Received: 14 June 2024 | Revised: 13 September 2024 | Accepted: 18 December 2024

DOI: 10.1111/tran.12745

ARTICLE

Examining the 'gendered' places and spaces of UK doctoral education using multilevel modelling

Laura Harriet Sheppard[1,2] | **Jonathan Reades**[1] | **Richard P. J. Freeman**[3]

[1]Centre for Advanced Spatial Analysis, University College London, London, UK

[2]Centre for Longitudinal Studies, Social Research Institute, University College London, London, UK

[3]IOE: Faculty of Education and Society, University College London, London, UK

Correspondence
Laura Harriet Sheppard, Centre for Advanced Spatial Analysis, University College London, London, UK.
Email: laura.sheppard@ucl.ac.uk

Funding information
Economic and Social Research Council

Abstract

Research on gender in higher education frequently focuses on micro- or macro-scale factors—power relations and working practices, or disciplinary norms and the educational 'pipeline'—overlooking the meso-scale of 'place' embodied in departments and institutions. This study bridges that gap by applying data science and multilevel modelling within a quantitative feminist geographical framework to analyse gendered PhD completion patterns in the UK from 1990 to 2020. Using the British Library's E-Thesis Online Service (EThOS), we identify 'department-like units' as pivotal, accounting for 10.7% of the variation in the likelihood of a PhD student being female—more than any other grouping. Overall, STEM fields remain male-skewed, while the Arts and Humanities, and Social Sciences show a female skew. Institutional histories and geography also matter: in Scottish and Northern Irish universities students are more likely to be female compared with English universities, while the likelihood in Wales is lower. The use of statistical methods through a feminist lens offers a foundation for targeted interventions: our results suggest a greater focus on departments in equality initiatives like Athena SWAN and adjustments to funding policies to enhance diversity in PhD cohorts, particularly in male-dominated disciplines. Future work should integrate intersectional approaches to deepen understanding of these dynamics, but these findings emphasise the value of place-based analysis in addressing gender disparities and guiding policy.

KEYWORDS

disciplines, equality, gender, higher education, institutions, multilevel modelling

The information, practices and views in this article are those of the author(s) and do not necessarily reflect the opinion of the Royal Geographical Society (with IBG).

1 | INTRODUCTION

Organisations are inherently gendered through social processes such as interactions between individuals and the distribution of power within hierarchies (Acker, 1990). Academia is no exception, and universities are gendered, racialised and classed places that can often marginalise certain groups such as people from working class and minority ethnic backgrounds and those with disabilities (Handforth, 2022). Substantial attention has been given to the fall-off in female staff securing permanent academic jobs (e.g., Gasser & Shaffer, 2014; Pell, 1996). This is in contrast to female participation in undergraduate and taught postgraduate study, which is why the relative paucity of research on the critical period of transition between student and academic is so unexpected. Although work on the overarching dynamics of gender in academia has been undertaken at both the fine (e.g., Sara Ashencaen Crabtree and Chris Shiel, 2019) and the wide (e.g., Kozlowski et al., 2022; Larivière et al., 2013) scales, few of these give much attention to the place of the doctoral student.

The three interlocking aims of this research are: to demonstrate the potential of a feminist-informed quantitative geography; to demonstrate the utility of 'accidental' data; and to demonstrate the power of a 'platial' approach to gender in UK Higher Education (HE). Drawing on data held by the British Library (BL), we combine data science and quantitative methods in a quantitative feminist geographical framework (Sheppard et al., 2023) to model the contributions that disciplines, institutions and departments make to the reproduction of gendered environments for PhD students in the UK. We also highlight the utility of a multi-scalar, 'platial' framework for advancing our understanding of gendered experiences.

The results of our Multilevel Models (MLMs) stress the risk that, in focusing on linear career models, we may lose track of how those careers are embedded in micro-, meso- and macro-scale contexts, each with the potential to complicate those trajectories. Our findings suggest that, in the UK, institutions have smaller relative effects on observed outcomes compared with disciplines and departments; we note that this points to a need to revisit assumptions embedded in, for example, the Athena SWAN framework about how to support diversity in UK HE.

Giving visibility to gender inequalities at this critical stage in the academic career path will aid in understanding the inequalities that arise further down the line as well as at the pre-doctoral level. When we know about the dynamics of the inequalities at play in the places that provide doctoral education, then we can better-understand 'where' to target equality initiatives and practices to improve the gender balance of academia as a whole. The 'platial' (Mocnik, 2022) aspect is critical to examining the ways in which a PhD student's experiences can vary significantly from discipline to discipline, institution to institution, and department to department.

1.1 | Women in academia

Research on diversity in HE often draws on the 'leaky pipeline' analogy (Berryman, 1983) to describe how individuals from minoritised groups are progressively 'lost' as they move along the academic career track. This analogy has been critiqued in the literature (e.g., Berhe et al., 2022; Jacob Clark Blickenstaff, 2005), and it has also been noted that research mainly focuses on women in senior positions in Europe and North America, with less attention given to women working in Asia, Africa and South America, or to early career researchers (ECRs) and doctoral students (Bourabain, 2020; Fisher et al., 2020). Gender disparities persist across publication rates, collaborations, teaching and pastoral commitments (Goulden et al., 2011; Jadidi et al., 2018; Kozlowski et al., 2022). Within geography, Franklin et al. (2021), Schurr et al. (2020), and Kaplan and Mapes (2016) identified barriers, including the lack of female journal editors and the impact of gendered doctoral supervision practices, on dynamics in the discipline.

The findings from UK HE contrast with the overall picture in secondary schools: in the final year examinations (A Levels) for 2023, 27.5% of female students achieved the highest grades (A*s and As) compared with 26.9% for boys (DfE, 2024, n.p.), though boys obtained a higher proportion of the highest 'A*' grade (9.1% overall, 15.9% in STEM disciplines) than girls (8.8% overall, 12.2% in STEM disciplines). For A Level geography, 9.0% of girls and only 3.9% of boys were awarded an A* grade (ibid.).

At the university level in the UK, 57% of undergraduates and 60% of taught postgraduates are female, but this falls to only 30.7% of full professors in 2022/23 (HESA, 2023a). This is partly a function of latency: current senior academics passed through a system much more inimical to women pursuing doctoral degrees and postdoctoral academic roles (Iaria et al., 2023). According to the Higher Education Statistical Agency (HESA), the picture for academic staff in 2022/23 is now more positive: overall, 48.6% are female, and in STEM disciplines 46.2% are female (HESA, 2024). Within Engineering and Technology, however, only 23.3% of academic staff are female, whereas the figure is 62.3% for Medicine, Dentistry and Health (HESA, 2023b). In short, there is wide variation within academia in terms of progress towards gender diversity.

We now turn our focus to postgraduate research (PGR) dynamics, which includes those studying for a PhD, professional doctorates or a research master's degree. Between 1917 and 1959, just 10% of PhD students were women (Simpson, 2009). Today, of the 114,405 PGR students in the UK, 57,250 (50.1%) are female and 480 (0.4%) identified as 'other' (HESA, 2023a). Across all years, female PGRs outnumbered males, while 0.7% identified as 'other', which is in line with the 2021 Census figure for England and Wales (ONS, 2023c). Table 1 shows the demographics of first year PGRs in 2021/22.

Returning to the present day, the percentage of PGRs declaring a disability has increased to 11.4%, which is less than the 17.8% for the general population of England and Wales (ONS, 2023a). Of UK-domiciled students, 76.5% identify as White, 8.7% as Asian, and 4.7% as Black, compared with 81.7%, 9.3% and 2.5% of the overall population in England and Wales, respectively (ONS, 2023b).

The most recent data from the UK's largest funder of doctoral research, UK Research and Innovation (UKRI), indicates that, of the 2020/21 studentship starts, 45% were female (UKRI, 2022). UKRI funds around a quarter of PhD students in the UK—one third of engineering and physical sciences PhDs and one fifth of social science PhDs (CFE Research and the University of York, 2021; EPSRC, 2021)—with the remainder self-funded or funded by individual universities or other charitable and research organisations. Table 2 shows UKRI PhD studentships broken down by the seven councils that fund individual domains: 65% of the social science and medical sciences studentships were awarded to females compared with about 30% for engineering and physical sciences and science technology. But nearly half of the UKRI studentships awarded over the last years were funded by EPSRC and over 10,000 of these went to male students (about 4000 to women). Consequently, nearly one third of UKRI studentships have been awarded to male engineers and physical scientists in the previous 5 years (UKRI, 2022).

These seemingly contradictory results—of an upward trend in female doctoral study but wide divergence within large fields of study—point to a need to consider scale as part of any analysis of gender in HE. Drilling down to the institutional level does little to address this apparent discrepancy as publicly available data that detail PGRs by institution and field are rarely accessible for disclosure reasons. The ecological fallacy suggests that we cannot assume that a university with an overall gender balance is necessarily balanced within any sub-unit such as a faculty or department. Moreover, the literature is quite clear that macro scales are not the only ones at which discrimination is experienced. The known challenges at the individual and departmental levels include caring responsibilities, toxic research environments, the 'chilly' climate (a research environment and culture that is more suited to male researchers and unwelcoming to women), and a lack of female mentors and role models (Britton, 2017; Casad et al., 2020; Rosa, 2022). In short, the micro scale is also important to a researcher's career trajectory, longevity and enjoyment, and there is a large gap in the 'doctoral data landscape'.

