professionals). Our evidence shows that:

- The workforce across most STEM industries and occupations in the UK is male-dominated. With particular attention to occupational roles within specific industry contexts, our evidence shows that the proportions of men are largest in STEM occupations within STEM industries. This evidence highlights the importance of considering the intersection between industrial and occupational configurations in understanding and bolstering gender diversity in STEM.

Second, building on the analysis of an original dataset of 11.2 million digital job advertisements in the UK, we provide fresh evidence on gender bias in STEM job advertising. Our evidence indicates that:

- The wording of job postings across most STEM industries and occupations in the UK is biased toward traits and social-psychological cues that are masculine and are likely to attract male job applicants whilst deterring female candidates.

Third, combining the analysis of data from the ONS Labour Force Survey and the digital job advertisements, we provide evidence on the association between gender bias in STEM job postings and the gendered composition of the STEM workforce. We find that:

- In STEM industries and occupations where the wording of job postings is more biased toward masculine traits and cues, the workforce is composed of a larger proportion of men as opposed to women.

In discussing the policy and practice implications of our findings, we draw on in-depth qualitative research conducted in STEM organisations as part of the BIAS project as well as state-of-the-art research on workforce diversity to shed further light on the statistical evidence we present in this report.

As job advertisements form the first point of contact between employers and job candidates, job advertising plays a crucial role in signalling employers’ preferences for their ideal candidates and thus shaping the gender composition of the workforce. Moreover, job postings can influence screening matrices and human judgement at later points in the hiring process, as specifications included in job postings are often used as key criteria in long-listing, short-listing, interviewing, and appointment processes. Therefore, our evidence illustrates the importance of scrutinising the role played by job advertising in ‘gatekeeping’ diversity in STEM.

# 1. INTRODUCTION

## 1.1. The BIAS Project

In this report, we provide fresh evidence on gender (in)equality in STEM from the interdisciplinary project 'BIAS: Responsible AI for labour market equality'. The BIAS project (see Konnikov et al., in press) aims to understand and tackle the role of AI algorithms in shaping ethnic and gender inequalities in the labour market, which is now increasingly digitalised. Potential 'biases' produced by AI technologies may significantly undermine workplace and labour market equality and stymie equitable and sustainable socio-economic development.

The empirical context of the BIAS project includes labour market processes in organisations that are mediated by digital job platforms, such as job advertising and hiring. Through a unique collaboration between researchers in the social and management sciences, computing, statistics, and mathematics, BIAS further aims to develop responsible AI algorithms and development protocols that help mitigate biases and attendant inequalities.

BIAS was funded as part of the UK-Canada joint funding initiative, 'Canada−UK artificial intelligence initiative: Building competitive and resilient economies through responsible AI' (https://esrc.ukri.org/files/funding/funding-opportunities/canada-uk-ai-call-specification/). Our project speaks directly to multiple national priority agendas in both the UK and Canada, including the gender pay gap, ethnic/racial disparity, and digital and industrial strategy.

## 1.2. Background and Foci of This Report

The hiring process consists of a series of steps (Bills et al., 2017; Bogen & Rieke, 2018), beginning with the employer posting a job advertisement and culminating with applicants being hired (Cohen & Mahabadi, 2021). Job postings are the first point of contact between job seekers and employers because it is through job postings that potential applicants understand what a job requires. Furthermore, specifications in job postings are often used as criteria that inform candidate screening processes (Bills et al., 2017; Rivera, 2020). Nevertheless, the language used in job postings is known to be biased in its gender implications, often reflecting explicit and implicit biases in the hiring organisations.

As an example, a job advertisement for a nursing position may include words such as 'support' and 'nurture', often associated with feminine social-psychological cues, and that for a CEO may include words such as 'competitive' or 'leader', i.e. words that signal masculine traits. Such biased language in job advertising can lead to prospective applicants being turned off because they may perceive that a particular job is not for them if it mentions attributes that they perceived to be biased against their gender (e.g. Gaucher, Friesen & Key, 2011). This can undermine diversity in STEM, including (1) reducing diversity in the pool of applicants for STEM jobs and (2) creating a negative/non-equitable experience for STEM job applicants.

Against this backdrop, this report presents fresh evidence regarding gender bias in UK STEM job postings. First, we provide an up-to-date description of the current state of gender segregation across STEM industries and occupations, based on our analysis of the 2018–2020 ONS Labour Force Survey data. Second, analysing a dataset of 11.2 million digital job advertisements, we provide new evidence on gender bias in online STEM job postings published by UK employers between 2018 and 2020. The dataset was collected by Emsi

Burning Glass (for further information, see economicmodeling.com), one of the largest international job-posting data repositories, and then curated and processed by the BIAS project team for analysis. Third, combining the analysis of data from the ONS Labour Force Survey and the online job postings, we provide evidence on the association between gender bias in STEM job postings and the gendered composition of the STEM workforce, to illustrate the potential role played by job postings in shaping gender diversity in the workforce. Finally, we draw on an in-depth study of recruitment, hiring and diversity/inclusion practices at one of the UK's largest job advertising companies, as well as state-of-the-art research on workforce diversity, to reflect on and interpret our statistical findings and to flesh out the policy and practice implications of our evidence.[1]

### 1.3. Key Findings

Our findings show strong evidence that (1) the workforce across most STEM industries and occupations (classified using the Standard Industrial Classification [SIC] and Standard Occupational Classification [SOC] systems) is dominated by men, with only a few exceptions; (2) the language and wording used in UK STEM job advertisements are biased toward a masculine orientation; (3) there is a positive association between male-biased job postings and a male-dominated STEM workforce, that is, in STEM industries and occupations where job postings have a stronger male bias, the workforce is composed of a larger share of men rather than women. In the following Section 2 of the report, we present detailed evidence from our analysis. The policy and practice implications of our evidence are discussed in Section 3.

## 2. EVIDENCE

In this section, we report new evidence on gendered STEM workforce composition and gender bias in STEM job advertising, and the relationship between the two from 2018 to 2020 in the UK.[2] In Section 2.1, we present our findings on the gendered composition of the STEM versus non-STEM workforce in the UK, drawing on our analysis of the ONS Labour Force Survey. In Section 2.2, we report the prevalence of gender bias in STEM versus non-STEM job postings, based on our analysis of a dataset of 11.2 million job postings in the UK.[3] Bringing together the analysis of data on the labour force gender composition and job postings, Section 2.3 presents evidence on the interrelation between gender bias in job advertising and the gendered composition of the STEM workforce. Our definition of STEM industry and occupation follows the Office for National Statistics classifications. Please refer to the Methodological Appendix included at the end of this report for further technical details.

### 2.1. Gender Composition of the UK STEM Workforce, 2018–2020

Existing evidence has firmly established that the STEM workforce is gendered in the UK and across a wider range of advanced economies (Kong et al. 2020). Drawing on the analysis of 407,840 valid records of working respondents from the 2018–2020 ONS Labour Force Survey,

[1] The company, employing over 3,000 staff members, specialises in job advertising across 20 sectors, and its digital job advertising platform is reported to be used by 85% of the UK's top 100 recruiting firms.

[2] Our analysis focuses on 2018–2020 because our curated job posting data focus on this period and that historical data before this period only provide an incomplete, non-representative coverage of all job postings. Our analysis of data from this period also provides an up-to-date description of the UK STEM workforce.

[3] The data was collected by Emsi Burning Glass, and the data have been further processed by the BIAS project team for the analysis presented here.

we go beyond existing research to provide up-to-date, nuanced evidence on the gender composition of the STEM (versus non-STEM) workforce in the UK. While past evidence has often described gender segregation in the STEM workforce across distinct industries and occupations, respectively, we pay particular attention to the intersection between industry and occupation. Overall, our findings show that the STEM workforce is primarily composed of men as opposed to women between 2018 and 2020. There are also considerable industry and occupation differences in the level of gender segregation.

**Key Findings**

- There is considerable gender segregation across STEM industries and occupations. Despite long-term efforts to bolster gender equality in STEM, gender segregation remains a major hurdle to progress toward diversity in STEM. Our results could be used to inform targeted policy development in STEM industries and occupations where gender segregation is most stubborn.
- Our findings further emphasise the importance of considering the industry-occupation intersection in understanding gender segregation in the STEM workforce. We recommend that policy developments should not only target specific occupational characteristics but also consider such characteristics with reference to the specific context and configuration of the industries in which the STEM occupations are found.

### *2.1.1. Overall Gender Segregation in the UK STEM Workforce*

Figure 1 depicts the proportions of men in STEM and non-STEM industries and occupations, with the red line indicating gender parity.[4] The graph shows that STEM occupations in STEM industries have the highest percentage of men (60.5%). By contrast, non-STEM occupations in non-STEM industries have the highest percentage of women (54.9%). These results show that the STEM workforce is particularly male-concentrated at the intersection between STEM industries and STEM occupations. As a result, the occupational structure and industrial configuration of STEM jointly contribute to gender segregation in the STEM workforce.

