Is the audience gender-blind? Smaller attendance in female talks highlights imbalanced visibility in academia

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Abstract

Although diverse perspectives are fundamental for fostering and advancing science, power relations have limited the development, propagation of ideas, and recognition of political minority groups in academia. Gender bias is one of the most well-documented processes, leading women to drop out of their academic careers due to fewer opportunities and lower recognition. Using decadal-scale data on talks (n=344, 2008-2019) from a seminar series in Ecology, Evolution, and Conservation Biology, we questioned whether affirmative actions focused on increasing women's representation affected their visibility and recognition, measured by audience size, as an indirect outcome. Specifically, we evaluated (i) the representation of females as speakers along academic levels and the effect of affirmative actions; (ii) whether the audience size of the talk depends on the speaker's gender, even accounting for the speaker's career length and productivity (iii), and (iv) if there were gender differences in the topics of the talks. The results indicate that women gave fewer talks than men, and this difference was greater for seminars given by professors. However, as expected, affirmative action increased the representativeness of women throughout their career positions. Female speakers had smaller audiences, especially among professors, indicating higher visibility for male professors even with comparable productivity metrics. We found no gender effect in the research topics presented, indicating that the difference in audience may also not be related to the topics of the talks. We raise the discussion that gender bias in the academic community in attending talks may decrease the visibility of research carried out by women, potentially impacting professional development and restricting the spread of ideas. Moreover, although encouraged, affirmative action increasing representativeness may not be enough against more subtle gender-stereotype biases. Our research contributes to the discussion of how gender inequity can influence visibility and reinforce the stigmatization of science.

Keywords: gender-science stereotype, gender equity, seminars, academic career, affirmative actions, audience, research topics.

Introduction

Diversity is a fundamental part of the advancement of science. Evidence shows that the current lack of social diversity, including gender, race, and ethnicity, in academia represents a highly inefficient equilibrium (Miriti, 2020, Pew Research Center Science, 2021, Doleac et al., 2021). Limiting the diversity of perspectives not only hinders the scope of inquiry but also reduces the potential for innovative solutions, underscoring the importance of inclusivity in fostering a more robust and dynamic scientific community (Hong, Page, 2004, Page, 2007). For instance, gender equity is listed as one of the 17 goals of the United Nations 2030 agenda (United Nations General Assembly, 2015).

The lack of representation and discrimination against women in academia is a reality that has been widely recognized. Women publish fewer first-authored articles (Larivière et al., 2013, Fox et al., 2016, 2023), receive smaller grants (Wennerås, Wold, 1997, Zandonà, 2022) and start-up funding (Sege et al., 2015, Oliveira et al., 2019), are paid less (Woolston, 2019), are less invited to talks (Schroeder et al., 2013), are promoted with reduced frequency, and hold fewer positions of power or influence (Niemeier, González, 2004, Amrein et al., 2011), such as being reviewers in scientific publications and grants (Astegiano et al., 2019) or in the editorial board of scientific journals (Fox et al., 2018, but see Barros et al., 2021). All of this contributes to the well-known phenomenon of the “leaky pipeline” of women's representation in science, i.e., women tend to leave the academic career path earlier than men (Shaw, Stanton, 2012, Zandonà, 2022).

Recent policies have been enacted to tackle the "leaky pipeline" phenomenon and increase the presence of women in university committees, journal editorial boards, scientific events, and organizations (Greska, 2023). While these measures primarily focus on enhancing female representation, gender-science stereotypes, which are entrenched and overly simplistic views about gender roles, continue to challenge these efforts by significantly shaping perceptions and behaviors (Nosek et al., 2002). Such stereotypes persist as a major source of gender bias in academia, with pervasive cultural effects against equity (Reuben et al., 2014, Miller et al., 2015, Calaza et al., 2021). These stereotypes typically present scientists as male (Mead & Metraux, 1957; Miller et al., 2015), creating an academic environment that diminishes the visibility and recognition of women's contributions. This reduced recognition leads to lower prestige for female scientists, perpetuating a vicious cycle that keeps them in a disadvantaged position within academia (Ross et al., 2022). Such dynamics illustrate the complex interplay between affirmative actions aimed at increasing representation and the deep-rooted biases and stereotypes that continue to impede true gender equity.

Using the audience in talks of a seminar series in Ecology, Evolution, and Conservation Biology, we evaluate whether affirmative actions focused on increasing women's representation as speakers affected their visibility and recognition in science, measured by audience size, as an indirect outcome. To do so, we first evaluated (i) the representation of females as speakers through academic levels and the effect of affirmative actions. Then, we analyzed (ii) whether audience size depends on the speaker's gender, academic level, and affirmative actions for women representativeness . As audience size can be influenced by speakers' attributes other than gender, we additionally evaluated (iii) if differences in the audience of male and female professors reflected differences in the speaker's career length and productivity and (iv) if there were gender differences in the topics of the talks.

We rely on the analysis of decadal-scale data (2008-2019) on women's representation among speakers, audiences, and topics of the talks in an ecological seminar series (n=344 talks) at one of the main Latin American universities, the University of São Paulo, Brazil. Such events are fruitful occasions to catalyze learning, discuss ideas, contribute to further developing the speaker's research, and expand collaboration networks. They are pillars for promoting individual and social changes within scientific communities locally and globally.

Methods

Seminar series in Ecology

The EcoEncontros is a seminar series of weekly talks at the Ecology Graduate Program at the University of São Paulo (PPGE-USP), Brazil. EcoEncontros started in 2008 and is organized by a committee formed mainly by graduate students (master's and doctorate), in which females comprised around 70% of the organizing committee members until 2019. The committee primarily operates with open calls for volunteer speakers. In the seminars, speakers present their research at any stage of development: as a project, preliminary results, published papers, or any other topics of interest. Although it is a graduate program seminar series, almost 20% of the speakers between 2008 and 2019 were affiliated with foreign institutions.

Affirmative action can take various forms to promote equal opportunities for women in science (Bird, 2011; Bardoel et al., 2012). In 2018, the EcoEncontros organizing committee became aware of gender imbalance in their seminar talks. Hence, it began pursuing to improve it in response to ongoing discussions about gender disparity in Science. However, these efforts aimed to preserve the seminars' decentralized, horizontal, and voluntary nature, which relies on open calls for volunteer speakers rather than direct invitations. The initiatives (henceforth affirmative actions) aimed to create a more inclusive environment and focused on reinforcing calls for women to encourage greater female participation and engagement. Ultimately, when multiple volunteers expressed interest in presenting a seminar on a given date, preference was given to women. However, if no women volunteered, the slot was assigned to a male volunteer to ensure continuity in the schedule.