TABLE 1 Personal characteristics of first year postgraduate research students in the UK in 2021/22 (source: HESA, 2022).

Sex	Count	Percentage
Female	17,460	51.5
Male	15,905	47.8
Other	235	0.7
Disability		
Known disability	3850	11.4
No known disability	30,060	88.6
Ethnicity of UK students		
White	15,115	76.5
Black	840	4.7
Asian	1535	8.7
Mixed	805	4.2
Other	440	2.3
Not known	650	3.4
Total (UK)	19,385	57.1
Total (all)	33,910	100

TABLE 2 Share of UK PhD studentships awarded to female students (source: UKRI, 2022).

Research council	% Female 2020/21	% Female 5-year mean (2015/16–2020/21)
Arts and humanities	61	58
Biological and biotechnological sciences	54	54
Engineering and physical sciences	30	29
Economic & social	65	62
Medical	65	61
Natural environment	57	52
Science and technology facilities	31	25

1.2 | The UK HE system

In the UK, universities are often categorised into different, overlapping groups (see fuller discussion in Singleton, 2010, Ch.2): the Ancient universities founded before 1600 (e.g., St Andrews, Glasgow), the 24 'research-intensive' institutions of the Russell Group (e.g., UCL, Bristol), the Plate Glass universities given their status in the 1960s (e.g., Warwick, York), and the Post-1992 group (e.g., Portsmouth, East London) that were given university status in 1992 as part of the reforms that did away with polytechnics. It is worth noting that not all of the Ancient universities are all Russell Group members, nor are all of the Plate Glass universities.

The Russell Group universities are typically (self-described) 'world-class universities', which play a role in the UK's 'intellectual life' and make large social, economic and cultural contributions (The Russell Group, 2023b, n.p.). The group's universities teach 'a quarter of all undergraduate students, a third of all postgraduate students, more than a third of engineers, four out of five doctors and dentists, 45% of linguists and 50% of physical scientists and mathematicians' (The Russell Group, 2023a, n.p.). As such, they are often contrasted with the post-92 (or 'new') universities that often emerged from more locally rooted and funded institutions with a focus on technical education.

2 | BRITISH LIBRARY'S EThOS DATA

In the absence of publicly available data, it is impossible to examine dynamics below the institutional or research council level. However, the BL holds metadata—data that describe and give information about other data—on approximately 98% of doctoral theses awarded by UK HE Institutions (HEIs) in their E-Thesis Online Service (EThOS). An EThOS record includes the title and author of the PhD, the name of the awarding HEI, the year of award, as well as (sometimes) department, (occasionally) PhD supervisor(s), and (rarely) funder(s). Nonetheless, it is a potentially rich source of knowledge about the postgraduate research community in the UK (British Library, 2023; Gould, 2016) and the metadata are freely available to download from the BL's website under a Creative Commons (CC0) licence.

EThOS is normally updated every 6 months, and for this research we have used the October 2022 release, which contains 610,535 records. Although the data are not complete, they nonetheless have an incredible potential that, with the notable exceptions of papers like Howe (2015), Catherine Montgomery (2019), and Reades and Williams (2023), have been surprisingly little exploited.

Before beginning the analysis, we cleaned the EThOS metadata as detailed in the accompanying GitHub repository (see: Additional Materials). In the first pass, PhDs completed before 1980 and doctoral qualifications other than PhDs (such as DClinPsy, EngD or EdD) were removed in order to focus on the 'current' PhD landscape. Universities with fewer than 100 PhD completions were also removed so as not to over-fit the model to institutions with only a handful of PhDs and to ensure the statistical power of the analysis.

Where possible, the BL's EThOS team also appended Dewey Decimal Classification numbers (DDCs) to each record. Proposed by Melvil Dewey in 1876, the eponymous system has been sharply critiqued for its limitations and biases (see, e.g., Sullivan, 2015; Lund & Agbaji, 2018). In geography, Meyer (1947, 1971) seems to have fought a long, and rather lonely, battle to rectify classification problems plaguing the discipline. Regardless, 'libraries in more than 135 countries use the DDC to organize and provide access to their collections, and DDC numbers are featured in the national bibliographies of more than 60 countries' (OCLE, 2003), making it the most widely used classification system in the world. For our purposes, the highest-level Class and Division identifiers are the most relevant: the Class was recorded in a 'subject discipline' column, mapping on to one of 19 'disciplines'; and the Division was mapped on to one of 99 sub-disciplines to provide a more granular perspective.

2.1 | Missing data

To model the gendered dynamics of doctoral research in the UK, we need data on gender (or proxy), department (or proxy), institution and discipline. We also need those fields to be reasonably complete and there are, unsurprisingly, issues since the EThOS data are harvested from institutional repositories via manual and automated data entry processes that can lead to errors and omissions. The author and department columns were of particular interest.

Of the 512,000-odd records in the original extract, roughly 60,000 contained initials instead of full first names. Where there is no first name, gender cannot be inferred for reasons detailed below. Further investigation (Figure 1) suggests that either authorship or institutional recording practices shifted sharply in the late-1980s and we decided to remove all PhDs from the 1980s as well, carrying forward only a post-1990 sample of approximately 451,000 records that did not include records with initials.

Roughly a third of records had a department attribute. We attempted to augment this via the extraction of departments from linked PDFs, but we were only able to extract this attribute for about 15,000 records. Consequently, there is insufficient coverage to make meaningful claims using the department field directly; however, about 93% of EThOS records have DDCs and work by Reades and Williams (2023) suggests that the assigned DDC and author's abstract are well matched.

Given the links between discipline and organisational units at universities, we opted to use the combination of DDC and institution as a 'department-like proxy'. The most recent records may not yet have been assigned a DDC and, consequently, there appears to be a drop in PhDs by discipline from 2019. In addition, this is not a 'real-time' data source: not only are records being added from many decades ago as historical dissertations are digitised, but the addition of recent records may be impacted by factors such as embargoing of research and, more pertinently, the impact of COVID-19 on

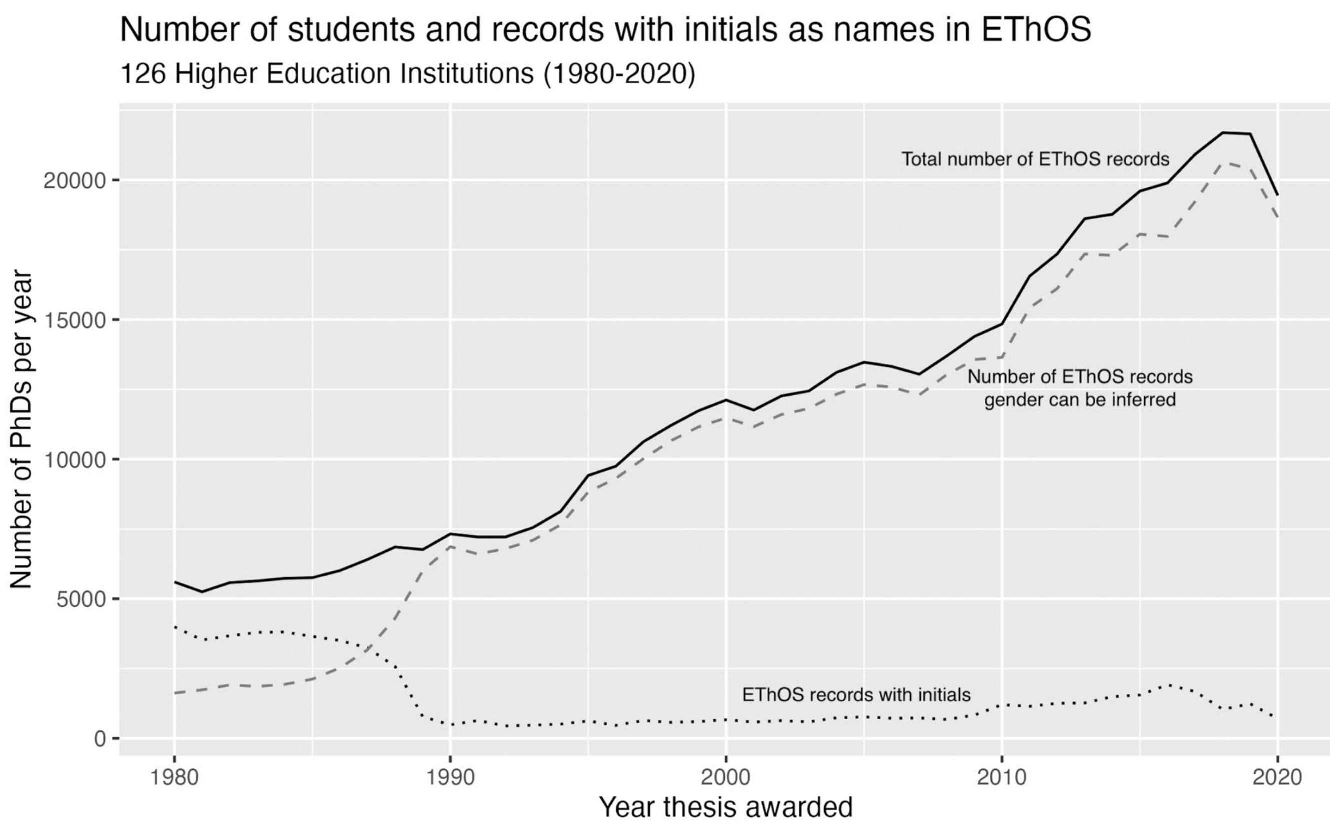

FIGURE 1 Number of EThOS (British Library's E-Thesis Online Service) records with initials as first names compared with the total number of EThOS records (1980–2020).

university practices, as well as the cyber-attack against the British Library (2024). In short, from 2019/20 there is a significant drop-off in the completeness of the data, but we expect it to be rectified over the coming year.