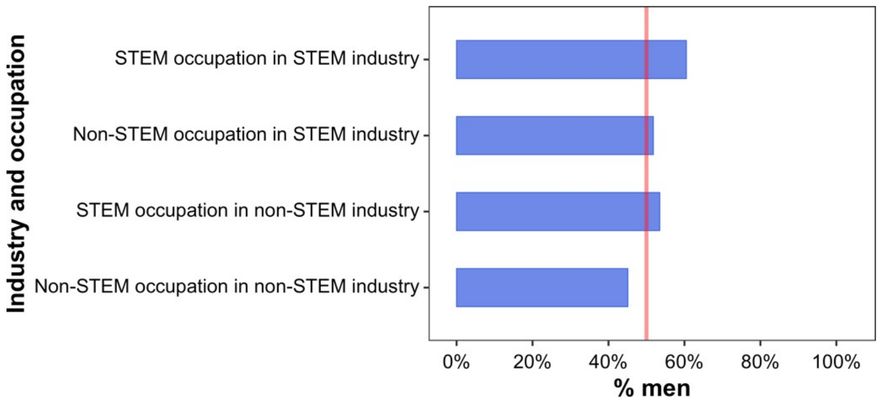


**FIGURE 1. STEM occupations within STEM industries have the largest proportion of men**
*Note*: Authors' calculation based on 407,840 valid records of working respondents from the 2018–2020 ONS Labour Force Survey. See Appendix Tables A1 and A2 for detailed lists of STEM industries and occupations. The red line indicates gender parity. Weighted statistics.

[4] Here and in Figures 2 and 3, we use 50% as the gender parity threshold, as the percentages of men (50.3%) and women (49.7%) are more or less even in the ONS Labour Force Survey sample. The threshold roughly represents the average gender composition of the full UK labour force.

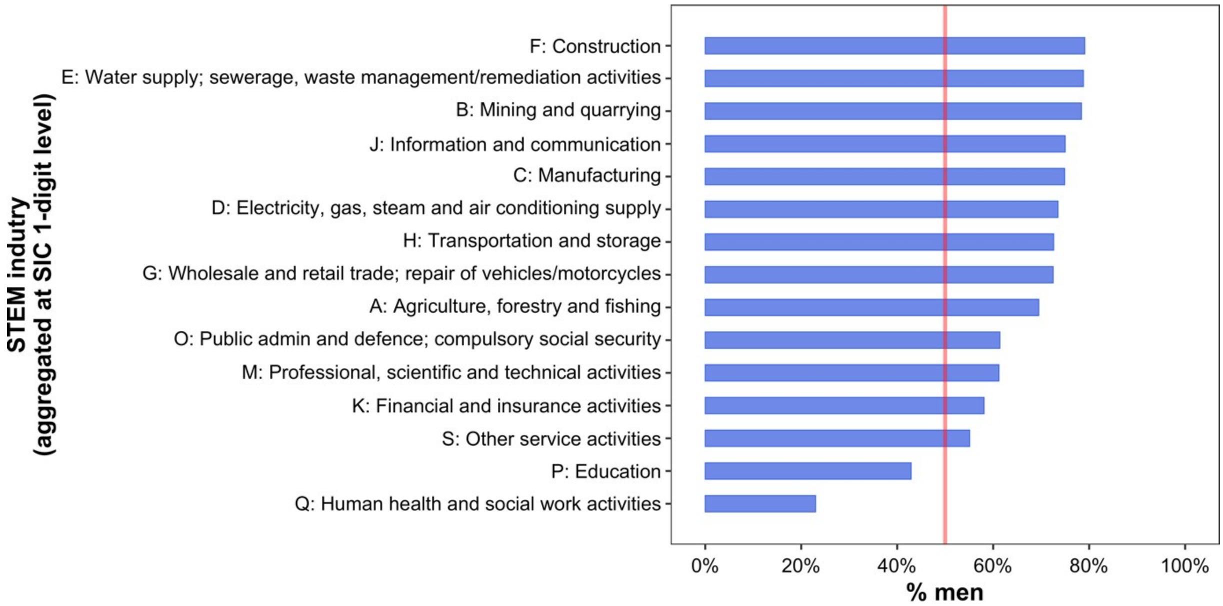


**FIGURE 2. Most STEM industries have a male-dominated workforce**
*Note*: Authors' calculation based on 407,840 valid records of working respondents from the 2018–2020 ONS Labour Force Survey. See Appendix Table A1 for a detailed list of STEM industries. Weighted statistics.

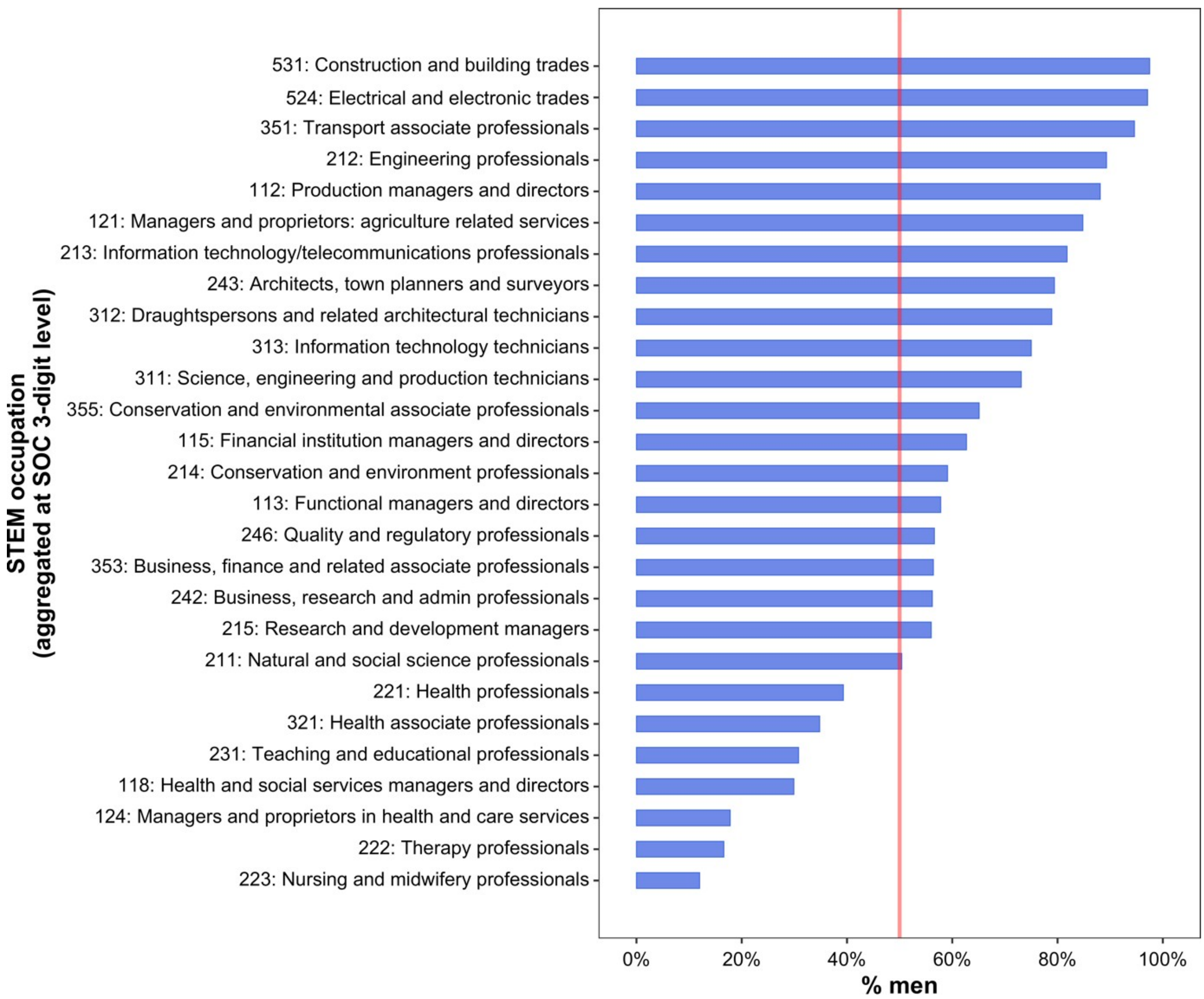


**FIGURE 3. Most STEM occupations have a male-dominated workforce**
*Note*: Authors' calculation based on 407,840 valid records of working respondents from the 2018–2020 ONS Labour Force Survey. Weighted statistics.