Data collection

We retrieved recorded information from all talks between 2008 and 2019 from the EcoEncontros committee attendance list archives (N=344 talks). We retrieved data about the speaker (gender, academic level, and affiliation) and the seminar (date, title, abstract, and audience size). We inferred the speaker's gender by name and photo (always present on the seminars' posters). Even though we are aware that the binary classification underrepresents gender diversity and may not reflect the self-declared gender of the speaker, we believe that any possible bias by the audience in attending the talks is also led by the same information.

We classified the speaker's academic level into 3 categories: student (bachelor's, master's, or doctoral degrees), postdoctoral researcher, and professor (assistant, associate, full, or lecturer). Senior researchers at non-university scientific institutions were also included in the professor category. We assessed audience size through the attendance list of the seminar, in which all attendees signed their names and affiliations. We excluded special seminars such as round tables and talks unrelated to the speaker's research, totaling 327 talks for the analyses. We classified talks in terms of whether they were presented before or after the start of the organizing committee's affirmative actions (2018): 256 talks (78%) were given before and 71(22%) after it.

Data analyses

Female speakers across academic levels

To investigate the representation of female speakers across academic levels and the effect of affirmative actions, we modeled the proportion of female speakers as a function of their academic level and whether the talk occurred before or after affirmative actions. We excluded talks from non-academic professionals, totaling 320 talks used in this analysis.

We used generalized linear mixed-effects models with a Binomial distribution (response variable: 0 for male; 1 for female) and set up models based on the combination of academic level and before-after affirmative actions (Table 1a). We included the year of the talk as a random intercept to account for differences in the proportion of female speakers through the years. We used model selection based on the Akaike Information Criterion (AIC) to infer the models that best fit our data (lower AIC),using the criterion of equality plausible models for those with a difference in AIC lower than 2.

Additionally, to differentiate gender bias in talks from the possible effect of gender unbalance in the Graduate Program community (PPGE), we performed a similar analysis with a subset of data for speakers from the PPGE (136 talks, 44% of the original dataset). The proportion of female academics in the PPGE community was calculated for each academic level and year (Figure S1) and used as a predictor variable in all competing models to represent the speaker's pool. That is, for each talk, this variable was the proportion of female academics in the program according to the year of the talk and the academic level of the speaker. Competing models were set up based on the combination of academic level and affirmative actions in additive models (Table S1). This way, we evaluate if the proportion of female speakers follows the gender ratio of the PPGE community or if it is more or less biased through male speakers in the different academic levels as well as whether these proportions changed before and after affirmative actions.

<u>Speaker gender differences in seminars audience and affirmative action effects</u>

To evaluate whether audience size depends on the speaker's gender, academic level, and the effects of affirmative actions, we modeled audience (number of attendants) as a function of the speaker's gender, academic level, and whether the talk occurred before or after the affirmative actions. We excluded talks from non-academic professionals and seminars when more than one speaker presented on the same day, totaling 298 talks for this analysis (see Table S2 for the descriptive summary). Similarly to the previous analysis, we modeled the year as a random intercept to account for possible differences in audience through time.

Given the considerable variation in the audience (ranging from 4 to 101), we used generalized linear models with negative binomial distribution. We set up models using the same procedure as previously explained (Table 1b).

To investigate if gender differences in the audience of professors reflected differences in the speaker's career length and productivity, we collected information on the professor's productivity, career length, and institution prestige rank. We collected the following information on each professor's Google Scholar profile: (1) career length, measured as the number of years from the first cited publication until the year of the talk; (2) i10-index, which measures the number of papers with at least ten citations; (3) H-index, which counts the number of papers with at least the same number of citations; (4) total number of citations; (5) cumulative number of citations until the year of the talk; (6) citations of the most cited paper. To measure the professor's institution rank, we used two Nature Indexes (Nature Index 2021): count and share. A count of one is to an institution or country if one or more authors of the research article are from that institution or country, regardless of how many co-authors there are from outside that institution or country (Nature Index, 2021). A fractional count (also called "share") considers the percentage of authors from that institution and the number of affiliated institutions per article. We performed a Principal Component Analysis (PCA) with all metrics and used the first axis as the predictor variable for the productivity index. We analyzed 87 professors' talks since we could not get productivity information for nine professors.

Gender differences in seminar topics

To investigate possible gender differences in the topics of the talks, which could explain part of the gender differences in the previous questions, we performed a text analysis with the titles and abstracts of the talks. We recovered talk titles from 320 talks (140 for females, 180 for males) and abstracts from 234 talks (99 for females, 135 for males). Titles and abstracts written in Portuguese or Spanish were translated into English. We compared the frequency of words used by male and female speakers using Pearson correlation. Given the small sample size for text analysis, we did not compare it by academic level. However, we also analyzed the data separately for professors, with 96 titles (24 for females, 72 for males) and 77 abstracts (20 for females, 57 for males).

To investigate differences in research topics of talks given by male and female speakers, we performed a topic modeling analysis, an unsupervised machine learning model to identify groups of similar words (i.e., topics) within a body of text. We used Latent Dirichlet Allocation (LDA), following Silge & Robinson (2017), which treats each document (abstracts and titles of the talks) as a mixture of topics and each topic as a mixture of words. We compared LDA models with different numbers of topics (k = 2, 3, 4, 5, 10, 20) using AIC model selection. After classifying the talks within topics, we compared the frequency of topics between male and female speakers with a Chi-squared test.

All data analysis was performed in R (version 4.3, R Core Team, 2022), using the main packages: *glmmTMB* (Brooks et al., 2017), *DHARMa* (Hartig, 2016), *bbmle* (Bolker, R Development Core Team, 2023), *performance* (Lüdecke et al., 2021), *ggeffects* (Lüdecke, 2018) for modeling; *tidytext* (Silge, Robinson, 2016), *topicmodels* (Grün, Hornik, 2011), *tm* (Feinerer et al., 2008), and *quanteda* (Benoit et al., 2018) for text analysis. The complete list of packages, together with all code and data, is openly available on the Zenodo repository (Leite, Barreto, 2024).

Results

From the 327 talks analyzed in 12 years, 184 were given by men (56%) and 143 by women (44%). When separated by academic level (N=320, excluding non-academic speakers), women gave fewer talks than men in higher academic levels, from 52% of the students and 43% of the postdocs to 24% of the professors' talks (Figure 1a). Before 2018, men were most of the speakers in 7 of 10 years (Figure 1b). In 2018 and 2019, after the affirmative actions began, gender balance among speakers was 52% and 50% of women in each respective year.