3 | METHODOLOGY

Since EThOS does not directly record gender, we need to derive this variable in order to begin modelling. The following section describes our use of Gender Inferencing Algorithms (GIAs) and Multilevel Models (MLMs). We also critically consider the robustness of the GIA approach and justify our choice of algorithm with reference to the kinds of errors that it produced during testing and validation.

3.1 | Modelling gender

To infer gender from author names, we tested a range of GIAs, including Genderize, Gender API, GenderR, Gender Guesser and Namsor. Some of these are free and open source, while others are closed source and potentially costly to use in bulk (Karimi et al., 2016; Santamaría & Mihaljević, 2018; Sebo, 2021). Regardless of the implementation, GIAs use the frequencies of name-to-gender combinations from sources like social media and birth records to predict the likelihood that a name is female, male or (in some cases) unknown.

We tested each of the five GIAs against a validation dataset that combined previously tested names published by Santamaría and Mihaljević (2018) with a stratified sample of manually labelled records from EThOS. The labels allowed us to measure the GIA predictions against the 'true' values using four metrics introduced by Wais (2016): the proportion of female names misclassified as male or unknown and vice versa; the same proportion, but without NAs/unknowns; the proportion of non-classifications; and a directional estimate of bias in the predictions. A positive score suggests the number of female names predicted is higher than the actual number and a negative score suggests the opposite (Santamaría & Mihaljević, 2018; Wais, 2016).

We concluded that the Namsor algorithm was the most suitable: it predicted over 81% of names correctly, with a slight bias towards female names. Gender API performed well too, with an overall accuracy of 81.5%, but as Namsor explicitly incorporates a cultural component using the surname and since the UK PhD population is highly international—43% of PGRs according to HESA (2022)—we felt that this was an important feature to include.

3.2 | Ethical considerations

While we have argued elsewhere (Sheppard et al., 2023) that quantitative research should look beyond the 'gender binary', the majority of gender data are still collected as either female/male or, more recently, male/female/other (D'Ignazio & Klein, 2020; Westbrook & Saperstein, 2015).

While drawing on a longer intellectual tradition that includes fields such as Critical Geographic Information Systems (GIS) (e.g., Harvey et al., 2005; O'Sullivan, 2006; Pavlovskaya, 2018), recent critical approaches to data science and research—notably D'Ignazio and Klein (2020), Safiya Umoja Noble (2018), and Caroline Criado Perez (2019)—have foregrounded questions of algorithmic bias in the reproduction of inequality. We therefore wish to highlight three areas in which our use of GIAs risks reproducing these inequalities: (1) the persistent biases of training data; (2) the reinforcement of a gender binary; and (3) the derivation of personal data.

First, the training data used by each GIA affect its ability to accurately infer the gender of names. GIAs are more likely to label Asian names as 'unknown' or to inaccurately predict gender based on irrelevant rules learned during the training process. This introduces a risk of false positives and false negatives that could alter our understanding of the processes that we are studying, or of the role that individual departments or institutions play in this process. Although we selected Namsor because our testing suggested that it performed best on non-European names, access to name and gender data following other cultural norms remains severely limited.

Second, GIAs seek to derive a binary gender variable from spatio-historical patterns of naming captured, primarily, in government birth and social security registries. As a result, in an absolute sense the GIAs discount transgender, non-binary and intersex identities because these have not, historically, been recorded. While some GIAs generate an 'unknown' category, it is in the sense of 'available data is not sufficient to make a prediction' rather than 'this name suggests a non-binary person'. The 0.7% PGRs in the HESA data who identify as some 'other' gender category are therefore not represented in this research.

The third issue which has not, to our knowledge, been discussed in a substantive way in the geographical literature is that, by using GIAs, personal or sensitive personal data can be created from public data. Disciplinarily, we have been primarily concerned with the ways in which personal and behavioural data can be used to 'unmask' individuals (i.e., that 'x' attribute reveals Alice), whereas this research inverts that relationship (i.e., that Alice reveals 'x' attribute). Therefore, we will not make the derived individual-level data publicly available, and the data cleaning process removed small institutions which pose particular disclosure risks. Although we believe that the potential benefits of this research outweigh the risks, this is an area for ongoing debate.

3.3 | Modelling UK HE

Once gender has been inferred, we needed a way to examine the role that the research environment and wider disciplinary norms play in the observed outcomes. Simpler regression models are unsuitable since they would assume that the gender of completed doctoral students is independent and that the errors are uncorrelated (Osborne & Waters, 2002). These assumptions are violated in multiple ways since outcomes are clustered by both location and group membership (Goldstein, 2011; Guo & Zhao, 2000), and ignoring this constraint would affect the estimates of effect sizes.

MLMs control for the fact that doctoral researchers cannot be studied in isolation from the power-structures within which they work. The MLMs allow us to observe hierarchical grouping effects in our data 'by allowing for residual components at each level in the hierarchy' (CMM, 2023, n.p.q). In short, they allow us to test not only how much of the variation observed in a dependent variable is accounted for by each level in the model, but also to work out each level's relative importance (Goldstein, 2011). MLMs are particularly popular in the study of health and education inequalities where these are seen as inherently spatialised: people are nested within neighbourhoods, while pupils are nested within classes and schools (Merlo et al., 2016; Owen et al., 2016; Rasbash et al., 2010).

Drawing on Acker's (1990) *Gendered Organisations Theory*, we employ a hierarchy of department-proxy, university and discipline to model PhD outcomes. We hypothesise that the degree of organisational gendering will differ both between levels and between units at the same level. In other words, the degree of gendering differs between disciplines, institutions and departments, but it also differs between departments at the same institution, and we anticipate that MLMs can help us to tease these differences apart. So, while not every model we develop contains all three levels, the underlying conceptual hierarchy for our analysis is as follows:

1. Level 1 (Micro): Individual PhD students; for the purposes of our modelling, their personal histories are unique and unknowable.
2. Level 2 (Meso): The places within which PhD students are nested; primarily, these will be the institutions and department-like units whose policies and power-structures shape the local research environment.
3. Level 3 (Macro): The larger contexts within which meso-scale places are nested; primarily, these will be the long-standing disciplinary and societal norms.

3.4 | Multilevel models for discrete dependent variables

MLMs for a binary dependent variable are used since the gender variable has two categories, female and male; these will be coded as 1 and 0, respectively (Guo & Zhao, 2000). To ensure that the predicted probabilities stay within the bounds of 0 and 1, a logit transformation of the binary variable is used. This impacts how the model output can be interpreted, such as how different variables and scales raise or lower the log odds of $y=1$ (Powers, 2012).

3.4.1 | Variance components models

Variance components models, which have no predictor variables, are used to assess the amount of variation associated with each level (Chi et al., 2021) when predicting the likelihood that a PhD student is female. These return an intercept (for the overall mean) and random effects for each level included in the model. The residual error term for the level 1 variance (PhD student) is fixed due to the binary dependent variable. A series of variance components models were run with different level 2 groups; for example, in a two-level model with disciplines at level 2, the random effect is assumed to follow a normal distribution with variance $\delta^2{}_0u$ that arises from unobserved similarities that influence the dynamics within a discipline. β_0 (the intercept) is shared by all disciplines while the random effect (u_{0j}) is specific to discipline j. The equation for the model is shown below.

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + u_{0j}$$

$$u_j \sim N\left(0, \delta^2 u\right)$$

Two measures were used to compare the variance components models; log-likelihood and the variance partition coefficient (VPC) (Powers, 2012; Rights & Sterba, 2020). The log-likelihood ratio test helps you to choose between two models by comparing their fit to determine which is more suitable for the data (Glen, 2023, np). Here, the null hypothesis is of no group differences in the gender variable (H_0 is $\sigma^2 = 0$), and we compare a single level null model to a MLM. H_0 can be rejected when the test statistic is large, indicating that the MLM is a significant improvement on the null model (Glen, 2023).

The VPC measures the 'percentage of variation in a data set that is attributed to a particular level or classification in the data set' because of differences between groups (Browne et al., 2005, p. 602). The value ranges between 0 and 1, and Browne et al. (2005, p. 600) state that 'partitioning the variance is not simply of technical value; rather the apportioned variances are of substantive interest in much of social science and biomedical research'. For binary data, there are the three ways to calculate the VPC: the latent variable approach, simulation and model linearisation (Browne et al., 2005). Leckie et al. (2019) showed that VPC estimates produced for binary variables differ slightly. The commonly used latent variable approach is both computationally feasible and appropriate since the simulation-based approach is difficult to use on three- and four-level models (Browne et al., 2005; Fernée & Trimmis, 2021). We note only that our preferred approach assumes that variance at level 1 is fixed, known and not estimated.

To calculate the probability that a PhD student is female in the mean group (when $u = 0$), we take the exponential of the fixed effects estimate of the intercept (u_{0j}) over $1 +$ the exponential of the fixed effects estimates of the intercept (u_{0j}). Finally, the Akaike Information Criterion (AIC) score and R-squared values are used to assess the goodness-of-fit of each model and how much variation is accounted for by each.