### *2.1.2. Gender Segregation across STEM Industries*

Figure 2 presents further details on gender segregation in the STEM workforce across major industries (1-digit level of the Standard Industry Classification [SIC]). The evidence clearly shows that across the 15 industries, only two have a workforce composed of a larger share of women than men—namely, education (42.9% men) and human health and social work (23.0% men). Among the 13 STEM industries that host a larger share of men than women, eight are male-dominated with over 70% of the workforce formed of men. The top three male-dominated industries are construction (79.1% men), water supply, sewage, waste management and remediation (78.8% men), and mining and quarrying (78.4% men).

### *2.1.3. Gender Segregation across STEM Occupations*

Figure 3 delineates the patterns of workforce gender segregation across STEM occupations. The evidence shows strong gender segregation across most STEM occupations. Out of the 27 STEM occupations (3-digit level of the Standard Occupation Classifications [SOC]), only seven have a larger proportion of women than men. Most of these seven occupations fall in the broad areas of health and education. Among the 20 occupations that have a larger proportion of men than women, 11 are male-dominated (> 70% men). Occupations such as construction and building trades (97.5% men), electrical and electronic trades (97.1% men), transport associate professionals (94.6% men), engineering professionals (89.3%), and production managers and directors (88.1%) are formed almost exclusively of men.

**TABLE 1. Workforce gender composition: STEM versus non-STEM occupations within each STEM industry**

| SIC 1-digit | STEM occupations<br>% men | Non-STEM occupations<br>% men | STEM versus non-STEM occupation gap<br>% men |
|---|---|---|---|
| A: Agriculture, forestry and fishing | 81.3 | 57.8 | 23.5 |
| B: Mining and quarrying | 78.8 | 77.9 | 0.9 |
| C: Manufacturing | 80.0 | 70.7 | 9.3 |
| D: Electricity, gas, steam and air conditioning supply | 86.0 | 59.2 | 26.8 |
| E: Water supply; sewerage, waste management and remediation activities | 74.3 | 80.6 | –6.3 |
| F: Construction | 85.8 | 71.1 | 14.8 |
| G: Wholesale and retail trade; repair of vehicles/motorcycles | 76.3 | 71.3 | 5.0 |
| H: Transportation and storage | 72.9 | 72.5 | 0.3 |
| J: Information and communication | 81.5 | 55.1 | 26.5 |
| K: Financial and insurance activities | 69.8 | 39.2 | 30.6 |
| M: Professional, scientific and technical activities | 69.6 | 46.2 | 23.4 |
| O: Public admin and defence; compulsory social security | 65.8 | 60.6 | 5.2 |
| P: Education | 48.6 | 33.4 | 15.2 |
| Q: Human health and social work activities | 24.8 | 20.3 | 4.6 |
| S: Other service activities | 67.2 | 41.7 | 25.5 |
| All STEM SIC | 60.5 | 51.8 | 8.6 |
| Non-STEM SIC | 53.5 | 45.1 | 8.4 |

*Note*: Authors' calculation based on 407,840 valid records of working respondents from the 2018–2020 ONS Labour Force Survey. See Appendix Tables A1 and A2 for detailed lists of STEM industries and occupations. Weighted statistics.

#### *2.1.4. Gender Segregation at the Intersection of STEM Industry and Occupation*

Table 1 probes further into each STEM industry and provides evidence on how, within each industry, the extent of gender segregation differs between STEM and non-STEM occupations. Our findings show that on top of gender segregation across STEM industries, occupational gender segregation further exacerbates the workforce gender imbalance within each STEM industry. For example, within the male-dominated industry of agriculture, forestry and fishing, STEM occupations are characterised by a much higher concentration of men (81.3%) than non-STEM occupations (57.8%). Such within-industry gender divide between STEM and non-STEM occupations is also prominent in the industries of electricity, gas, steam and air conditioning supply; information and communication; finance and insurance; and professional, scientific and technical activities. Even in the supposedly ‘gender-neutral’ education industry, the proportion of men is 15.2 percentage points higher in the STEM than non-STEM occupations.

### 2.2. Gender Bias in STEM Job Postings, 2018–2020

Job advertising is a first step in the hiring process. Research has provided clear evidence that job postings signal, both explicitly and implicitly, employers’ preferences for certain types of candidates, which may lead to potential gender biases (Gaucher et al., 2011). Research has also provided evidence that employers use job postings to inform the criteria they use for candidate selection (Rivera, 2020). While effort has been made to eliminate explicitly gendered language in job postings, far less attention has been paid to detecting and mitigating implicit gender bias in job postings. Such bias can include gendered social-psychological cues, content relating to work-family policies (e.g. childcare and parental leave), organisational culture and practice (e.g. diversity pledge) and so on (see Konnikov et al. [2022], the BIAS word inventory, for a full list of dimensions).

In the BIAS project, we analyse all these dimensions to provide a comprehensive assessment of gender bias in hiring processes. While much of this work is still ongoing, we hereby present the first part of our results—i.e. gender bias inherent in social-psychological cues and traits included in job postings. Theoretically, it is well established that gendered social-psychological cues in job postings tend to attract candidates of a particular gender, whilst deterring candidates of other genders (Gaucher et al., 2011).

The evidence we present here is based on our analysis of 11.2 million UK-based job postings collected by Emsi Burning Glass from mainstream job advertising platforms between 2018 and 2020 and further curated by the BIAS team. Utilising natural language processing techniques, we matched the wording of the job postings against a word/lexicon list combining three inventories of gendered language use: the Bem (1974) sex-role inventory, the Gaucher et al. (2011) inventory, and the BIAS inventory (Konnikov et al., 2022). The matching procedure generated a gender bias score indicating the feminine–masculine orientation of each job posting. The score ranges from –1 (most female-biased) to 1 (most male-biased), with 0 indicating that a given posting is gender-neutral insofar as social-psychological cues are concerned. We calculated the average gender bias scores across distinct STEM industries and occupations. Moreover, we classified job postings with a gender bias score greater than 0 as male-biased postings and calculated the proportions of male-biased postings across industries/occupations. Further technical details can be found in the Methodological Appendix.

**Key Findings**

- Job advertising, a key, first step in the hiring process, is biased toward a masculine orientation in the language and wording of job postings across most STEM industries and occupations.
- The prevalence of gender bias in job postings varies across STEM industries and occupations. Instead of taking a one-size-fits-all approach to tackling gender bias in STEM job advertising, it is important to consider the intersection between industry and occupation in understanding such biases and providing targeted interventions.

#### *2.2.1. Overall Gender Bias in STEM Job Postings*

Figure 4 depicts the aggregate job-posting gender bias scores and percentages of male-biased job postings (i.e. gender bias score > 0) in STEM and non-STEM industries and occupations, with the red lines indicating gender neutrality. The results show that all job postings in the UK between 2018–2020 analysed in our project are skewed toward a masculine orientation in the social-psychological cues they contain, with a mean gender bias score of 0.260. Furthermore, 64.6% of all job postings in the UK are male-biased in their wording between 2018 and 2020.

When job postings in STEM industries are concerned, they have a higher, more masculine gender bias score (0.296) than job postings in non-STEM industries (0.250); and a larger proportion of job postings are classified as male-biased in STEM industries (67.9%) than in non-STEM industries (63.7%).

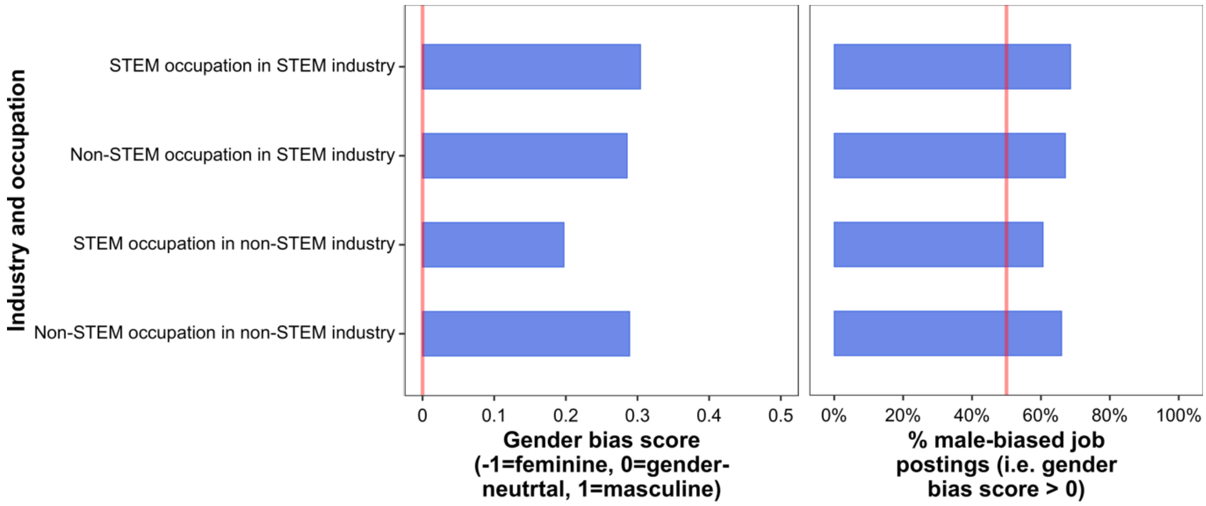


**FIGURE 4. Job postings in STEM occupations within STEM industries are most male-biased**

*Note*: Authors' calculation based on 11.2 million job postings from the Emsi Burning Glass data. The red lines indicate gender neutrality. See Appendix Tables A1 and A2 for detailed lists of STEM industries and occupations.