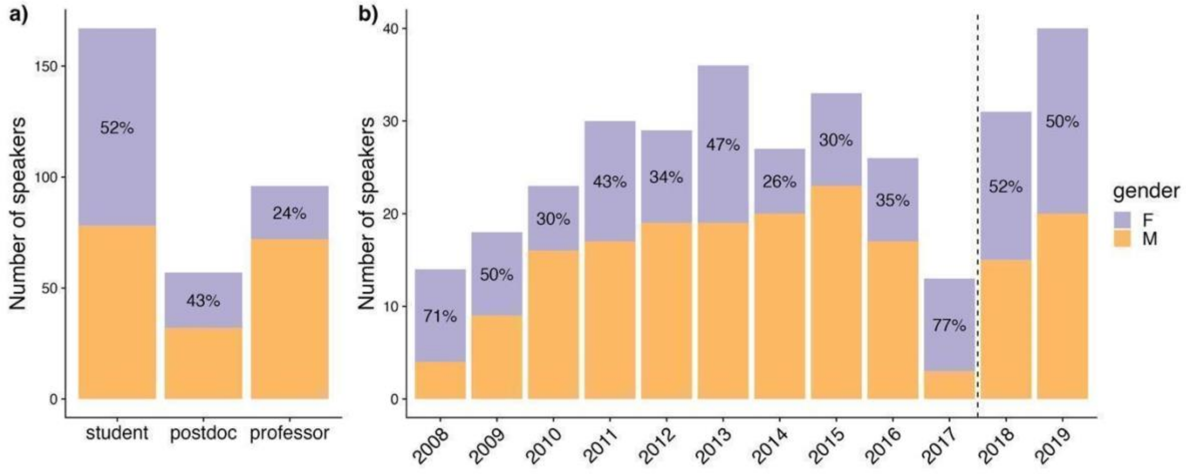

Figure 1. a) Total number of speakers by gender (females in purple and males in yellow) and academic level for all talks in 12 years of the EcoEcontros seminar series. b) Number of talks by gender for each year. The dashed vertical line indicates the beginning of affirmative action to increase women's representation. Percentages in both figures are the proportion of female researchers within each academic level in (a) and year in (b).

Female speakers across academic levels

Two models were equally plausible for the proportion of female speakers (Table 1a). Both models included academic level as a predictor, with the difference that the best-fitted model includes affirmative actions and the interaction between them (conditional $R^2 = 0.15$, marginal $R^2 = 0.12$, Figure 2). Before the start of affirmative action, we found a decrease in the proportion of female speakers through academic levels, with female speakers being only 21% of the professors' speakers (Figure 2, gold lines). After implementing affirmative action, the proportion of females in all academic levels was more balanced and did not differ from 50% (Figure 2, green lines). If we consider the second most plausible model, the proportion of females also decreased with academic level, being smaller than 50% only for female professors (26%, Figure S3).

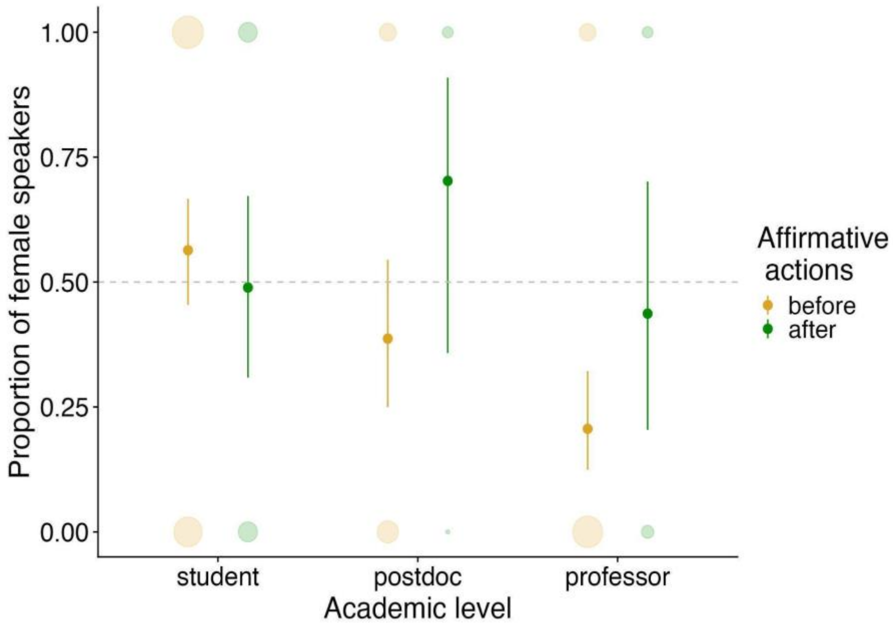

Figure 2. Proportions of female speakers according to academic level and affirmative actions (before in gold and after 2018 in green) predicted by the best-fitted model (Table 1a). Vertical line ranges mean 95% confidence intervals for the estimated proportions. The size of the circles is proportional to the number of talks given by a male (y-axis 0) and female (y-axis 1) in each category, ranging from 3 (smallest circle - male postdocs after affirmative actions) to 69 (largest circle - male professors before the affirmative action).

When considering the subset data for the Graduate Program academic community, we found that the proportion of female speakers closely followed that of female academics within each academic level (best-fitting model, Figure 3), showing no inherent gender bias in speaker selection within the academic community. However, there was high uncertainty in the model selection with all models being equally plausible ($\Delta AIC < 2$), except the null (Table S1), probably due to a smaller (44% of the original dataset) and unbalanced data between academic levels (99 students, 24 postdocs, 13 professors) and affirmative actions (109 before, 27 after).