3.4.2 | Random intercept models

Random intercept models build on variance components models and contain predictor variables; they allow the intercepts for each group to vary. When one or more predictors are included in the model, it separates the fixed and random effects since the levels make up the random component and the predictor variables make up the fixed component (Goldstein, 2011). By controlling for external factors, which is possible in a random intercepts model, we can examine the variance within disciplines. The equation for the model is shown below.

$$\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + \beta_1 x_{ij} + u_{0j}$$

$$u_j \sim N\left(0, \delta^2 u\right)$$

4 | RESULTS

4.1 | Exploratory data analysis

Most UK PhDs—all of the top-20 in EThOS—are awarded by HEIs that are members of the research-intensive Russell Group; of these, Cambridge has awarded over 28,000, Oxford over 27,000, and UCL just under 24,000 since 1990.

Loughborough University, ranked 22nd, is the top awarding university outside the Russell Group. Organising records by the 19 DDC-derived disciplines (Figure 2) shows that five areas dominate recorded PhD completions since 1990: 61% of all PhDs awarded come from Medicine and Health, Engineering and Technology, and the Social, Physical, and Biological Sciences. Librarianship and Information Science, Music, and Architecture and Planning are the least common disciplines. Four of the top five disciplines are STEM subjects, and Arts and Humanities subjects account for the smallest overall number of doctorates.

Using the same four high-level groupings, Figure 3 shows how the gender composition has changed over time. In the Arts and Humanities, and Life Sciences, completions by female students surpassed male students in about 2000, and in both the gender gap has since continued to widen in favour of female students. In the Social Sciences the gender gap has been narrowing since the 1990s and female students 'overtook' male students in 2018. The Physical Sciences and Engineering has the largest gender gap, and it has not noticeably narrowed despite a significant increase in overall numbers. See discussion of missing data for explanation of apparent sharp decrease from 2019/20.

4.2 | Variance components models

We now turn to the MLMs to establish where the variation in the likelihood that a PhD student is female arises. For the variance components models, a series of level two variables were chosen, which included: disciplines, institutions, sub-disciplines, years and geographical regions, as well as combinations of some of these. Table 3 shows the results of these models with information on the probability that a PhD student is female, the VPC at level two, and the AIC score for the model. As discussed earlier, the lower completeness of the department column led to its replacement by the combinations of discipline and institution, and sub-discipline and institution, to serve as proxies. We are primarily interested in the VPC column in Table 3 since that tells us where differences arise in outcomes. The levels that account for the least variation are geographical regions and years, while the combinations of institution and discipline or sub-discipline accounting for more of the variation in the dependent variable.

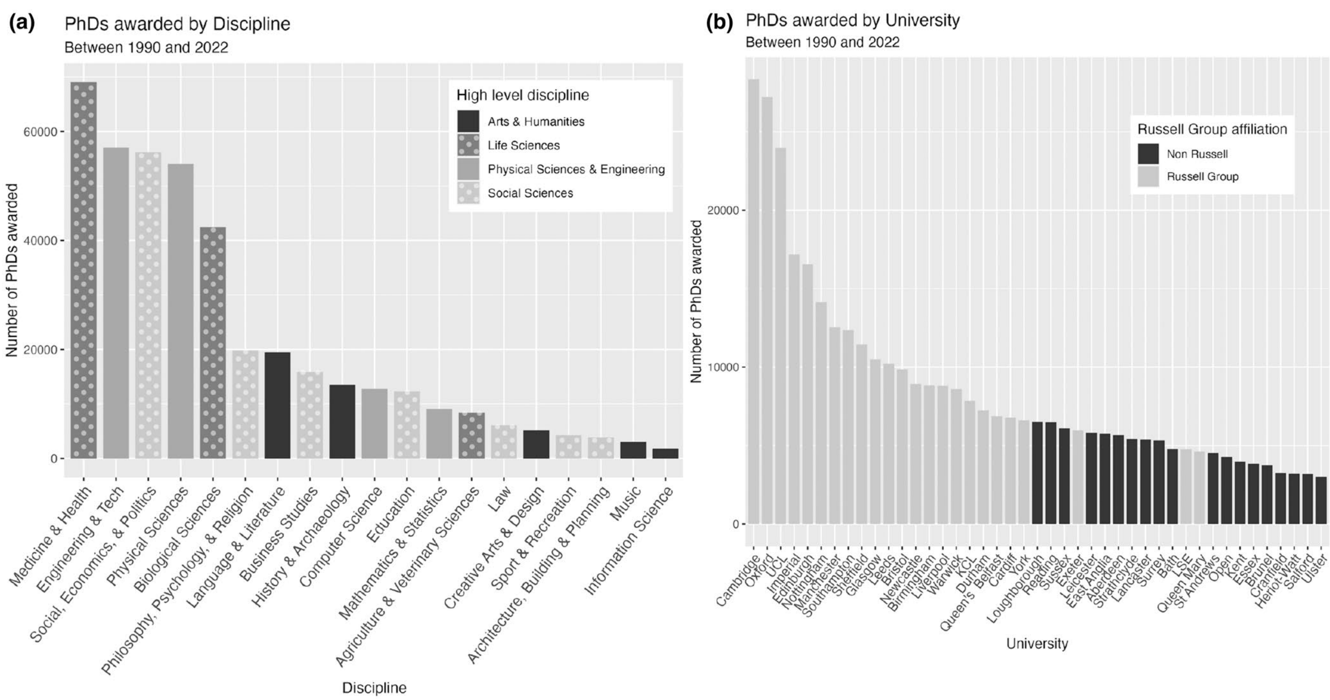

FIGURE 2 (a) Number of PhDs awarded by discipline (1990–2022) with the bars filled in with their high level discipline (Arts and Humanities, Life Sciences, Physical Sciences and Engineering, and Social Sciences). (b) Number of PhDs awarded by university (1990–2022) with the bars filled in with their Russell Group affiliation.

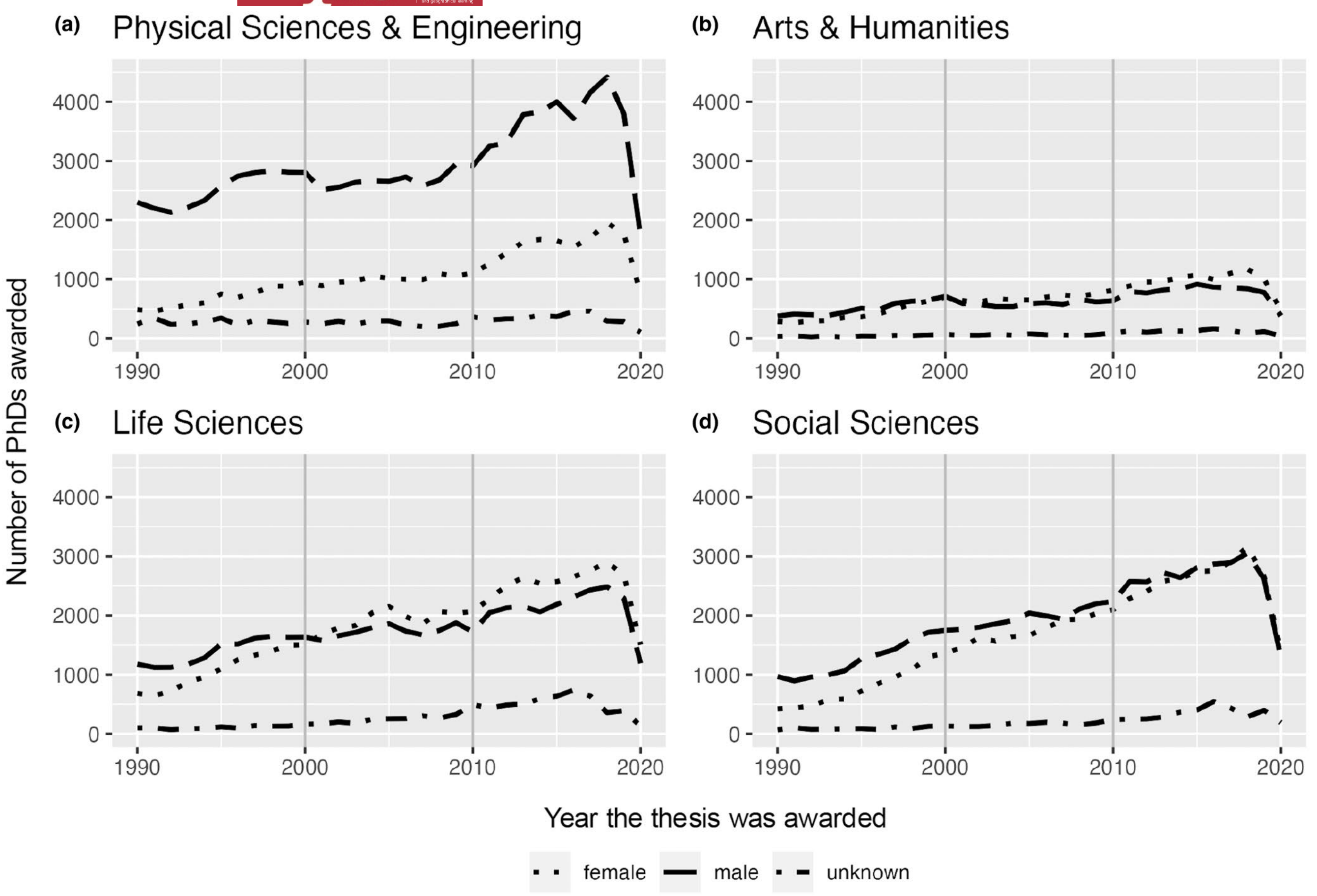

FIGURE 3 Inferred gender of PhD students by high-level disciplines (Physical Sciences and Engineering [a], Arts and Humanities [b], Life Sciences [c] and Social Sciences [d]) between 1990 and 2020. 'Unknown' represents names with initials or names that the gender inferencing algorithm could not find in their database.