By contrast, opposite results are found for STEM versus non-STEM occupations, with the latter being slightly more 'masculine' than the former. While job postings for non-STEM occupations have an average gender bias score of 0.288, postings for STEM occupations have an average gender bias score of 0.225. Compared with job postings for non-STEM occupations (66.2% male-biased), a smaller proportion of job postings for STEM occupations (62.6%) are male-biased in their wording.

Scrutinising the intersection between industry and occupation, our results show that job postings for STEM occupations within STEM industries are most male-biased in their wording, with an average gender bias score of 0.304 and with 60.5% of the job postings classified as 'male-biased' rather than 'female-biased' or 'gender-neutral'. While the aggregate statistics provide evidence of 'gender bias intensification' that male-oriented gender bias in job postings is reinforced at the intersection of STEM industry and STEM occupation, it is important to go beyond the aggregate pattern and scrutinise differences across more detailed industry and occupation groups, as we do below.

#### *2.2.2. Industry-Level Differences in Gender Bias in STEM Job Postings*

Figure 5 presents the gender bias scores and the percentages of male-biased job postings (i.e. gender bias score > 0) across major STEM industries (1-digit SIC). The left panel of Figure 5 shows that job posting across all STEM industries have a positive and thus male-biased gender bias score. Particularly skewed toward a strong masculine orientation are job postings in finance and insurance (gender bias score: 0.552); mining and quarrying (0.481); electricity, gas, steam and air conditioning supply (0.478); and agriculture, and forestry and fishing (0.450). At the other end of the spectrum are job postings for industries such as education (0.221) and human health and social work (0.098), which have gender bias scores that are relatively less male-biased and closer to the gender-neutral point of zero.

In the right panel of Figure 5, the results for the percentages of male-biased job postings across different STEM industries are more or less consistent with those for gender bias scores presented above. Across all industries, the percentages of male-biased job postings are all over 50%, indicating that male-biased job postings outnumber gender-neutral and female-biased job postings across all STEM industries.

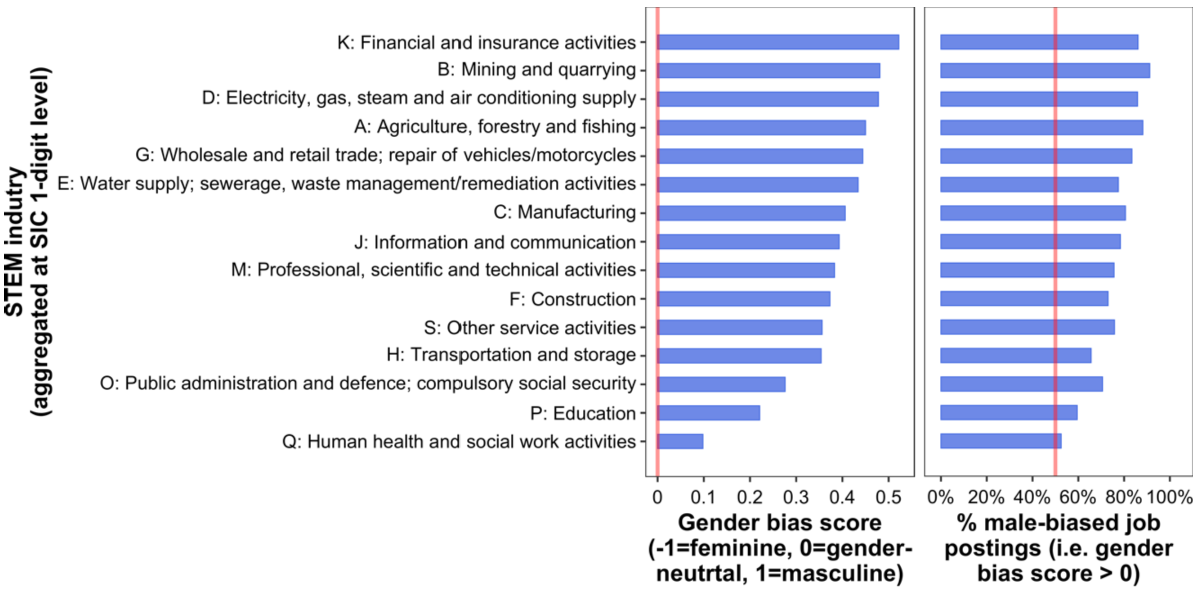


**FIGURE 5. Job postings for most STEM industries are strongly male-biased**

*Note*: Authors' calculation based on 11.2 million job postings from the Emsi Burning Glass data. The red lines indicate gender neutrality. See Appendix Table A1 for a detailed list of STEM industries.

#### *2.2.3. Occupational Differences in Gender Bias in STEM Job Postings*

Figure 6 presents the gender bias scores and the percentages of male-biased job postings across STEM occupations (3-digit SOC). The left panel of Figure 6 shows that job postings across all but one STEM occupations have a positive gender bias score and are thus skewed toward a masculine orientation. With the highest gender bias scores, job postings are found to be most male-biased for occupations including functional managers and directors (0.473); business, research and administrative professionals (0.462) and associate professionals (0.441); managers and proprietors in agriculture-related services (0.451); production managers and directors (0.443); architects, town planners and surveyors (0.418); and information technology and telecommunications professionals (0.408).

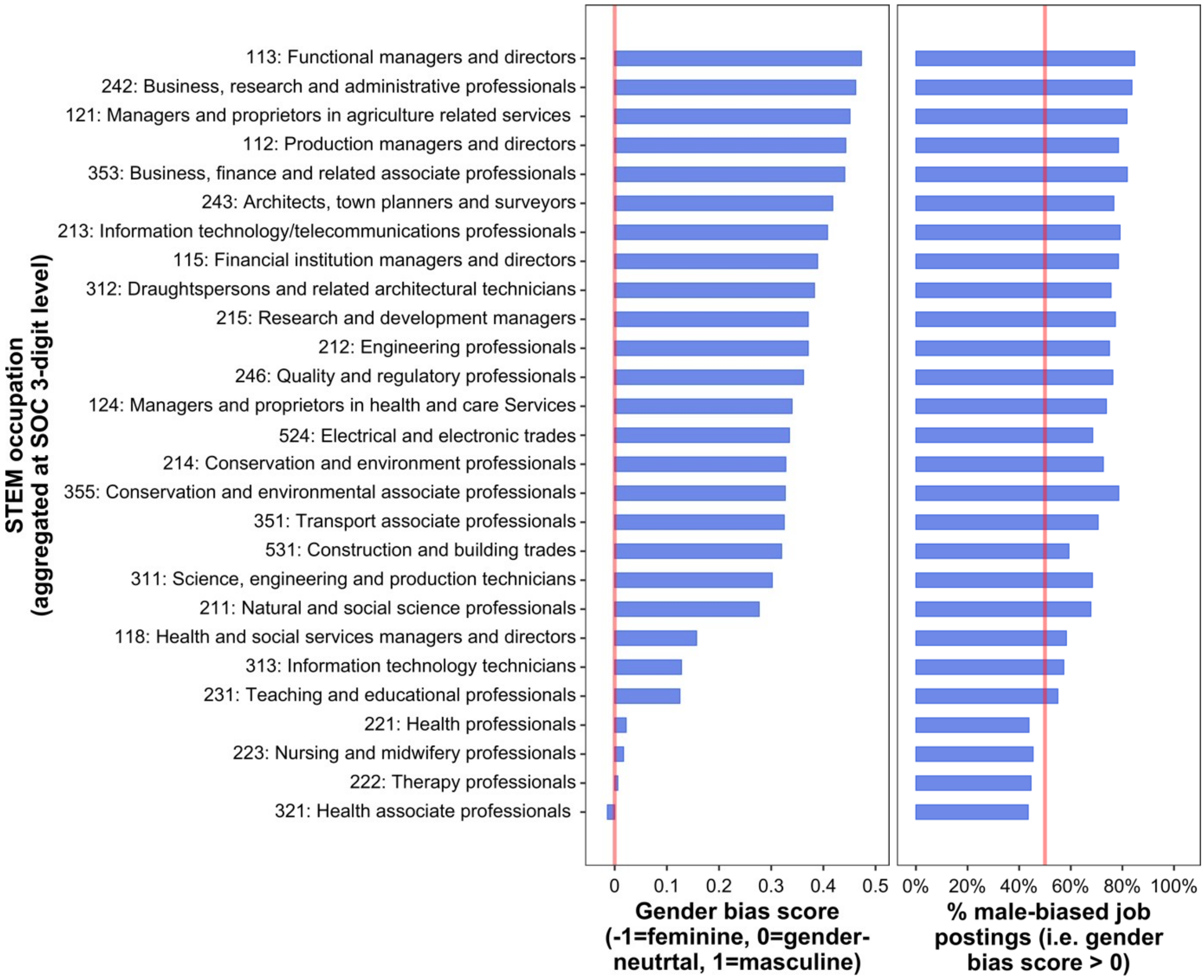


**FIGURE 6. Job postings for most STEM occupations are strongly male-biased**

*Note*: Authors' calculation based on 11.2 million job postings from the Emsi Burning Glass data. The red lines indicate gender neutrality.