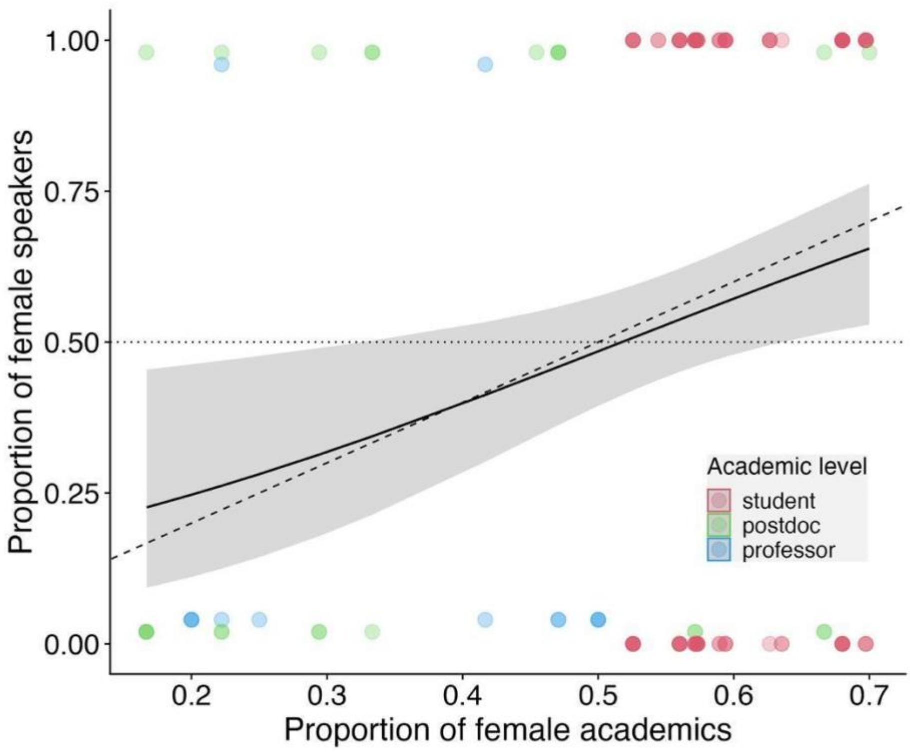

Figure 3. Predictions of the proportion of female speakers according to the proportion of female academics at the Graduate Program in Ecology (PPGE-USP) population. The solid black line is the predicted relationship from the best-fitting model (Table S1), and the shaded area indicates a 95% confidence interval of the estimates. The dashed line indicates the 1:1 relationship between the proportion of female academics and the proportion of female speakers per year and academic level. Dots represent the 136 talks of females (1) and males (0), and the proportion of female academics according to the speaker's academic level (colors), which are different for each year (not shown). We created little displacement in the y-axis around zeros and ones to better show the data for each academic level.

Table 1: Model selection results for (a) the proportion of female speakers according to academic level and affirmative actions; (b) the audience (number of attendants in the seminar) according to the gender of the speaker, the academic level, and affirmative actions; and (c) the audience of professors according to the gender, productivity index and affirmative actions. All sets of models include year as random intercepts (not shown). For (b), we are presenting only the models with weights above 0.01. Equally plausible models (dAIC <2) are in bold. Asterisks between predictors mean the model includes the predictors` main effects and the interaction between them.

Models	AIC	dAIC	df	weight
a) Proportion of female speakers (N=320)				
~ academic level * affirmative actions	**422.53**	**0.00**	**7**	**0.53**
~ academic level	**423.56**	**1.03**	**4**	**0.32**

~ academic level + affirmative actions	425.08	2.55	6	0.15
~ NULL	440.30	17.77	3	0.00
~ affirmative actions	441.18	18.65	4	0.00
b) Audience (N=298)				
~ gender * academic level + affirmative actions	**2160.03**	**0.00**	**9**	**0.45**
~ gender + academic level + affirmative actions	**2161.43**	**1.41**	**7**	**0.22**
~ gender * academic level	2161.27	2.24	8	0.15
~ gender + academic level	2163.49	3.47	6	0.08
~ gender + academic level * affirmative actions	2166.62	3.95	9	0.06
~ gender * academic level * year	2167.07	6.59	14	0.02
c) Audience for professors' speakers (N=87)				
~ gender + productivity index + affirmative actions	**691.32**	**0.00**	**6**	**0.60**
~ gender * productivity index + affirmative actions	**692.95**	**1.64**	**7**	**0.27**
~ productivity index + affirmative actions	695.04	3.73	5	0.09
~ gender + affirmative actions	696.94	5.62	5	0.04
~ affirmative actions	702.13	10.82	4	0.00

Speaker gender differences in the seminars audience

We found that male professors had the largest audience on average for their talks (Figure 4a, Table S2). The two equally plausible models for the audience (Table 1b) included gender, academic level, and affirmative actions as predictors, with the difference that the best-fitted model included an interaction of gender and academic level (conditional $R^2 = 0.22$, marginal $R^2 = 0.18$, Figure 4a). For both models, (1) male speakers had, on average, a larger audience than female speakers, (2) the higher the academic level, the larger the audience, and (3) affirmative actions increased the audience of the seminars. According to the best-fit model, male professors' talks had, on average, 1.4 times the audience size of female professors' talks (predicted values from the model: before affirmative action - 27 and 19 attendees, respectively; after affirmative action - 34 and 24 attendees, respectively).

For the subsequent analysis of professors' talks (N=87), the PCA results (Figure 4b) show that career length and productivity metrics for professors were highly correlated with the first axis (52% of variance explained), while the institution indexes composed the second PCA axis (21% of variation explained). In general, male and female professors did not show multivariate differences in career length and productivity metrics.

To explain the professor's audience, we used the first PCA axis as a proxy of productivity (Figure 4b). As expected, professors' audience increased with productivity for both equally plausible models (Table 1c). However, male professors still had, on average, an audience 1.4 times higher than female professors regardless of the productivity index (Figure 4c). The marginal R^2 of the best-fitted model was 0.21.