TABLE 3 Summary results from two-level variance components models.

Level 2	Probability PhD is Female	Log-likelihood	VPC (%)	AIC
Institution	0.440	8268	2.6	569,620
Discipline	0.430	76,350	6.5	501,540
Sub-discipline	0.456	86,900	10.7	491,000
Discipline and institution	0.435	76,490	8.7	501,400
Sub-discipline and institution	0.435	87,950	10.0	489,940
Region	0.423	5419	0.1	572,470
Year	0.407	8804	1.6	569,090

4.2.1 | Institutions

Although only 2.6% of variation is accounted for by the institution, it is nonetheless useful to note that, the most heavily skewed institutions towards women are the University of Roehampton and Queen Margaret University, and for men it is Cranfield University and Heriot-Watt University (random effects shown in Figure 4a). The histories of these institutions help to explain these results: Roehampton (in South West London) was originally four separate teacher training colleges for women, and Queen Margaret (in Edinburgh) was initially a women's only institution for cooking and domestic economy (Queen Margaret University, 2023; University of Roehampton, 2023); in comparison, Cranfield (in Bedfordshire)

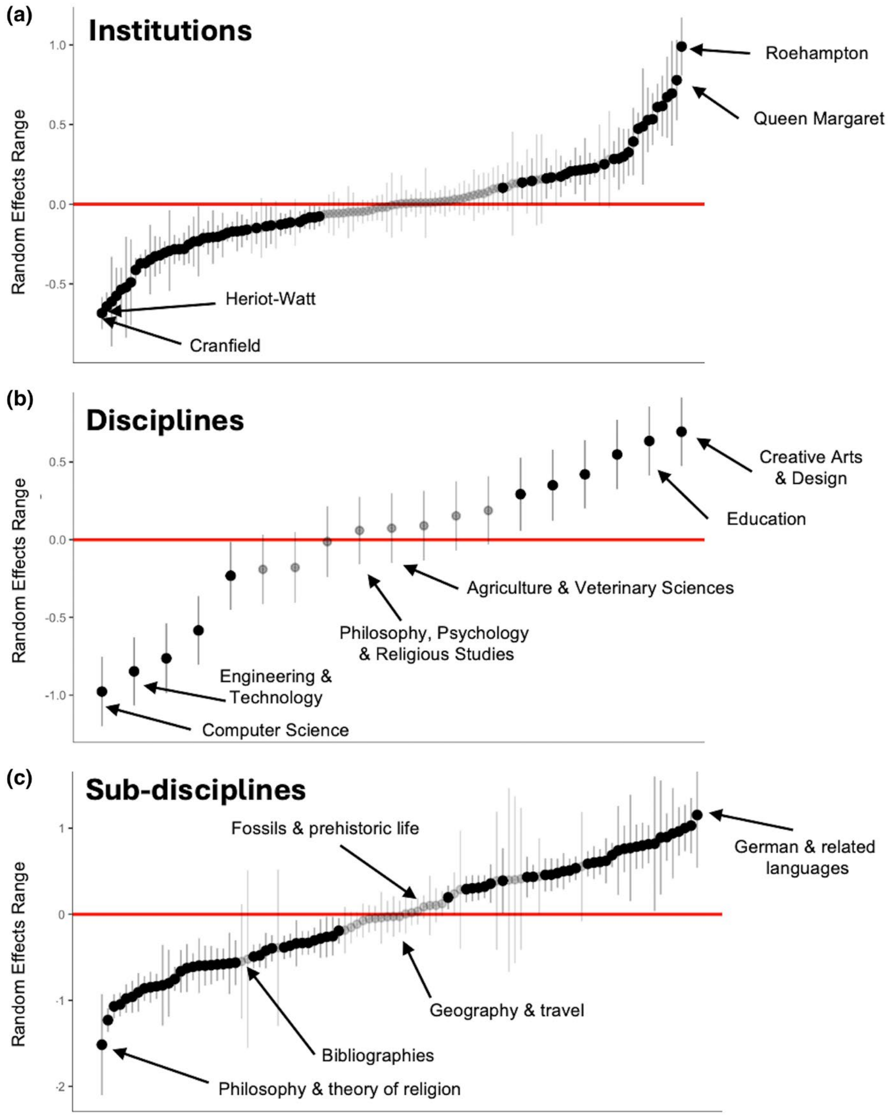

FIGURE 4 The random effects for institutions (a), disciplines (b), and sub-disciplines (c) from the two-level variance components models. For (a), (b) and (c), negative random effects suggest a bias towards male PhD students and the positive random effects suggest a bias towards female PhD students.

was established as a College of Aeronautics, and Heriot-Watt (in Edinburgh) was the 'world's first mechanics' institute' (Cranfield University, 2023; Heriot-Watt University, 2023). These institutional histories prove extremely durable: all four continue to excel in 'applied research' informed by their original, gendered missions.

4.2.2 | Disciplines and sub-disciplines

Disciplines account for a greater proportion of the observed variation in outcomes (6.5%) than institutions. Unsurprisingly, STEM fields such as Computer Science, Engineering and Technology, Mathematics and Statistics, and Physical Sciences are the most strongly male skewed; the humanities and social sciences, such as Arts and Design, Education, Language and Literature are strongly female skewed (random effects shown in Figure 4b). The notable exception is that Medicine and Health is also strongly female skewed.

Digging into the sub-disciplines (10.7% of observed variation), however, adds nuance to this picture. Figure 4c shows the size of the random effects for each sub-discipline: each dot represents the 'best estimate' of a sub-discipline's skew while the lines extending up and down represent uncertainty about the estimate. Longer lines equate to greater uncertainty, typically for smaller disciplines, whereas for larger sub-disciplines like Physics and Computer Science there is relatively little uncertainty. The lack of a line signals that the direction of skew is uncertain because the sub-discipline is quite balanced in its composition. According to our model, Geography and Travel, Christian Practice, Library and Information Sciences, Fossils and Prehistoric Life, and the History of Africa and Europe are all balanced in their overall gender composition.

Combining the historical information on gender skewed universities with the results from these models, it is perhaps unsurprising that an institution once focused on education continues to be female skewed, and an institution which focused on engineering is still more skewed towards male PhD students.

Table 4 shows the six most heavily skewed sub-disciplines: we can be fairly confident that both Physics and Computer Science are heavily skewed (with low standard errors) because they are larger sub-disciplines ($n > 10{,}000$); whereas the other sub-disciplines are relatively small ($n < 300$) and the two most skewed sub-disciplines in either direction (Philosophy and Theory of Religion and German) have barely 100 theses between them.

4.2.3 | Disciplines and institutions

The 'best' model, however, is the combination of sub-discipline and institution as a proxy for department-like-units. This model identifies the 'places' that are most heavily skewed and for the average proxy department (whose random effect was 0 on the logit scale), the probability that a PhD student is female is 43.4%, with 10.0% of the variation attributed to the differences between sub-discipline-institution combinations (Table 5).

The most male-skewed places for PhDs are Manufacturing at the University of Bath and the University of Nottingham, and Computer Science at the University of Cambridge. The most female-skewed places are Arts at University of Leicester, Italian and Romanian Literature at University of Oxford, and Psychology at University of Southampton. Of course, we should note that as these are proxies, and not always specific departments, it is possible that these students come from more than one department, institute or school.

That said, there are places that appear to confound expectations by being less gender-skewed places than the rest of their disciplines: Loughborough, Birmingham and Ulster Computer Science are the least male-dominated computer science 'departments', while Arts and Design at Heriot-Watt, Brunel and Middlesex are the least female skewed.

TABLE 4 The male and female skewed sub-disciplines.

Sub-discipline	Variance	SE	n	Rank
Philosophy and theory of religion	−1.533	0.292	71	1
Physics	−1.226	0.020	14,870	2
Computer science	−1.058	0.022	11,841	3
Customs, etiquette and folklore	0.991	0.129	270	97
Italian and Romanian literatures	1.038	0.149	204	98
German	1.175	0.286	37	99

TABLE 5 The male and female skewed sub-discipline and institution combinations.

'Department'	Variance	SE	n	Rank
Bath: Manufacturing	−1.416	0.382	31	1
Nottingham: Manufacturing	−1.389	0.250	98	2
Cambridge: Computer Science	−1.386	0.121	487	3
Southampton: Psychology	1.341	0.126	319	6773
Oxford: Italian and Romanian Literature	1.388	0.340	32	6774
Leicester: Arts	1.443	0.336	34	6775

TABLE 6 Results from the random intercepts model including the fixed and random effects.