By contrast, job postings for health-related occupations – namely, health professionals (0.022) and associate professionals (–0.014); therapy professionals (0.006); and nurses and midwives (0.017) – are found to be more or less gender-neutral.

A similar pattern of occupational differences in job-posting gender bias is noted in the right panel of Figure 6, which delineates the percentages of male-biased job postings across different STEM occupations. For the occupations of functional managers and directors, business, research and administrative professionals and associate professionals, managers and proprietors in agriculture-related services, and production managers and directors, over 80% of the job postings were found to fall in the male-biased category. At the other end of the spectrum, less than half of the job postings for health-related occupations were classified as male-biased.

### *2.2.4. Gender Bias in STEM Job Postings: Intersection of STEM Industry and Occupation*

Table 2 probes further into each STEM industry and describes how, within each industry, the extent of gender bias in job advertising differs between STEM and non-STEM occupations. Our findings show that on top of gender bias in job advertising across different STEM industries, gender bias in job postings between STEM and non-STEM occupations add a further layer of potential bias in some industries. For example, in the human health and social work industry where the overall gender bias score (0.098) is the closest to being gender-neutral among all industries, the job postings for STEM occupations have a much higher gender bias score (0.153) and are thus more male-biased, compared with the gender bias score for non-STEM occupations (0.044). This difference is similarly reflected in the higher percentage of male-biased job postings for STEM occupations (56.4%) than for non-STEM occupations (48.3%) within the human health and social work industry.

**TABLE 2. Job-posting gender bias in each STEM industry: STEM versus non-STEM occupations**

| | Gender bias score (positive and high = male-biased) | | | % of male-biased postings (i.e. gender bias score > 0) | | |
|---|---|---|---|---|---|---|
| SIC 1-digit | STEM occupation | Non-stem occupation | STEM–non-STEM occupation gap | STEM occupation | Non-stem occupation | STEM–non-STEM occupation gap |
| A: Agriculture, forestry and fishing | 0.434 | 0.461 | –0.027 | 83.9 | 80.7 | 3.2 |
| B: Mining and quarrying | 0.488 | 0.473 | 0.015 | 90.7 | 90.6 | 0.1 |
| C: Manufacturing | 0.409 | 0.402 | 0.007 | 81.1 | 79.3 | 1.8 |
| D: Electricity, gas, steam and air conditioning supply | 0.461 | 0.506 | –0.046 | 85.1 | 86.1 | -0.9 |
| E: Water supply; sewerage, waste management/remediation activities | 0.426 | 0.442 | –0.016 | 77.4 | 76.9 | 0.5 |
| F: Construction | 0.377 | 0.368 | 0.009 | 73.5 | 71.8 | 1.8 |
| G: Wholesale and retail trade; repair of vehicles/motorcycles | 0.473 | 0.431 | 0.042 | 86.1 | 81.8 | 4.3 |
| H: Transportation and storage | 0.368 | 0.351 | 0.017 | 72.1 | 64.1 | 8.0 |
| J: Information and communication | 0.388 | 0.400 | –0.012 | 77.6 | 79.3 | –1.7 |
| K: Financial and insurance activities | 0.528 | 0.515 | 0.013 | 86.1 | 85.5 | 0.6 |
| M: Professional, scientific and technical activities | 0.393 | 0.371 | 0.022 | 75.6 | 75.2 | 0.4 |
| O: Public admin and defence; compulsory social security | 0.294 | 0.262 | 0.032 | 72.6 | 68.5 | 4.1 |
| P: Education | 0.206 | 0.249 | –0.043 | 57.9 | 62.4 | –4.5 |
| Q: Human health and social work activities | 0.153 | 0.044 | 0.109 | 56.4 | 48.3 | 8.2 |
| S: Other service activities | 0.398 | 0.327 | 0.071 | 79.8 | 72.0 | 7.8 |
| All STEM SIC | 0.304 | 0.286 | 0.019 | 68.6 | 67.1 | 1.4 |
| Non-STEM SIC | 0.197 | 0.289 | –0.092 | 60.6 | 66.0 | –5.4 |

*Note*: Authors' calculation based on 11.2 million job postings from the Emsi Burning Glass data. See Appendix Tables A1 and A2 for detailed lists of STEM industries and occupations.

Interestingly, the STEM versus non-STEM occupational difference is found to run in the opposite direction in a few industries where the job postings are strongly male-biased overall: e.g. agriculture, forestry and fishing; electricity, gas, steam and air conditioning supply; water supply, and sewerage; and waste management and remediation activities. In these industries, job postings for STEM occupations are marginally less male-biased than those for non-STEM occupations. Nevertheless, it is worth noting that as these differences are very small in size, even the relatively less male-biased job postings for STEM (as opposed to non-STEM) occupations in these industries are skewed toward a strong masculine orientation.

The results in Table 2 underline the necessity of considering the intersection between industry and occupation in assessing gender bias in STEM job advertising. Such consideration, as we have shown, suggests that interventions should target the constellations of different occupations in specific industrial contexts. For example, in industries where the overall gender bias in job advertising is low (e.g. human health and social work) but the difference in gender bias between STEM and non-STEM occupations is large, interventions should target occupation-related configurations. By contrast, in industries with a narrow or even reverse STEM versus non-STEM occupational male gender-bias divide but a high overall industry-level male gender bias (e.g. agriculture, forestry and fishing; information and communication), the effectiveness of potential interventions could be enhanced by seeking to understand and effectively target the industrial context and configuration.

## 2.3. Gender Segregation in the STEM Workforce is Closely Associated with Gender Bias in STEM Job Postings

In this section, we bring together the separate lines of inquiry into gender segregation in the STEM workforce and gender bias in STEM job postings, to investigate the relationship between the two. To do so, we fit a series of statistical models to examine the extent to which the gendered workforce composition across STEM industries and occupations are associated with gender bias in STEM job postings.

**Key Findings**

- The gendered workforce compositions across STEM industries and occupations are closely associated with gender bias in STEM job postings.
- In STEM industries/occupations where the job postings are male-biased, the workforce is more likely to be composed of a larger proportion of men and more likely to be male-dominated.

In Figure 7, the blue dotted lines present the predicted relationships between job-posting gender bias and the gender composition of STEM industries (left panels, 3-digit SIC) and STEM occupations (right panels, 3-digit SOC), respectively. The red lines represent the threshold of gender neutrality, i.e. a gender bias score of zero (top panels) and an even split between male-biased and non-male-biased postings (bottom panels). Blue dots above the red lines indicate that the job postings are male-biased, blue dots below the red lines indicate that the postings are female-biased, and blue dots close to the red lines are close to being gender-neutral.

To demonstrate the robustness of our findings, we present two sets of results based on the continuous gender bias score (top panels) and the proportion of male-biased job postings in each industry/occupation (bottom panels). The highly similar results from the two sets of analyses indicate that our evidence is robust to the two alternative ways of measuring and modelling gender bias in job postings.

The left panels of Figure 7 confirm a strong positive association between the proportion of men and male bias in job postings across STEM industries. Job postings in STEM industries that are formed mostly of women have gender bias scores that are closest to the gender-neutral point of zero, and they are also closest to having an even split (50%) between male-biased and non-male-biased job postings. With the increase of the gender bias score (toward a more masculine orientation), we see an increase in the percentage of men across the STEM industries.