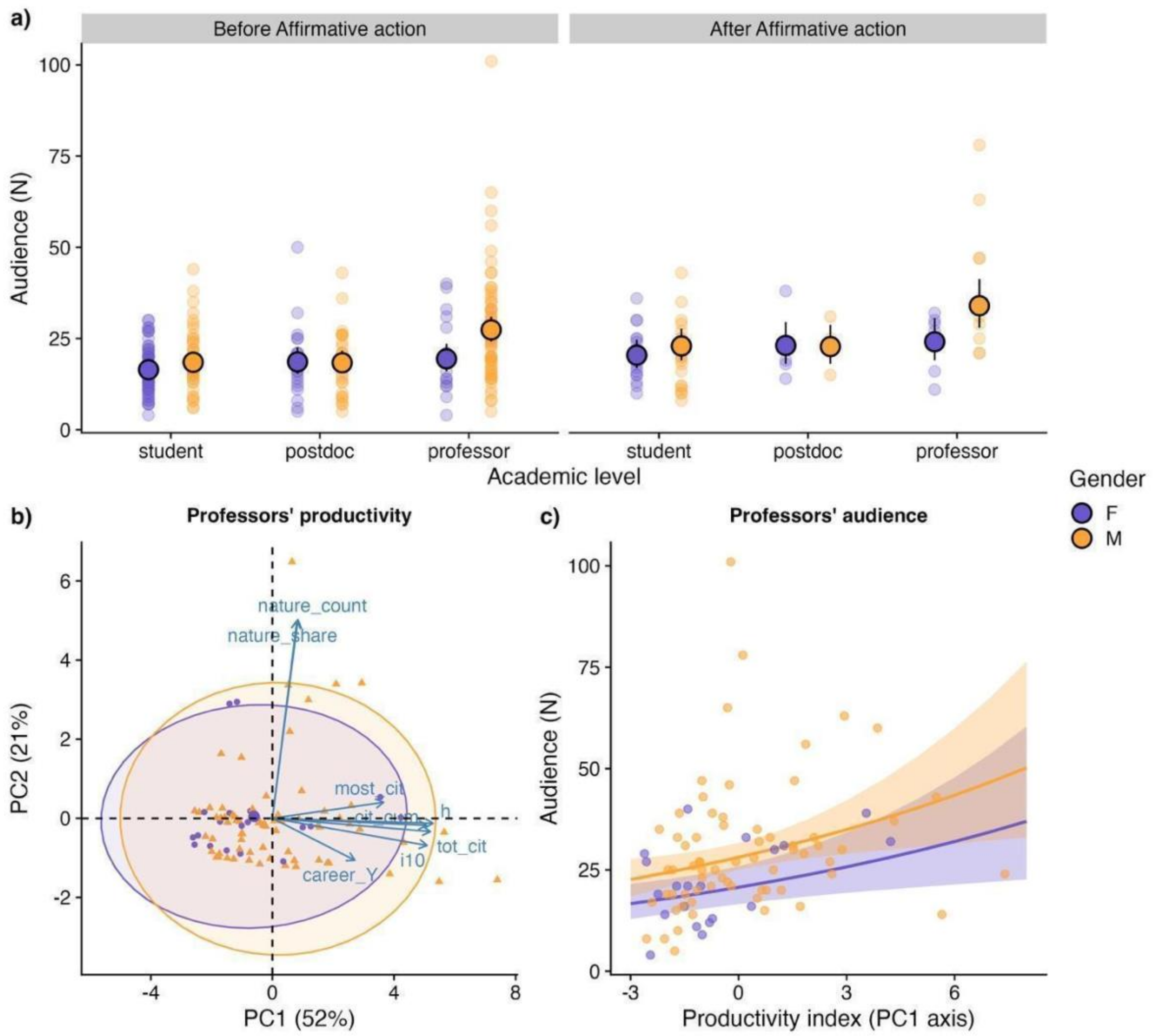

Figure 4. a) Audience (number of attendants) in seminars according to gender, academic level, and affirmative actions (before and after 2018) with the prediction (black contour circles) and confidence intervals (vertical black lines) from the best-fitted model for the audience (Table 1b). b) Principal Component Analysis (PCA) for the productivity metrics for professors and institutions (N=87); for variables code, see Table S3. c) The professor's audience analysis is based on the gender and productivity index (PCA first axis). Lines and

shaded areas represent marginal predictions and 95% confidence intervals for the estimates of the best-fitted model with additive effects of productivity index, gender, and affirmative actions. We fixed the affirmative action to ‘before’ to display the predictions because most data come from this period (N=67).

Gender differences in topics of research presentation

The frequencies of the most used words by male and female speakers were highly correlated (all data r_p = 0.87; professors r_p = 0.66), indicating that there is no clear distinction between the words used by male and female speakers in their titles and abstracts (Figure 5 all speakers, Figure S4 only professors). We found no difference in topics between male and female talks in general (Chi-square = 0.28, df =1, p-value = 0.59), neither for professors (Chi-square = 0.50, df =1, p-value = 0.48).

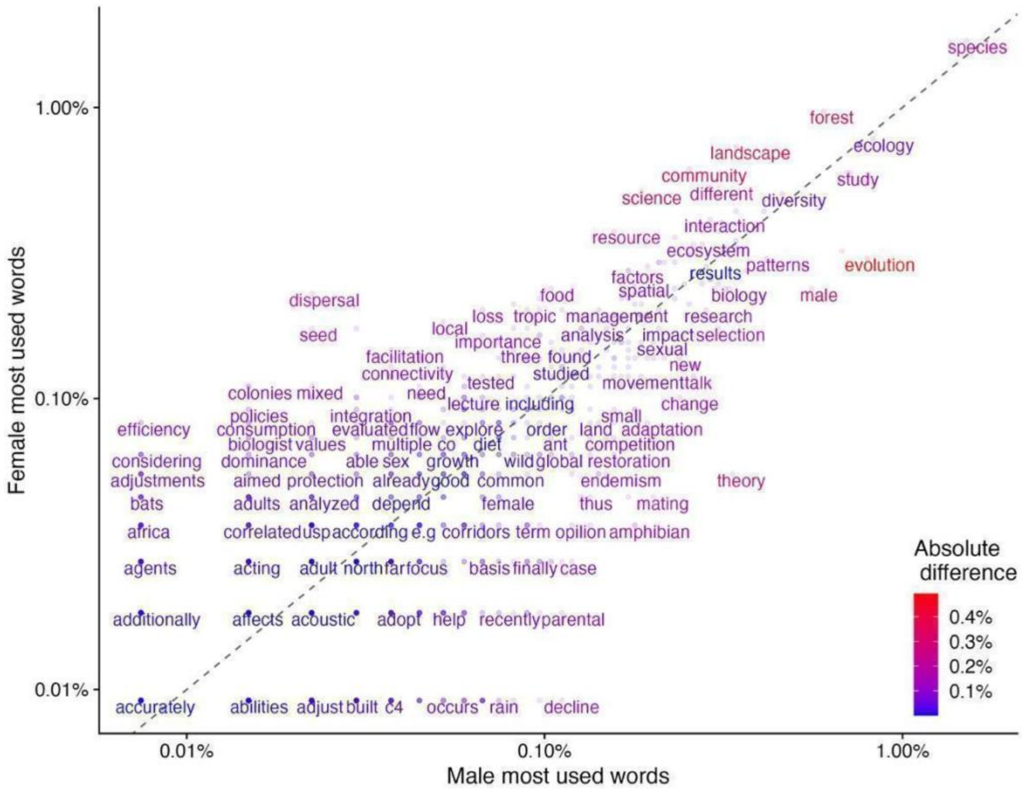

Figure 5. Frequency plot of the most used words in the titles and abstracts of the seminars given by female (y-axis) and male (x-axis) speakers. Both axes are at the logarithm 10 scale. The color scale indicates the absolute percentage differences between male and female speakers. Words with the exact same frequency were randomly assigned to display. The dashed line indicates the slope of 1; words closer to it have similar frequencies in both sets of texts The Pearson correlation between word frequencies was 0.87 for all talks (this plot) and 0.66 for professors only (Figure S4).