Predictors	Odds ratio	Confidence interval	*p*-Value
(Intercept)	0.01	0.01–0.01	**<0.001**
Log % female	2.14	2.06–2.22	**<0.001**
Log % female STEM	1.84	1.73–1.97	**<0.001**
Physical Sciences	0.44	0.35–0.57	**<0.001**
Ancient university	0.96	0.90–1.01	0.137
Urban university	0.97	0.93–1.02	0.235
Scottish university	1.05	1.00–1.10	0.055
Welsh university	0.91	0.85–0.98	**0.014**
Northern Irish university	1.10	1.00–1.21	**0.047**

Note: Bold values indicate statistical significance to a 95% confidence interval.

4.2.4 | Change over time

Table 3 indicated that just 1.8% of the variation in the gender of PhD students can be attributed to differences between years, so we wondered if breaking up the data by decade would reveal impacts such as the introduction of the Athena Swan charter in 2005 (Advance, 2023). Accordingly, the EThOS records were divided into three time periods—the 1990s, the 2000s and the 2010s—and the same models were re-run to look at how the levels had changed over time.

In the 1990s, when accounting for the variation observed in disciplines, the probability of a PhD student being female was significantly lower (35%) than in either the 2000s (43%) or the 2010s (47%). The most heavily skewed disciplines remained stable over that time, but more variation was observed at the sub-disciplinary scale. For example, although Physics and Computer Science appeared in all three decades among the most male-skewed disciplines, their rank order varied. The same was true of the female-skewed sub-disciplines: although Customs and Folklore, German, and Italian and Romanian Literature appear in all the three decades, their ranks are more volatile. A similar pattern is observed when accounting for the variation observed in institutions.

4.3 | Random intercepts model

The final set of MLMs to discuss are random intercepts models—of which only the best-performing model will be discussed here—which incorporate additional predictor variables that were either provided by the BL or were inferred from other variables in EThOS such as the university's location, the percentage of female PhDs in an institution that year, and the percentage of female PhDs studying STEM. For some of these variables the logarithm (log) was taken so that the variables were on similar scales and the model was able to converge.

The best random intercepts model contains eight independent variables and three levels (individuals, institutions and sub-disciplines), and accounts for 13.7% of the variation in the probability that a PhD student is female. 8.1% of that variation is accounted for between-sub-disciplines, with only 0.09% of the variation accounted for between institutions, within sub-disciplines. In terms of the fixed effects estimates, all but the ancient and urban university variables were statistically significant at the 95% confidence level. There were no high variance inflation factors to indicate collinearity between the variables.

Table 6 shows the odds ratio of each of the fixed and random effects in this model. If the odds ratio is greater than 1, there is a positive association between the two events and if it is less than 1, there is a negative association between the two. For example, the logs of the percentage of female PhDs (0.761) and percentage of females doing STEM PhD (0.612) have positive relationships with the likelihood that the completed PhD graduate was female. Conversely, there is a decrease if the female PhD student is in the physical sciences domain (−0.814) or at a Welsh university (−0.089). Using England as the 'reference category', there is a positive relationship for PhD students in Scottish and Northern Irish universities. Only the physical sciences dummy was kept; the other dummies were statistically significant, but prevented convergence, suggesting that the resulting model did not fit the data well.

5 | DISCUSSION AND CONCLUSION

The three interlocking aims of this research were to demonstrate the potential of a feminist-informed quantitative geography, to demonstrate the utility of 'accidental' data, and to demonstrate the power of a 'platial' approach to gender in UK HE. While largely confirmatory, our results are nonetheless able to shed new light on the dynamics within institutions at the site where gendered interactions play out with the most immediate effect and greatest impact.

Applying a quantitative feminist geographical framework to UK doctoral education enables us to 'place' a PhD student within a larger, hierarchical structure of departmental proxies, institutions and disciplines. While not perfect, through EThOS we have created data that are not only otherwise unavailable *from* the UK's largest research funders, but that are also unavailable *to* them due to their own institutional histories of restructurings, changing IT platforms, and shifting data collection practices. In short, these accidental and open data that are 'everywhere accessible' (Arribas-Bel, 2014) offer insights into platial dynamics that escape 'traditional' approaches to statistical collection and publication.

So yes, we have rather unsurprisingly 'proved' that 'traditionally feminine' disciplines are skewed towards female PhDs, while 'traditionally masculine' disciplines are male skewed. And, again unsurprisingly, we see a clear divide between STEM disciplines, and the Arts, Humanities, and Social Sciences. However, we also see that under these broad categories there is a great deal of sub-disciplinary variation that has, in many cases, persisted across nearly 30 years of doctoral study despite substantial movement towards equality overall.

This research also showed the persistence of institutional history in their research profiles: the universities of Roehampton and Queen Margaret with their roots in teaching, the universities of Cranfield and Heriot-Watt with their technical focus. When it came to gender-skewed 'places', we found places like Cambridge Computer Science and Southampton Psychology were strongly skewed towards male and female PhDs, respectively. We must reiterate that this does not *necessarily* equate to specific departments, but it does point towards the gendering of research activity clusters within universities that will have consequences for the diversity of research and the resilience of the innovation ecosystem produced (Department for Science, Innovation, & Technology, 2023). By allowing us to contextualise these activities within institutions, these results allow us to identify places demonstrating good practice in promoting gender diversity in their PhD cohort relative to the 'typical' institutional sub-group in their field.

Could part of the cause of the ongoing gendered divide between STEM and non-STEM disciplines be a result of funding priorities? As we know, nearly one third of UKRI's studentships were awarded to male EPSRC students in the previous 5 years (UKRI, 2022). Of the seven research councils, the EPSRC has the largest funding allocation of £1.93 billion (over 3 years) and can therefore fund more PhD students than other councils, even if the proportion that they spend is comparable to that of other councils (UKRI, 2022). Although UKRI do not themselves select the PhD students that they fund—with decisions made by the universities, Centres for Doctoral Training, and Doctoral Training Partnerships—there is an opportunity with the UKRI EDI strategy and 'New Deal for PGRs' to change their policies and frameworks to diversify their PhD cohorts (UKRI, 2023a, 2023b). We can draw parallels with inequalities in access to PhD funding for non-white students and disabled students identified by Leading Routes (2019) and the TIGERs in STEMM (2019) group. Indeed, an obvious 'next step' for this work is to incorporate ethnicity and intersectional inequalities into our research on doctoral education.

Of course, there is no simple solution to reducing the divide between the feminised life sciences and the masculinised physical sciences: the Science and Technology Committee (2023) found that gendered divides occurred at every stage of education leading up to the research degree too, making it a whole-system issue. However, the findings point to the need for more active strategies to recruit women and other minoritised groups for EPSRC-funded PhDs.

Finally, for gender equality charters such as Athena SWAN, the results suggest that a greater emphasis on departmental awards could benefit PhD students, as this is where they are likely to see and feel the greatest impact. While recognising that what we see at the doctoral stage is the product of a cumulative effect that begins well before entry to HE—and whose effects continue well past the doctoral award—we still argue the need for more women to pursue PhDs in the physical sciences and engineering subjects and more men to pursue PhDs in the arts and humanities. But unless academia as a sector takes a renewed and active approach to improving these figures so that minoritised groups are comfortable entering these gender-skewed disciplines, we will not see sustained and meaningful change in the near future. Indeed, the evidence from EThOS suggests that in some research areas it may well take decades to close this gender gap.

ACKNOWLEDGEMENTS

The results of this research formed part of Laura Sheppard's PhD project on gender inequalities in UK doctoral education. The work was funded by the Economic and Social Research Council (part of UKRI) through the UCL, Bloomsbury, and East London Doctoral Training Partnership, and by the British Library as an industry partner. We would like to thank them for their support during Laura's PhD research. The data were analysed using R (2021) and lme4 (Bates et al., 2015), with processing in dplyr (Wickham et al., 2023) and visualisation in ggplot2 (Wickham, 2016).

DATA AVAILABILITY STATEMENT

The data that support the findings of this research are openly available in the British Library's repository at https://doi.org/10.23636/kvwc-ty06. The data are publicly available under a CC0 Licence, and the metadata are available to download at: https://bl.iro.bl.uk/. Reference: British Library and Heather Rosie; 2022; E-Thesis Online Service; British Library Research Repository; Version 9; https://doi.org/10.23636/kvwc-ty06.

ADDITIONAL MATERIALS

Link to GitHub repository for cleaning EThOS data: https://github.com/LauraSheppard.

ORCID

Laura Harriet Sheppard https://orcid.org/0000-0003-2522-3625

REFERENCES

Acker, J. (1990) Hierarchies, jobs, bodies: A theory of gendered organizations. *Gender and Society*, 4, 139–158. Available from: https://doi.org/10.1177/089124390004002002

Advance, H.E. (2023) *Athena swan charter*. Available from: https://www.advance-he.ac.uk/equality-charters/athena-swan-charter.