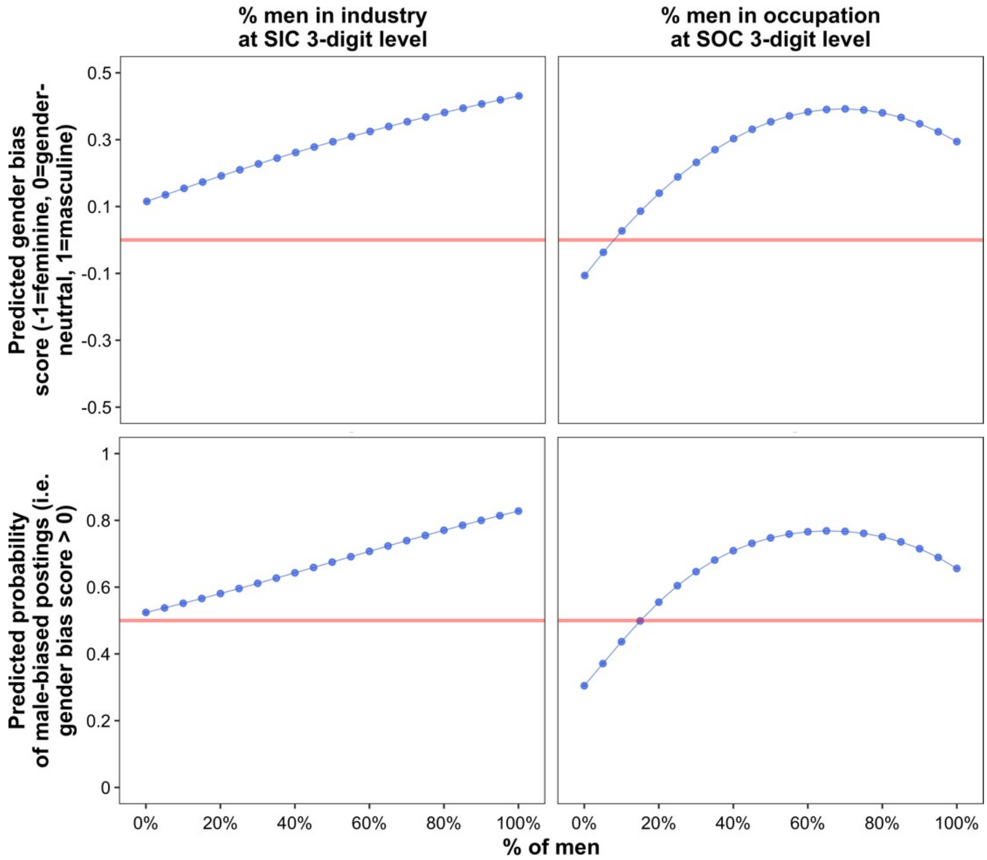


**FIGURE 7. Male-biased job postings are closely associated with a male-dominated workforce across STEM industries and occupations**

*Note*: Authors' calculation based on the merged ONS Labour Force Survey and the Emsi Burning Glass data. Ordinary least squares regression models were used for the top panels and logit regression models were used for the bottom panels, and all models include the first-order and quadratic terms of both industry (3-digit SIC) and occupational (3-digit SOC) gender compositions. The red lines indicate gender neutrality. See the Methodological Appendix for technical details and full model results.

In the right panels of Figure 7, the results similarly depict a positive association between the percentage of men in the workforce and job-posting male bias across STEM occupations. In STEM occupations with a female-dominated workforce, the job gender-bias scores tend to concentrate around the gender-neutral point of zero, and there is also a smaller proportion of job postings that are male-biased. By contrast, in male-dominated STEM occupations, the gender bias scores tend to be high and thus male-biased, and male-biased job postings are found to substantially outnumber female-biased and gender-neutral postings.

Notably, the curves in the right panels of Figure 7 suggest that although the proportion of men across STEM occupations increases with the level of male bias in job postings, this increase only extends up to the point where men account for around 70% of the workforce in a given occupation. Among male-dominated STEM occupations (> 70% men), an increase in male bias in job postings is not associated with a further increase in the proportion of men in these occupations.

# 3. POLICY IMPLICATIONS

In this section, we interpret the findings from our analysis and draw on our in-depth qualitative study of recruitment and diversity practices in one of the UK's largest job recruitment organisations, as well as state-of-the-art research on workforce diversity, to provide the policy implications of our evidence at three levels: (1) the STEM labour market; (2) STEM organisations and employers; and (3) STEM job seekers.

## 3.1. Implications for Labour Market Policy

Our analysis of over 400,000 records from the 2018–2020 ONS Labour Force Survey has provided up-to-date evidence of the gender composition of the STEM workforce in the UK, by industry sector, by occupation, and by the intersection between the two.

### *3.1.1. Intervention in and Policy Response to Male-dominated STEM Workforce*

We found that the UK STEM workforce is heavily male-dominant, with the workforce in most STEM industries and occupations made up of > 50% men and many made up of > 70% men. Policy initiatives to increase female workforce participation in STEM should be particularly directed to the male-dominated industries and occupations identified in our analysis (cf. Section 2.1). These can include STEM scholarships for female students undertaking university-level or diploma studies, incentivising female apprenticeships in these industries and occupations, and support for professional associations in these male-dominated STEM industries and occupations to help develop and strengthen female-oriented professional networks. These schemes have been found to be effective in attracting, retaining, and facilitating women's career progression in male-dominated trades (Gyarmati et al., 2017).

### *3.1.2. Healthcare and Social Work*

Among STEM industries, human health and social work is an exceptional case in its overall female-dominated workforce. However, our deeper analysis has revealed that occupations such as midwifery, nursing, therapy, and other health associates within this industry are even more skewed toward women, in contrast to more leadership-oriented occupations such as healthcare managers and proprietors. An interesting finding is that the job advertisements in these female-dominated industries are neutral and not skewed toward women. This augurs well for greater male participation in the healthcare and social work industries.

Policy initiatives should address the occupational divides in the health and social work industries. To do so, policies should be developed to remove the structural barriers to women's career progression and promotion in these industries. On the one hand, initiatives could be developed to encourage and enable female workforce members of occupations such as nursing to develop leadership skills and experience and to take up leadership-oriented positions such as directors of health services. On the other hand, the NHS, professional associations (e.g. nurses and midwives associations), social work agencies, and local authorities need to play an active role in framing and implementing such policies and initiatives. Specifically, these employers need to examine their employee competency profiles at senior levels, as well as the promotion pathways into leadership and managerial positions.

#### *3.1.3. The Intersection between STEM Industry and Occupation*
Overall, STEM occupations within STEM industries are more male-dominated than non-STEM occupations within STEM industries. Our findings thus suggest that the occupational structure of STEM and the STEM industry-specific context layer upon each other in exacerbating gender segregation in the STEM workforce.

Policy initiatives to facilitate greater female participation in the workforce should target all occupational levels within each STEM industry. Occupation-based professional associations such as engineering and science associations (e.g. IEEE and ACM) need to be encouraged to frame and implement policies that cut across different STEM industries. But as our findings have shown, STEM occupations are located in their specific industry contexts and thus any occupation-based policies cannot be designed and implemented in a one-size-fits-all manner. Rather, they need to be tailored to the specific industries in which the STEM occupations are located.

### 3.2. Policy Implications for Employers and Digital Job Platforms
At the level of employers and job advertising platforms, we provide policy recommendations for (1) increasing women's participation in the STEM workforce; (2) addressing the potential effects of male gender bias in STEM job advertisements; and (3) leveraging the role of leading UK digital job platforms.

#### *3.2.1. Increasing Women's Participation in the STEM Workforce*
Given the preponderance of men in the STEM workforce, STEM employers, particularly those in the more strongly male-dominated industries reported in Section 2.1, need to make greater efforts to attract and recruit female employees. Policy initiatives should incentivise and enable STEM employers to develop a Diversity, Equity, and Inclusion (DEI) agenda and to establish links between their DEI strategy and hiring strategy. Such an agenda should drive systematic action to develop a DEI oriented organisational culture that enables women to be recruited and progress in their careers. Recent studies (e.g. Dobbin & Kalev [2016]) have identified several organisational factors that are particularly effective in increasing workforce diversity: voluntary diversity training, self-managed teams, cross-training (that allows people to try their hands at different jobs), targeted recruitment, mentoring, diversity taskforce, and diversity managers. Our evidence underlines job advertising as a key area where diversity interventions are needed, thus adding a new factor to this list.

Our findings also suggest that employers need to address the STEM versus non-STEM gender gap in specific occupations within their specific industries rather than just industry-level barriers to women's participation in STEM. Of particular importance is increasing the participation of women in senior and managerial occupations and achieving STEM gender parity across occupational ranks. Gender-sensitive, meaningful mentorship and sponsorship programmes could be developed to bring together women across different ranks and occupations to provide support and enable the diffusion of relevant knowledge (Ibarra, 2019).

#### 3.2.2. *Addressing Gender Bias in the Language of Job Postings by STEM Employers*

Our findings show that most STEM job postings published by UK employers are biased toward a masculine orientation. Moreover, there is a strong positive correlation between the male-dominated composition of the STEM workforce and the prevalence of male-oriented wording in STEM job postings.