Discussion

Our results revealed a smaller audience in women professors' talks, suggesting a persistent lower visibility and recognition of women in an academic seminar. Although the affirmative actions successfully increased the representation of female speakers across all academic levels as expected, it did not produce a proportional increase in the recognition of women speakers (estimated through changes in audience size). The fact that female professors attract smaller audiences, even when presenting on similar topics and having comparable productivity to male professors, suggests that there may be underlying biases or cultural factors at play that we can partially attribute to the gender-science stereotype that is pervasive in the academic and non-academic communities.

To the best of our knowledge, this is the first decadal-scale study evaluating audience gender bias in a seminar series covering themes in Ecology, Evolution, and Conservation. Studies from different disciplines found contrasting results. For example, the audience size for female speakers was smaller in Philosophy (Carter et al., 2018), similar in Biology and Psychology (Carter et al., 2018), and higher in Economy (Dupas et al., 2021). However, unlike what we did, these studies did not investigate further reasons for the observed differences. Nevertheless, our study complements what was found by many other studies on gender bias in seminar and conference talks (e.g., Davenport et al., 2014, Schmidt et al., 2017, Doleac et al., 2021), showing that the culture of seminars is not gender-neutral and the audience is not blind to gender (Dupas et al., 2021). Women speakers are usually treated differently, receiving more questions in general (Davenport et al., 2014, but see Schmidt et al., 2017) and even harsher and more patronizing questions (Dupas et al., 2021). It seems unlikely that the fact that female speakers attracted smaller audiences could reflect any explicit decision by seminar attendees to treat women differently. Instead, our results may indicate a systemic bias favoring male scientists (Reuben et al., 2014, Miller et al., 2015). In this regard, the male-scientist stereotype (Mead & Metraux, 1957; Miller et al., 2015), rooted in our male-dominated culture (Young et al., 2013) and especially stronger for college-educated people (Miller et al., 2015), provides the best hypothesis to explain the academic’s willingness to attend a seminar based on the speaker's gender. Our study presents another layer of evidence of how gender-biased stereotypes still influence the visibility and recognition of women in science.

Seminars and talks are a way for academics to get feedback, disseminate their work, and expand their professional networks (Schmidt et al., 2017, Doleac et al., 2021). Similar to what happens in many other instances, the academic community's gender bias in attending talks given by women may decrease the visibility of research carried out by them, potentially impacting professional development and restricting the reach of the research. In the long run, smaller visibility and recognition of women in science perpetuates the gender productivity gap (Astegiano et al., 2019) if it does not force women to evaluate whether they have chosen the right career (Dupas et al., 2021). Therefore, it is utterly important to address the underlying cultural and systemic factors that may be contributing to the gender bias in academic speaking opportunities and audience attendance. Our results highlight the need for continued efforts to promote gender diversity and to challenge gender stereotypes at all levels of academia, while at the same time providing support and resources to women academics to succeed in their careers.

On the one hand, we found that the problem of gender bias in the audience of female speakers seems harder to address with the most common affirmative actions towards representativeness (Bird, 2011; Helitzer et al., 2017), in our case, those supporting and encouranging female speakers. On the other hand, we found that even simple changes in how committees motivate women to participate were successful in the short term. This highlights the importance of communities taking action to promote equal opportunities for women in science regardless of its forms (Bardoel et al., 2011; Bird, 2011). Moreover, we found no inherent gender bias in volunteered speakers within the academic community studied. The smaller proportion of women speakers followed the already biased gender ratio of the community across the academic levels, which is a well-known phenomenon in science (Shaw & Stanton, 2012; Dutch et al., 2012; Johson et al., 2017) . We argue that since female scientists provide positive role models for women (Young et al., 2013), attending seminars presented by a woman not only increases the scientist's visibility but may help reduce the implicit stereotype that science is masculine in the culture-at-large (Young et al., 2013). Although this positive feedback may seem hard and slow to achieve, it is crucial to increase awareness of the commonly ignored biases (Calaza et al., 2021). Addressing gender disparities in scientific events demands a more comprehensive and sustained approach.

Many different levels of affirmative actions to promote community engagement and to support inclusive, socially aware, and diverse sciences (Calaza et al., 2021, Diele-Viegas et al., 2021) are necessary to speed up the time to achieve equity and ban the skewed societal tendency to perceive scientists as an elder white man (Mead & Metraux, 1957; Miller et al., 2015). For instance, our institute organized a webinar with experts in social research to explore stereotypes, visibility, and recognition in light of our findings. We invited our community to reflect on why we put more effort into attending certain talks and not others and to pay attention to whether there may be any unnoticed bias regarding the characteristics of the speaker in this decision. We, as academics, should be able to ask ourselves the following question: If the same seminar were given by a prestigious male professor, would I attend?

While our study provides valuable insights into gender bias in academic seminars, it has limitations, such as focusing on a specific seminar series at one institution, the indirect nature of the affirmative actions implemented, and its timeframe. Moreover, a two-year range (after affirmative actions) might be too short to assess any indirect effects of affirmative actions focusing on women's representation in the audience. Our findings, however, provide a starting point to ignite discussions and more studies. For example, future research expanding the scope to encompass a broader range of institutions and disciplines could shed light on whether the phenomenon of a smaller audience for female academics is widespread or specific to some disciplines in science. Exploring the intersectionality of gender with other factors such as race, ethnicity, and geographic origin is also necessary to address ways to improve diversity in academia (Schmidt et al., 2017, Diele-Viegas et al., 2021). Since our study is observational, we also encourage experimental approaches, such as Bertrand & Mullainathan (2004) for racial discrimination in the labor market and Moss-Racusin et al. (2012) for gender discrimination in academic science. Future experimental studies could, for instance, assess the willingness to attend talks depending on the features of the speaker. By addressing these gaps, academia can continue to work towards creating a more equitable and inclusive scientific community where all voices are valued and represented.

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Data and code availability

All the data used and the analysis code produced in this study is available in the Zenodo repository https://doi.org/10.5281/zenodo.11237445 (Leite, Barreto, 2024). Names were omitted from the available dataset to preserve the speakers' anonymity.

Conflict of interest

We declare no conflict of interest relating to the content of this article.