Arribas-Bel, D. (2014) Accidental, open, and everywhere: Emerging data sources for the understanding of cities. *Applied Geography*, 49, 45–53. Available from: https://doi.org/10.1016/j.apgeog.2013.09.012

Bates, D., Mächler, M., Bolker, B. & Walker, S. (2015) Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. Available from: https://doi.org/10.18637/jss.v067.i01

Berhe, A.A., Barnes, R.T., Hastings, M.G., Mattheis, A., Schneider, B., Williams, B.M. et al. (2022) Scientists from historically excluded groups face a hostile obstacle course. *Nature Geoscience*, 15(1), 2–4. Available from: https://doi.org/10.1038/s41561-021-00868-0

Berryman, S.E. (1983) *Who will do science? Trends, and their causes in minority and female representation among holders of advanced degrees in science and mathematics. A special report*. New York: The Rockefeller Foundation. Available from: https://eric.ed.gov/?id=ED245052

Bourabain, D. (2020) Everyday sexism and racism in the ivory tower: The experiences of early career researchers on the intersection of gender and ethnicity in the academic workplace. *Gender, Work and Organization*, 28, 248–267. Available from: https://doi.org/10.1111/gwao.12549

Britton, D.M. (2017) Beyond the chilly climate: The salience of gender in Women's academic careers. *Gender and Society*, 31(1), 5–27. Available from: https://doi.org/10.1177/0891243216681494

Browne, W.J., Subramanian, S.V., Jones, K. & Goldstein, H. (2005) Variance partitioning in multilevel logistic models that exhibit overdispersion. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 168(3), 599–613. Available from: https://doi.org/10.1111/j.1467-985X.2004.00365.x

Caroline Criado Perez. (2019) *Invisible women: Exposing data bias in a world designed for men*. London: Chatto and Windus.

Casad, B.J., Franks, J.E., Garasky, C.E., Kittleman, M.M., Roesler, A.C., Hall, D.Y. et al. (2020) Gender inequality in academia: Problems and solutions for women faculty in STEM. *Journal of Neuroscience Research*, 99(1), 13–23. Available from: https://doi.org/10.1002/jnr.24631

Catherine Montgomery. (2019) Surfacing "southern" perspectives on student engagement with internationalization: Doctoral theses as alternative forms of knowledge. *Journal of Studies in International Education*, 23(1), 123–138. Available from: https://doi.org/10.1177/1028315318803743

Centre for Multilevel Modelling. (2023) *What are multilevel models and why should I use them?* Available from: http://www.bristol.ac.uk/cmm/learning/multilevel-models/what-why.html

CFE Research and the University of York. (2021) *ESRC review of the PhD in the social sciences*. October 2021. Available from: https://esrc.ukri.org/files/skills-and-careers/review-of-the-phd-in-the-social-sciences/

Chi, B., Dennett, A., Oléron-Evans, T. & Morphet, R. (2021) Shedding new light on residential property price variation in England: A multi-scale exploration. *Environment and Planning B: Urban Analytics and City Science*, 48(7), 1895–1911. Available from: https://doi.org/10.1177/2399808320951212

Cranfield University. (2023) *History and heritage*. Available from: https://www.cranfield.ac.uk/about/history-and-heritage.

D'Ignazio, C. & Klein, L. (2020) *Data feminism*. Cambridge, MA: The MIT Press. Available from: https://mitpress.mit.edu/9780262547185/data-feminism/

Department for Education. (2024) *A level and other 16 to 18 results*. April 2024. Available from: https://explore-education-statistics.service.gov.uk/find-statistics/%20%20a-level-and-other-16-to-18-results/2022-23#main-content

Department for Science, Innovation & Technology. (2023) *UK Innovation Strategy: Leading the future by creating it*. Available from: https://www.gov.uk/government/publications/uk-innovation-strategy-leading-the-future-by-creating-it/uk-innovation-strategy-leading-the-future-by-creating-it-accessible-webpage

Engineering and Physical Sciences Research Council. (2021) *Review of EPSRC-funded doctoral education*. Swindon: UK Research and Innovation (UKRI). Available from: https://www.ukri.org/wp-content/uploads/2021/10/EPSRC-071021-ReviewDoctoralEducationSupport.pdf. October 2021.

Fernée, C.L. & Trimmis, K.P. (2021) Detecting variability: A study on the application of Bayesian multilevel modelling to archaeological data. Evidence from the neolithic Adriatic and the bronze age Aegean. *Journal of Archaeological Science*, 128, 105346. Available from: https://doi.org/10.1016/j.jas.2021.105346

Fisher, M., Nyabaro, V., Mendum, R. & Osiru, M. (2020) Making it to the PhD: Gender and student performance in sub-Saharan Africa. *PLoS One*, 15(12), e0241915. Available from: https://doi.org/10.1371/journal.pone.0241915

Franklin, R.S., Houlden, V., Robinson, C., Arribas-Bel, D., Delmelle, E.C., Demšar, U. et al. (2021) Who counts? Gender, gatekeeping, and quantitative human geography. *The Professional Geographer*, 73(1), 48–61. Available from: https://doi.org/10.1080/00330124.2020.1828944

Gasser, C.E. & Shaffer, K.S. (2014) Career development of women in academia: Traversing the leaky pipeline. *The Professional Counsellor*, 4, 332–352. Available from: https://doi.org/10.15241/ceg.4.4.332

Glen, S. (2023) *Likelihood-ratio tests (probability and mathematical statistics)*. Available from: https://www.statisticshowto.com/likelihood-ratio-tests/

Goldstein, H. (2011) *Multilevel statistical models*, 4th edition. Chichester: Wiley and Sons Ltd.

Gould, S. (2016) UK theses and the British library EThOS service: From supply on demand to repository linking. *Interlending and Document Supply*, 44(1), 7–13. Available from: https://doi.org/10.1108/ILDS-10-2015-0033

Goulden, M., Mason, M.A. & Frasch, K. (2011) Keeping women in the science pipeline. *The Annals of the American Academy of Political and Social Science*, 638, 141–162. Available from: https://doi.org/10.1177/0002716211416925

Guo, G. & Zhao, H. (2000) Multilevel modelling for binary data. *Annual Review of Sociology*, 26, 441–462. Available from: https://doi.org/10.1146/annurev.soc.26.1.441

Handforth, R. (2022) *Belonging, gender and identity in the doctoral years: Across time and space*. Cham, Switzerland: Springer Nature.

Harvey, F., Kwan, M.-P. & Pavlovskaya, M. (2005) Introduction: Critical GIS. *Cartographica: The International Journal for Geographic Information and Geovisualization*, 40(4), 1–4. Available from: https://doi.org/10.3138/04L6-2314-6068-43V6

Heriot-Watt University. (2023) *Our history*. Available from: https://www.hw.ac.uk/uk/about/history

HESA. (2022) *Who's working in HE?: personal characteristics*. Available from: https://www.hesa.ac.uk/data-and-analysis/staff/working-in-he/characteristics

HESA. (2023a) *Who's studying in HE?* Available from: https://www.hesa.ac.uk/data-and-analysis/students/whos-in-he [Accessed 20th February 2024].

HESA. (2023b) *Who's working in HE?: Personal characteristics*. Available from: https://www.hesa.ac.uk/data-and-analysis/staff/working-in-he/characteristics [Accessed 20th February 2024].

HESA. (2024) *Who's working in HE?: Personal characteristics*. Available from: https://www.hesa.ac.uk/data-and-analysis/staff/working-in-he/characteristics [Accessed 20th February 2024].

Howe, K. (2015) *A novel use of PhD data: Investigating the state of the dementia workforce*. British Library. Available from: https://blogs.bl.uk/science/2015/09/a-novel-use-of-phd-data.html. September 2015.

Iaria, A., Schwarz, C. & Waldinger, F. (2023) *The glass ceiling in the ivory tower*. London: Centre for Economic Policy Research. Available from: https://cepr.org/voxeu/columns/glass-ceiling-ivory-tower-century-gender-gaps-academia-across-globe [Accessed 20th February 2024].

Jacob Clark Blickenstaff. (2005) Women and science careers: Leaky pipeline or gender filter? *Gender and Education*, 17, 369–386. Available from: https://doi.org/10.1080/09540250500145072

Jadidi, M., Karimi, F., Lietz, H. & Wagner, C. (2018) Gender disparities in science? Dropout, productivity, collaborations and success of male and female computer scientists. *Advances in Complex Systems*, 21, 1750011. Available from: https://doi.org/10.1142/S0219525917500114

Kaplan, D.H. & Mapes, J.E. (2016) Where are the women? Accounting for discrepancies in female doctorates in U.S. Geography. *The Professional Geographer*, 68(3), 427–435. Available from: https://doi.org/10.1080/00330124.2015.1102030

Karimi, F., Wagner, C., Lemmerich, F., Jadidi, M. & Strohmaier, M. (2016) Inferring gender from names on the web: A comparative evaluation of gender detection methods. In *Proceedings of the 25th international conference companion on world wide web*, pp 53–54.

Kozlowski, D., Larivière, V., Sugimoto, C.R. & Monroe-White, T. (2022) Intersectional inequalities in science. *Proceedings of the National Academy of Sciences*, 119(2), e2113067119. Available from: https://doi.org/10.1073/pnas.2113067119

Larivière, V., Ni, C., Gingras, Y., Cronin, B. & Sugimoto, C.R. (2013) Bibliometrics: Global gender disparities in science. *Nature*, 504(7479), 211–213. Available from: https://doi.org/10.1038/504211a

Leading Routes. (2019) *The broken pipeline: Barriers to black PhD students accessing research council funding*. London: UCL/Leading Routes. Available from: https://leadingroutes.org/mdocs-posts/the-broken-pipeline-barriers-to-black-students-accessing-research-council-funding [Accessed 20th February 2024].