Gendered language in job advertisements signal an employers' preferences for employees of a given gender, whilst deterring prospective applicants who identify with other gender identities (Gaucher et al., 2011). As STEM employers that already have a male-dominated workforce tend to use male-biased language and wording in their job postings, our findings suggest that gendered job advertising plays a crucial role in reproducing and reinforcing male domination in the UK STEM workforce. We suggest that policies and actions should help enable STEM employers to do the following to mitigate gender bias in job postings:

- Establish contact with and attract a wider pool of candidates by posting on different types of job advertising platforms that can reach diverse demographics;
- Use tools, such as gender checkers, to analyse the extent to which the language used in job postings is inclusive and not (gender) biased;
- Diversify hiring teams to allow for diverse input in the formulation of the job description, and avoid a male-dominated interviewing process;
- Develop and implement training programmes to help hiring teams avoid unintentional bias in developing skill matrices, job postings, and recruitment strategies;
- Cross-industry/employer learning in the drafting of job postings. Our findings show that job postings in some STEM industries and occupations have achieved gender neutrality, and their job advertising practices may provide a good template for other, more male-dominated industries.

#### 3.2.3. *Leveraging the Influence of Leading Digital Job Platforms*

As mainstream job platforms play a crucial role in disseminating job postings, they have the potential to play a major role in helping address gender bias in STEM job postings. Such platforms are uniquely placed because of their wide reach to client STEM employers across industries and occupations. Potential actions job platforms can take include the following:

- Help client employers understand the gender composition of their existing workforce and more broadly the importance of gender diversity and DEI in STEM;
- Provide client employers with DEI consultancy in the drafting and dissemination of job postings, and help clients develop job postings and specifications that are not gendered/biased;
- Conduct periodic audits of clients' key hiring processes and language use in job postings;
- Develop and deploy (gender) bias detection and mitigation tools in job advertising.

In the BIAS project, through our unique interdisciplinary collaboration, we have developed two debiasing toolkits—one taking advantage of statistical techniques of causal inference (Ding et al., 2021) and the other reducing bias using Bayesian techniques with text-level mitigation (Hu et al., 2022). We are extending our toolkits to detect other forms of bias related to sexuality, race and ethnicity, disability, and migrant and citizenship status. We are also in the process of integrating these toolkits into an open-source software package. We will work with major job advertising platforms to trial and roll out the package.

### 3.3. Support Job Seekers

The presence of gender bias in STEM job advertisements suggests the need for policies that support job seekers in their application processes. One implication from our finding is a need for employers and job advertising platforms to take feedback from applicants on their job postings, vis-à-vis how they perceived the language, and take corrective actions based on any perceived gender bias. As Correll (2017) has shown, such 'small win' changes can motivate employers to take further action and are crucial building blocks of organisational transformation in their progress toward gender diversity. In the BIAS project, a key objective of the next phase of our research is to understand job seekers' perceptions and responses to employers' use of artificial intelligence and other bias-inducing automation tools in the application and hiring processes. We hope to develop policy related insights from the next phase of our project in due course.

## 4. CONCLUDING REMARKS

In the UK, the Equality Act 2010 and its precursor, the Sex Discrimination Act 1975, provide equal employment opportunities that prohibit, among other things, gender discrimination in hiring and recruitment by organisations. Yet, 47 years after the Sex Discrimination Act 1975, our findings provide robust and current evidence that not only does the STEM workforce remain male-dominated in the UK, the language used in UK STEM job postings is also biased toward a masculine orientation. As a result, the very first point of contact between job applicants and employers is biased against women, which can discourage women from engaging with STEM job advertisements and from applying for the jobs in question. As hiring practitioners often use specifications included in job postings to inform their candidate selection, the adverse impact of gender bias in job advertising also cascades through the hiring process. In the post-Brexit era, these challenges are further complicated by the decoupling of the UK from the European Union, which poses potential risks to gender diversity in STEM and the broader labour force (Fagan & Rubery, 2018).

STEM industries and occupations play a crucial role in driving and sustaining the UK's economic growth. It is estimated that the UK loses £1.5 billion every year due to a shortage of STEM skills (STEM Learning, n.d.). Other factors notwithstanding, women's low participation in the STEM workforce represents a major loss of human capital for the UK economy. Our evidence suggests that tackling gender bias in STEM job advertising is a crucial and promising step to take to bolster diversity in STEM.

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# METHODOLOGICAL APPENDIX

## Data and Sample

The evidence presented in this report draws on two main data sources. The first data source is the ONS Quarterly Labour Force Survey spanning 2018–2020 (for more information, see https://beta.ukdataservice.ac.uk/datacatalogue/series/series?id=2000026#!/faqs). The data were obtained through the UK Data Service. All working respondents who provided valid information on the industry in which they worked, their occupation, and gender were included in our analysis ($N$ = 407,840). See the next 'Measurement' section for information on the definition and classification of industries and occupations. The weight provided as part of the dataset was used in all our analyses to adjust for sampling design and non-response bias such that our results are representative of the UK population.

Our second source of data, i.e. the job postings, were collected by Emis Burning Glass (see economicmodeling.com for more information), one of the largest international organisations that collect and monitor job postings across a wide range of countries including the UK. The BIAS project team further processed and prepared the dataset using natural language processing techniques for the analysis presented in this report. A total of 11,216,459 job postings were analysed, of which 2,333,420 were in STEM industries and 5,024,515 were STEM occupations. Our analysis focused on the titles and main text for each job posting, but not secondary attachment files such as person specifications. Our underlying assumption is that information included in the job title and main advertisement text provides potential job candidates with the first impression of a job posting, which may play a strong role in determining whether the candidates seek further information about and apply for a given job.

Notably, for the results presented in Section 2.3, we combined the above two data sources in our analysis. We linked the two datasets using industry (3-digit SIC) and occupation (3-digit SOC) combinations, yielding a valid, matched sample of 7,842,834 job postings, of which 2,211,773 were in STEM industries and 3,049,279 were STEM occupations.

## Measures

### *Industry*

We measured industry using the 2007 Standard Industrial Classification (SIC). For the results presented in Sections 2.1 and 2.2, we measured industry at the 1-digit level of SIC, i.e. major industrial sectors, to present the results in a parsimonious manner. For the results presented in Section 3, we measured industry at the 3-digit level of SIC to provide a more nuanced delineation of the relationship between the gendered STEM workforce composition and gender bias in STEM job postings. Our definition of STEM industries follows past Parliamentary and Office for National Statistics reports (e.g. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/adhocs/009751employmentinsciencetechnologyengineeringandmathematicsstemoccupationsandindustriesscotland2011and2017). A detailed list of 3-digit SIC codes and descriptions for STEM industries are presented in Table A1 at the end of this report.

### *Occupation*

We measured industry using the 2010 Standard Occupational Classification (SOC). For all analyses presented in this report, we measured occupation at the 3-digit level of SOC. Our definition of STEM occupations follows past Parliamentary and Office for National Statistics reports (ibid). A detailed list of 3-digit SIC codes and descriptions for STEM occupations are presented in Table A2 at the end of this report.

***Workforce Gender Composition***

To capture workforce gender composition and segregation, we limited our measurement of gender to a binary construct distinguishing between women and men, but we recognise that future research could extend our analysis to consider a more diverse range of gender identities. Based on the industry and occupation classifications noted above, we calculated the proportion of the workforce in each industry or occupation that is made up of men.

***Gender Bias Score and Male-biased Job Postings***

To generate a gender bias score for each job posting, we built on and extended the method developed by Gaucher et al. (2011). In the first step, the method assigns a score of –1 to the presence of every feminine word/lexicon, a score of 0 for every gender-neutral word/lexicon, and a score of 1 for every masculine word/lexicon. In the second step, we followed Gaucher et al. (2011) and categorised job postings with an overall positive score as 'male-biased' postings, those with a negative score as 'female-biased' postings, and those with a score of 0 as 'gender-neutral' postings.

In the third step, we went beyond Gaucher et al. (2011) to further differentiate and measure the degree of female or male bias within the pools of female-biased and male-biased postings, respectively. To do so, we first subtracted the total number of feminine words/lexicons in a given posting from the number of masculine words/lexicons in the same posting. Then, within the pool of female-biased job postings, we divided the value yielded from the subtraction by the total number of feminine words/lexicons in that posting; within the pool of male-biased postings, we divided the value yielded from the subtraction by the total number of masculine words/lexicons in that posting. The resultant continuous gender bias score ranges between –1 and 1 at the job posting level, with –1 indicating strongly female-biased postings, 0 indicating gender-neutral postings, and 1 indicating strongly male-biased postings.

The list of words and lexicons used for generating the gender bias score in this report combined three validated and tested gender-bias word inventories: namely, the Bem's (1974) sex-role inventory, the Gaucher et al. (2011) inventory, and the BIAS inventory produced as part of our project (Konnikov et al., 2022; Hu et al. 2022)

Based on the gender bias score for each job posting, we calculated the average gender bias score across industries and occupations. Classifying job postings with a positive gender bias score (> 0) as male-biased postings, we also calculated the proportion of job postings in each industry/occupation that are male-biased.