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Supplementary material of Barreto et al. (2024)

Is the audience gender-blind? Smaller attendance in female talks highlights imbalanced visibility in academia

The proportion of female speakers in the PPGE population

We collected information on the gender balance for each academic level in the Graduate Ecology Program during the same period of the seminar series (2008-2019). We used that information to calculate the population gender ratio for each academic level to represent the speakers' pool. Over the years, women represented, on average, 61% of the graduate students (master's and doctorate), 48% of the postdoctoral researchers, and 38% of the professors (Figure S1).

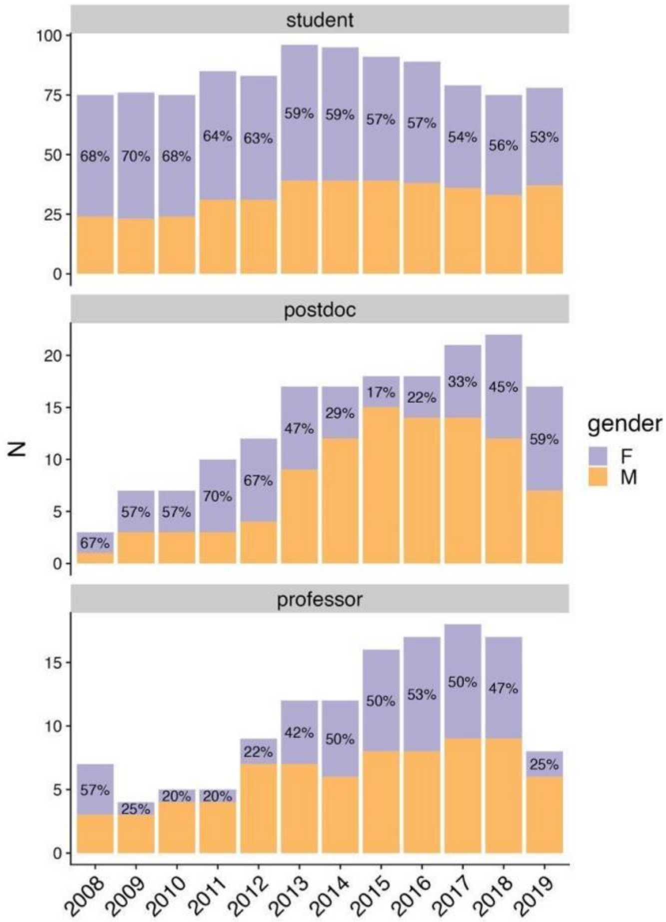

Figure S1. Gender balance per academic level and year for the Graduate Program of Ecology (PPGE-USP). This information was used to calculate the population gender ratio for each academic level and year as the source of speakers for the EcoEncontros seminar.

Graduates Program’s community subgroup analysis

Table S1: Model selection results for the proportion of female speakers with only speakers from the PPGE community according to the proportion of female academics, academic level, and affirmative actions. All models include year as random intercepts (not shown). The proportion of female academics was calculated for each academic level and year separately.

Models	AIC	dAIC	df	weight
a) Proportion of female speakers (N = 136)				
~ prop. female academics	186.43	0.00	3	0.33
~ academic level + prop. female academics	186.64	0.21	5	0.30
~ affirmative actions + prop. female academics	187.75	1.32	4	0.17
~ academic level + affirmative actions + prop. female academics	187.75	1.31	6	0.17
~ 1	192.24	5.82	2	0.02

Audience analysis: supplementary information

Table S2. Descriptive summary of the audience of talks by academic level and gender.

Academic level	Gender	N	Min	Mean	SD	Median	Max
Student	F	77	4	17.58	6.69	18.0	36
Student	M	70	6	19.83	8.20	19.0	44
Postdoc	F	23	5	19.52	10.34	18.0	50
Postdoc	M	32	5	18.97	8.78	18.0	43
Professor	F	24	4	21.54	9.78	21.0	40
Professor	M	72	5	29.51	16.46	26.5	101

Table S3. Variables used to measure the professors' productivity, career length, and institution prestige rank. Variables codes are presented in the PCA results in Figure 3b.

Variable	Code	Description
Career length	career_Y	The number of years from the first cited publication until the year of the talk
i10-index	i10	The number of papers with at least ten citations
H-index, which counts;	h	The number for papers with at least the same number of citations
Total citations	tot_cit	Total number of citations
Cumulative number of citations	cit_cum	Cumulative number of citations until the year of the talk
citations of the most cited paper	most_cit	Number of citations of the most cited paper
Nature index Count	nature_count	A count of one is to an institution or country if one or more authors of the research article are from that institution or country, regardless of how many co-authors there are from outside that institution or country
Nature Index Share	nature_share	A fractional count considers the percentage of authors from that institution and the number of affiliated institutions per article

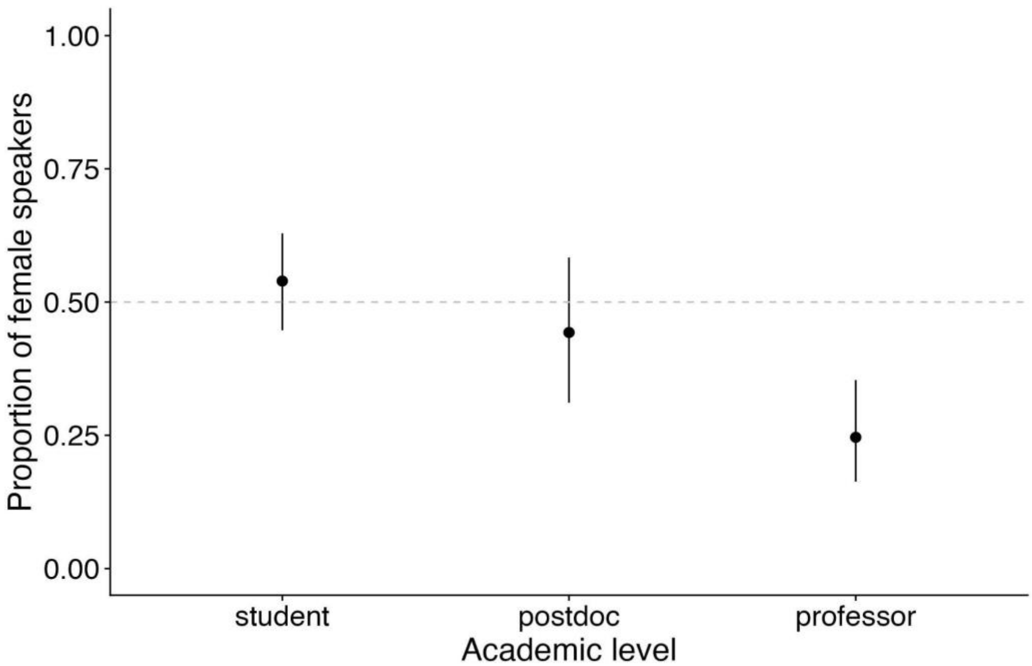

Figure S2. The proportion of female speakers per academic position of the second most plausible model (see Table 1a in the main text), which has academic position and the population gender ratio as predictors. The population gender ratio was fixed at 1 for the predictions.