Leckie, G., Browne, W., Goldstein, H., Merlo, J. & Austin, P. (2019) Partitioning variance partitioning in multilevel models for count data. *Psychological Methods*, 25, 787–801.

Lund, B. & Agbaji, D. (2018) Use of Dewey decimal classification by academic libraries in the United States. *Cataloging & Classification Quarterly*, 56(7), 653–661. Available from: https://doi.org/10.1080/01639374.2018.1517851

Merlo, J., Wagner, P., Ghith, N. & Leckie, G. (2016) An original stepwise multilevel logistic regression analysis of discriminatory accuracy: The case of neighbourhoods and health. *PLoS One*, 11(4), e0153778. Available from: https://doi.org/10.1371/journal.pone.0153778

Meyer, A.H. (1947) A geographic classification of geography material as based upon the dewey classification system. *Annals of the Association of American Geographers*, 37(2), 209–222. Available from: https://doi.org/10.1080/00045604709351961

Meyer, A.H. (1971) Resolving parallel problems in geography classification under the dewey decimal and library of congress systems. *The Professional Geographer*, 23(1), 5–10. Available from: https://doi.org/10.1111/j.0033-0124.1971.00005.x

Mocnik, F.-B. (2022) Putting geographical information science in place – Towards theories of Platial information and Platial information systems. *Progress in Human Geography*, 46(3), 798–828. Available from: https://doi.org/10.1177/03091325221074023

O'Sullivan, D. (2006) Geographical information science: Critical GIS. *Progress in Human Geography*, 30(6), 783–791. Available from: https://doi.org/10.1177/0309132506071528

Office for National Statistics. (2023a) *Disability, England and Wales: Census 2021*. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthandwellbeing/bulletins/disabilityenglandandwales/census2021 [Accessed 20th February 2024].

Office for National Statistics. (2023b) *Ethnic group, England and Wales: Census 2021*. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/ethnicity/bulletins/ethnicgroupenglandandwales/census2021 [Accessed 20th February 2024].

Office for National Statistics. (2023c) *Gender identity, England and Wales: Census 2021*. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/culturalidentity/genderidentity/bulletins/genderidentityenglandandwales/census2021 [Accessed 20th February 2024].

Online Computer Library Centre. (2003) *Summaries: DDC: Dewey decimal classification*. Available from: https://www.oclc.org/content/dam/oclc/dewey/resources/summaries/deweysummaries.pdf [Accessed 20th February 2024].

Osborne, J. & Waters, E. (2002) Four assumptions of multiple regression that researchers should always test. *Practical Assessment, Research and Evaluation*, 8(2), 2. Available from: https://doi.org/10.7275/r222-hv23

Owen, G., Harris, R. & Jones, K. (2016) Under examination: Multilevel models, geography and health research. *Progress in Human Geography*, 40, 394–412. Available from: https://doi.org/10.1177/0309132515580814

Pavlovskaya, M. (2018) Critical GIS as a tool for social transformation. *The Canadian Geographer/Le Geographe Canadien*, 62(1), 40–54. Available from: https://doi.org/10.1111/cag.12438

Pell, A.N. (1996) Fixing the leaky pipeline: Women scientists in academia. *Journal of Animal Science*, 74, 2843–2848. Available from: https://doi.org/10.2527/1996.74112843x

Powers, D.A. (2012) Multilevel models for binary data. *New Directions for Institutional Research*, 154, 57–75. Available from: https://doi.org/10.1002/ir.20014

Queen Margaret University. (2023) *History*. Available from: https://www.qmu.ac.uk/about-the-university/history/

Rasbash, J., Leckie, G., Pillinger, R. & Jenkins, J. (2010) Children's educational progress: Partitioning family, school, and area effects. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 173(3), 657–682. Available from: https://doi.org/10.1111/j.1467-985X.2010.00642.x

Reades, J. & Williams, J. (2023) Clustering and visualising documents using word embeddings. *Programming Historian*, 12. Available from: https://doi.org/10.46430/phen0111

Rights, J.D. & Sterba, S.K. (2020) New recommendations on the use of r-squared differences in multilevel model comparisons. *Multivariate Behavioural Research*, 55(4), 568–599. Available from: https://doi.org/10.1080/00273171.2019.1660605

Rosa, R. (2022) The trouble with 'work–life balance' in neoliberal academia: A systematic and critical review. *Journal of Gender Studies*, 31, 55–73. Available from: https://doi.org/10.1080/09589236.2021.1933926

Safiya Umoja Noble. (2018) *Algorithms of oppression: How search engines reinforce racism*. New York: New York University Press.

Santamaría, L. & Mihaljević, H. (2018) Comparison and benchmark of name-to- gender inference services. *PeerJ Computer Science*, 4, e156.

Sara Ashencaen Crabtree and Chris Shiel. (2019) Playing mother: Channelled careers and the construction of gender in academia. *SAGE Open*, 9(3), 285. Available from: https://doi.org/10.1177/2158244019876285

Schurr, C., Müller, M. & Imhof, N. (2020) Who makes geographical knowledge? The gender of Geography's gatekeepers. *Professional Geographer*, 72(3), 317–331. Available from: https://doi.org/10.1080/00330124.2020.1744169

Science and Technology Committee. (2023) *Diversity and inclusion in STEM*. Available from: https://committees.parliament.uk/publications/34531/documents/190060/default/ [Accessed 20th February 2024].

Sebo, P. (2021) Performance of gender detection tools: A comparative study of name-to-gender inference services. *Journal of the Medical Library Association*, 109(3), 414–421. Available from: https://doi.org/10.5195/jmla.2021.1185

Sheppard, L., Reades, J. & Freeman, R.P.J. (2023) Gendering and diversifying the research pipeline: A quantitative feminist geographical approach to gender in higher education. *Annals of the American Association of Geographers*, 113(4), 817–833. Available from: https://doi.org/10.1080/24694452.2022.2160302

Simpson, R. (2009) *The development of the PhD degree in Britain, 1917–1959 and since: An evolutionary and statistical history in higher education*. Lewiston, New York: The Edwin Mellen Press.

Singleton, A.D. (2010) *Educational opportunity: The geography of access to higher education*. Farnham: Ashgate.

Sullivan, D. (2015) *A brief history of homophobia in Dewey decimal classification*. Victoria: Overland. Available from: https://overland.org.au/2015/07/a-brief-history-of-homophobia-in-dewey-decimal-classification/ [Accessed 20th February 2024].

The British Library. (2023) *EThOS: E-thesis online service*. Available from: https://ethos.bl.uk/ [Accessed 20th February 2024].
The British Library. (2024) *Learning Lessons from the Cyber-Attack: British Library cyber incident review*, 8 March 2024. Available from: https://www.bl.uk/home/british-library-cyber-incident-review-8-march-2024.pdf [Accessed 20th February 2024].
The Russell Group. (2023a) The Russell group. Available from: https://russellgroup.ac.uk/about/ [Accessed 17th November 2023].
The Russell Group. (2023b) Our universities. The Russell group. Available from: https://russellgroup.ac.uk/about/our-universities/ [Accessed 17th November 2023].
Tiger in STEMM. (2019) *Accessibility in STEM: Barriers facing disabled individuals in research funding processes*. Available from: https://osf.io/preprints/osf/uzsdk [Accessed 20th February 2024].
UK Research and Innovation. (2022) *EDI funding data 2022*. Available from: https://public.tableau.com/app/profile/uk.research.and.innovation.ukri./viz/EDIFundingdata2022forpublication/Awardratebyvalue [Accessed 20th February 2024].
UK Research and Innovation. (2023a) A new Deal for postgraduate Research response to the call for input. UK Research & Innovation. September 2023. https://www.ukri.org/what-we-do/developing-people-and-skills/new-deal-for-postgraduate-research/ [Accessed 20th February 2024]
UK Research and Innovation. (2023b) UKRI's equality, diversity and inclusion strategy: Research and innovation by everyone, for everyone. Available from: https://www.ukri.org/publications/ukrisequality-diversity-and-inclusion-strategy/ukris-equality-diversity-and-inclusion-strategy-research-and-innovation-by-everyone-for-everyone [Accessed 20th February 2024]
University of Roehampton. (2023) *Our history*. Available from: https://www.roehampton.ac.uk/our-history [Accessed 20th February 2024].
Wais, K. (2016) Gender prediction methods based on first names with genderizeR. *R Journal*, 8(1), 17. Available from: https://doi.org/10.32614/rj-2016-002
Westbrook, L. & Saperstein, A. (2015) New categories are not enough: Rethinking the measurement of sex and gender in social surveys. *Gender and Society*, 29(4), 534–560. Available from: https://doi.org/10.1177/0891243215584758
Wickham, H. (2016) *ggplot2: Elegant graphics for data analysis*. New York: Springer-Verlag. Available from: https://ggplot2.tidyverse.org [Accessed 17th November 2023].
Wickham, H., François, R., Henry, L., Müller, K. & Vaughan, D. (2023) dplyr: A grammar of data manipulation. R package version 1.1.4. Available from: https://github.com/tidyverse/dplyr; https://dplyr.tidyverse.org [Accessed 17th November 2023].

How to cite this article: Sheppard, L.H., Reades, J. & Freeman, R.P.J. (2025) Examining the 'gendered' places and spaces of UK doctoral education using multilevel modelling. *Transactions of the Institute of British Geographers*, 00, e12745. Available from: https://doi.org/10.1111/tran.12745