## Regression Analysis Underpinning the Results in Section 2.3

To examine the relationship between gendered STEM workforce composition and gender bias in STEM job postings, we fitted two sets of regression models. The dependent variable was the gender bias score at the job-posting level in the first set of ordinary least squares regression models, and the dependent variable was a dummy variable indicating whether a job posting was male-biased in the second set of binomial logit regression models. In both sets of models, the predictors included the proportion of men in each STEM industry (3-digit SIC level) and that in each STEM occupation (3-digit SOC level), as well as the quadratic terms for the two to account for potential non-linear relationships. Robust standard errors were estimated. To aid the interpretation of the results, we calculated and present the predictive margins in Section 2.3 of the report. Detailed statistical results from the regression models can be found in the table below.

**Regression models examining the relationship between gendered STEM workforce composition and gender bias in STEM job postings**

| Predictor | Predicting job-posting gender bias score across STEM industries | Predicting job-posting gender bias score across STEM occupations | Predicting the probability of male-biased job postings across STEM industries | Predicting the probability of male-biased job postings across STEM occupations |
|---|---|---|---|---|
| Proportion of men (SIC3) | 0.399*** | 0.670*** | 1.098*** | 2.913*** |
| | (0.009) | (0.007) | (0.038) | (0.029) |
| Proportion of men (SIC3)$^2$ | –0.084*** | –0.478*** | 0.417*** | –2.204*** |
| | (0.008) | (0.006) | (0.039) | (0.029) |
| Proportion of men (SOC3) | 1.388*** | 1.439*** | 5.995*** | 6.221*** |
| | (0.006) | (0.006) | (0.027) | (0.029) |
| Proportion of men (SOC3)$^2$ | –1.051*** | –1.038*** | –4.917*** | –4.739*** |
| | (0.006) | (0.005) | (0.024) | (0.025) |
| Intercept | –0.256*** | –0.295*** | –1.382*** | –1.621*** |
| | (0.002) | (0.002) | (0.009) | (0.008) |
| *N* (job postings) | 2,211,773 | 3,049,279 | 2,211,773 | 3,049,279 |
| $R^2$ (pseudo $R^2$ for the logit models) | 0.075 | 0.062 | 0.051 | 0.038 |

*Note*: Coefficients reported, with robust standard errors in parentheses. Authors' calculation based on the merged ONS Labour Force Survey and the Emsi Burning Glass data. Ordinary least squares regression models were used for the first two columns and logit regression models for the latter two columns.
*** $p < 0.001$.

**Table A1. List of STEM industries**

| Description | SIC 3 -digit code | SIC 1-digit code |
|---|---|---|
| Support services to forestry | 02.4 | A |
| Extraction of crude petroleum | 06.1 | B |
| Extraction of natural gas | 06.2 | B |
| Support activities for petroleum and natural gas extraction | 09.1 | B |
| Manufacture of tobacco products | 12.0 | C |
| Printing and service activities related to printing | 18.1 | C |
| Reproduction of recorded media | 18.2 | C |
| Manufacture of refined petroleum products | 19.2 | C |
| Manufacture of basic chemicals, fertilisers and nitrogen compounds, plastics and synthetic rubber in primary forms | 20.1 | C |
| Manufacture of pesticides and other agrochemical products | 20.2 | C |
| Manufacture of paints, varnishes and similar coatings, printing ink and mastics | 20.3 | C |
| Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations | 20.4 | C |
| Manufacture of other chemical products | 20.5 | C |
| Manufacture of man-made fibres | 20.6 | C |
| Manufacture of basic pharmaceutical products | 21.1 | C |
| Manufacture of pharmaceutical preparations | 21.2 | C |
| Casting of metals | 24.5 | C |
| Manufacture of weapons and ammunition | 25.4 | C |
| Treatment and coating of metals; machining | 25.6 | C |
| Manufacture of electronic components and boards | 26.1 | C |
| Manufacture of computers and peripheral equipment | 26.2 | C |
| Manufacture of communication equipment | 26.3 | C |
| Manufacture of consumer electronics | 26.4 | C |
| Manufacture of instruments and appliances for measuring, testing and navigation; watches and clocks | 26.5 | C |
| Manufacture of irradiation, electromedical and electrotherapeutic equipment | 26.6 | C |
| Manufacture of optical instruments and photographic equipment | 26.7 | C |
| Manufacture of magnetic and optical media | 26.8 | C |
| Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus | 27.1 | C |
| Manufacture of batteries and accumulators | 27.2 | C |
| Manufacture of wiring and wiring devices | 27.3 | C |
| Manufacture of electric lighting equipment | 27.4 | C |
| Manufacture of domestic appliances | 27.5 | C |
| Manufacture of other electrical equipment | 27.9 | C |
| Manufacture of metal forming machinery and machine tools | 28.4 | C |
| Manufacture of other special-purpose machinery | 28.9 | C |
| Building of ships and boats | 30.1 | C |
| Manufacture of railway locomotives and rolling stock | 30.2 | C |
| Manufacture of air and spacecraft and related machinery | 30.3 | C |
| Manufacture of military fighting vehicles | 30.4 | C |
| Other manufacturing | 32.9 | C |
| Repair of fabricated metal products, machinery and equipment | 33.1 | C |

| | | |
|---|---|---|
| Installation of industrial machinery and equipment | 33.2 | C |
| Electric power generation, transmission and distribution | 35.1 | D |
| Manufacture of gas; distribution of gaseous fuels through mains | 35.2 | D |
| Steam and air conditioning supply | 35.3 | D |
| Water collection, treatment and supply | 36.0 | E |
| Sewerage | 37.0 | E |
| Waste collection | 38.1 | E |
| Waste treatment and disposal | 38.2 | E |
| Materials recovery | 38.3 | E |
| Remediation activities and other waste management services | 39.0 | E |
| Development of building projects | 41.1 | F |
| Construction of residential and non-residential buildings | 41.2 | F |
| Construction of roads and railways | 42.1 | F |
| Construction of utility projects | 42.2 | F |
| Construction of other civil engineering projects | 42.9 | F |
| Wholesale on a fee or contract basis | 46.1 | G |
| Other specialised wholesale | 46.7 | G |
| Support activities for transportation | 52.2 | H |
| Software publishing | 58.2 | J |
| Wired telecommunications activities | 61.1 | J |
| Wireless telecommunications activities | 61.2 | J |
| Satellite telecommunications activities | 61.3 | J |
| Other telecommunications activities | 61.9 | J |
| Computer programming, consultancy and related activities | 62.0 | J |
| Data processing, hosting and related activities; web portals | 63.1 | J |
| Other information service activities | 63.9 | J |
| Activities auxiliary to financial services, except insurance and pension funding | 66.1 | K |
| Activities auxiliary to insurance and pension funding | 66.2 | K |
| Management consultancy activities | 70.2 | M |
| Architectural and engineering activities and related technical consultancy | 71.1 | M |
| Technical testing and analysis | 71.2 | M |
| Research and experimental development on natural sciences and engineering | 72.1 | M |
| Other professional, scientific and technical activities | 74.9 | M |
| Veterinary activities | 75.0 | M |
| Defence activities | 84.22 | O |
| Higher education | 85.4 | P |
| Other education | 85.59 | P |
| Hospital activities | 86.1 | Q |
| Medical and dental practice activities | 86.2 | Q |
| Other human health activities | 86.9 | Q |
| Activities of employer members organisations | 94.11 | S |
| Repair of computers and communication equipment | 95.1 | S |

*Source*: Office for National Statistics. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/adhocs/009751employmentinsciencetechnologyengineeringandmathematicsstemoccupationsandindustriesscotland2011and2017

**Table A2. List of STEM occupations**

| Description | SOC Code |
|---|---|
| Production managers and directors | 112 |
| Functional managers and directors | 113 |
| Financial institution managers and directors | 115 |
| Health and social services managers and directors | 118 |
| Managers and proprietors in agriculture related services | 121 |
| Managers and proprietors in health and care services | 124 |
| Natural and social science professionals | 211 |
| Engineering professionals | 212 |
| Information technology and telecommunications professionals | 213 |
| Conservation and environment professionals | 214 |
| Research and development managers | 215 |
| Health professionals | 221 |
| Therapy professionals | 222 |
| Nursing and midwifery professionals | 223 |
| Teaching and educational professionals | 231 |
| Business, research and administrative professionals | 242 |
| Architects, town planners and surveyors | 243 |
| Quality and regulatory professionals | 246 |
| Science, engineering and production technicians | 311 |
| Draughtspersons and related architectural technicians | 312 |
| Information technology technicians | 313 |
| Health associate professionals | 321 |
| Transport associate professionals | 351 |
| Business, finance and related associate professionals | 353 |
| Conservation and environmental associate professionals | 355 |
| Electrical and electronic trades | 524 |
| Construction and building trades | 531 |

*Source*: Office for National Statistics. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/adhocs/009751employmentinsciencetechnologyengineeringandmathematicsstemoccupationsandindustriesscotland2011and2017

***(January 2022)***