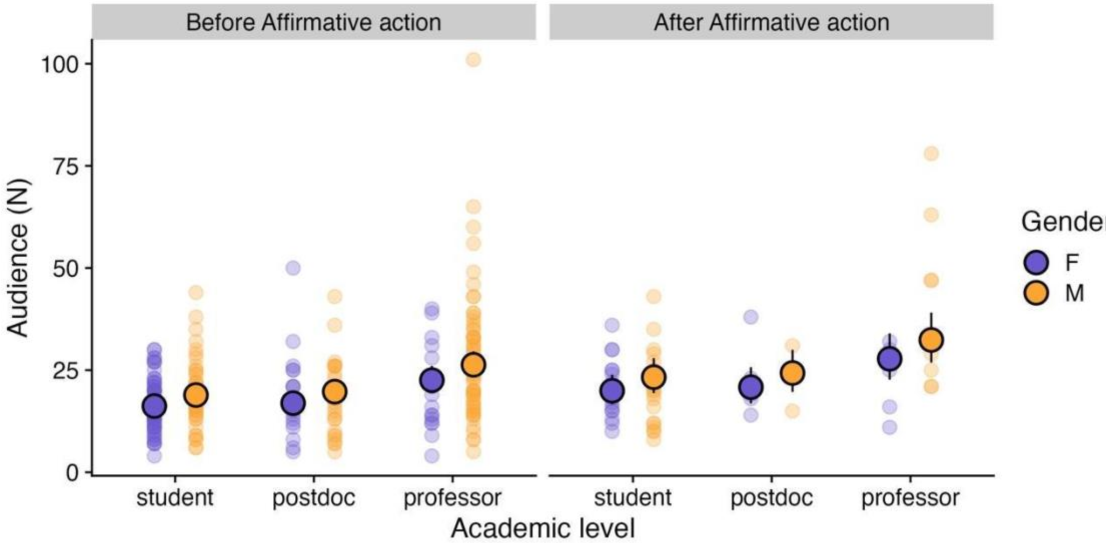

Figure S3. Audience (number of attendees) in seminars according to gender, academic position, and affirmative actions (before and after 2018) with the prediction (black contour circles) and confidence intervals (vertical black lines) from the second best-fitted model for the audience (Table 1b in the main text).

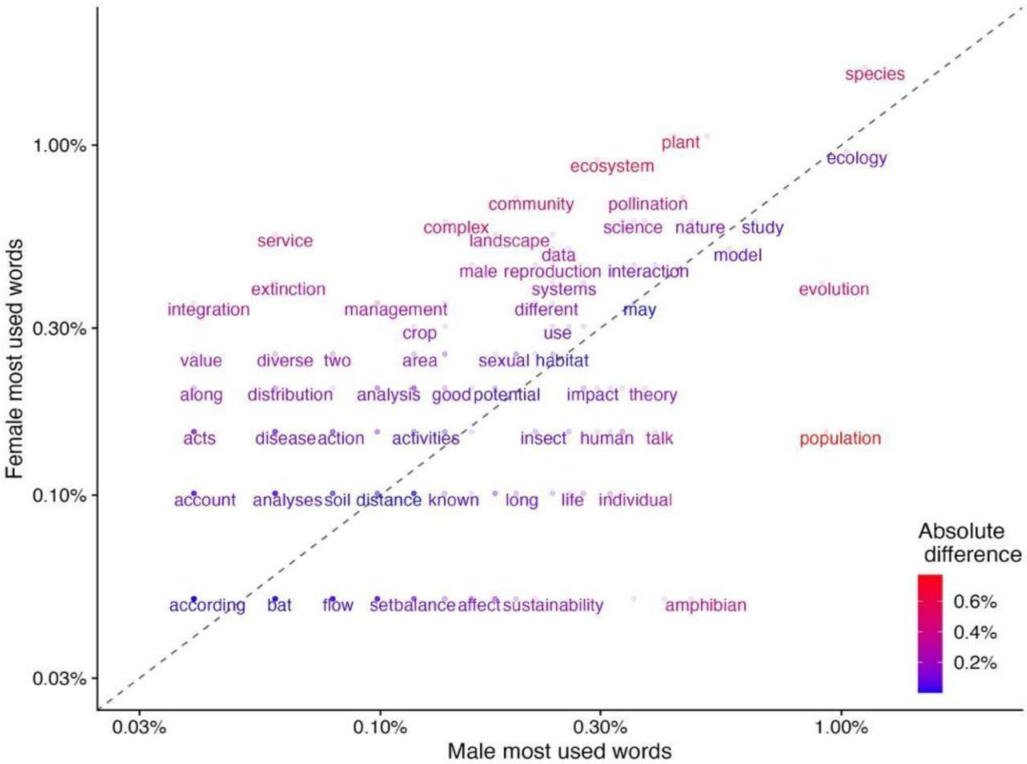

Figure S4: Frequency plot of the most used words in the titles and abstracts of the seminars given by female (y-axis) and male (x-axis) professor speakers. Both axes are at the logarithm 10 scale. The color scale indicates the absolute difference in the percentage of use between male and female speakers. Only the most common words are displayed, words with the exact same frequency were randomly assigned to display. Words that are close to the dashed line have similar frequencies in both sets of texts. The Pearson correlation between word frequencies was 0.87 for all talks (Figure 4, main text) and 0.66 for professors only (this figure).

Figure S5. Word clouds generated from the titles and abstracts of the seminars given by female (purple) and male (yellow) <u>speakers for all talks</u>. The size of each word represents its frequency in the text. The Pearson correlation between word frequencies was 0.87 for all speakers (p-value <0.001).

Figure S6. Word clouds generated from the titles and abstracts of the seminars given by female (purple) and male (yellow) <u>professors only</u>. The size of each word represents its frequency in the text. The Pearson correlation between word frequencies was 0.66 for professors only (p-value <0.001).