“To be or not to be quoted: are more diverse research teams more cited? An analysis in the social sciences”

Abstract
This study investigates whether the gender composition of research teams influences the citation performance of scientific publications in the Social Sciences. Using a dataset of 145,000 peer-reviewed articles (2010–2025), we apply topic modeling and normalize citation counts to control for publication year. We adopt a five-category typology of team gender composition, revealing that men-dominated teams receive significantly more citations than women-dominated or all-women teams. Gender-balanced teams perform similarly to all-men teams. Our findings suggest that internal gender hierarchies within teams, not diversity per se, are systematically associated with scholarly visibility.

Keywords
Gender Diversity; Research teams composition; Citations; Social sciences.

JEL Code: I23, J16, D83

1. Introduction

In recent years, the question of whether diversity fosters excellence in science has gained renewed attraction across disciplines and policymaking arenas. Gender diversity (GD) is increasingly seen not only as a normative goal, but also as a strategic asset for improving the quality, creativity, and social relevance of scientific knowledge (Valantine & Collins, 2015; European Commission, 2013). Grounded in theories of cognitive variety and social identity, scholars argue that gender-diverse teams benefit from broader repertoires of perspectives, which in turn facilitate novel problem framing, critical questioning, and innovation (Page, 2008; Wu et al., 2022). Despite this widespread expectation, empirical evidence on the relationship between gender diversity and scientific impact remains inconclusive. Some studies highlight the positive effects of diverse teams on creativity and novelty (Freeman & Huang, 2015; Griffin et al., 2021), while others report mixed or null associations with performance indicators such as citation counts (Campbell et al., 2013; Nielsen & Börjeson, 2019).

This paper addresses this gap by examining whether and to what extent the gender composition of authorship teams influences the citation impact of academic publications in the Social Sciences field. Our key research question is: *to what extent does gender composition—understood not only as diversity but also as internal balance—affect a publication’s scholarly visibility, after accounting for structural factors such as topic and publication year?*

To answer this question, we build a novel large-scale dataset of approximately 145,000 peer-reviewed articles published between 2010 and 2025 in 155 Scopus-indexed Social Science journals, enriched with journal-level metrics from Scimago Journal Rankings. The dataset includes information on team gender composition, research topic (via LDA topic modeling), and citation counts. Our empirical strategy proceeds in two steps. First, we normalize citation counts by estimating their residuals from a regression on publication year, thus adjusting for time-dependent citation patterns. These residuals are standardized (z-scores) and used as our dependent variable, representing citation performance net of temporal effects. Second, we regress these standardized citation scores on two key predictors: topic classification and authorship group typology. Importantly, we move beyond traditional binary distinctions (e.g., all-men vs. all-women vs. mixed teams) by adopting a five-category typology: (i) all-men teams, (ii) all-women teams, (iii) men-dominated mixed teams (>50% men) (iv) women-dominated mixed teams (<50% men), and (v) gender-balanced teams (50%-50%).

Our findings reveal systematic disparities. All-women and women-dominated teams consistently receive fewer citations than other team types, even after adjusting for topic and publication year. In contrast, men-dominated teams—especially within mixed-gender configurations—enjoy a significant advantage in normalized citation performance. Gender-balanced teams perform comparably to all-men teams, but not as well as men-dominated ones. These results suggest that the mere presence of diversity is insufficient to equalize outcomes; rather, internal gender hierarchies within teams are associated with distinct patterns of scholarly recognition.

This study contributes to the literature in three main ways. First, it provides a refined empirical analysis of the effects of gender diversity at the team level by employing a novel classification scheme that captures internal asymmetries within mixed-gender groups. Second, it introduces a rigorous normalization procedure to isolate citation performance from structural publication factors, such as publication year. Third, it advances the debate on gender equity in science by demonstrating that citation practices may implicitly favor men-prevalent team structures, thereby raising critical questions about bias in scholarly visibility and recognition.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on gender diversity and academic impact. Section 3 presents the dataset and methodological approach. Section 4 reports empirical findings. Section 5 discusses broader implications for research policy and academic equity. Section 6 concludes.

2. Literature review

Does GD shape scientific productivity? The existing literature on this topic is quite scarce, inconsistent, and often field specific. While some studies suggest a positive relationship between GD and research impact, others find neutral or contradictory results. These discrepancies often depend on how GD is measured, the field investigated and which dimensions of scientific productivity are considered.

Based on a systematic review of the literature, Nielsen and Börjeson (2019) found only five studies addressing GD in Science and only two out of five studies showed benefits of GD at the team level (Campbell et al., 2013; De Saá-Pérez et al., 2015). Campbell et al. (2013) found that, while women continue to be underrepresented as working group participants in Biology, peer-reviewed publications with gender-heterogeneous authorship teams received 34% more citations than publications produced by gender-uniform authorship teams. However, the positive effect of GD decreases with the share of women authors. The paper uses the share of women as an indicator for diversity. De Saá-Pérez et al. (2019) found a moderate and positive link between GD and publication rates in national scientific journals of Spain but such effect vanishes in international journals. To shed light across these inconsistencies, which use different outcomes of interest, Nielsen and Borjeson (2019) analyzed 25,000 Management papers, finding no significant relationship between GD and citation outcomes. On the reverse, their work highlights horizontal sex segregation, whereby women and men authors tend to cluster in different topical domains—women more in human-centered areas and men in technical ones—but find that diversity itself does not robustly predict citation impact. They use two different measures of diversity, including an indicator that varies with the level of representativeness of both sexes. In the same line, Nielsen et al. (2018) emphasize how the benefits of gender diversity are conditional on its degree and the type of performance measured. While acknowledging the importance of GD, Nielsen et al. (2018) argue that to realize its full potential, GD needs to be supported by careful stewardship and management techniques, i.e. the impact of GD are conditional on specific settings.

Some other papers are more optimistic, finding a positive effect of GD. Maddi and Gingras (2021) analyze over 300,000 publications in the Management and Economics field, and detect a modest advantage for mixed-gender collaborations. Despite within the same field, their results differ from that of Nielsen and Börjeson (2019), possibly due to variations in the diversity indicators used. In their work, in fact, Maddi and Gingras (2021) use a traditional indicator that accounts for gender composition of the team, distinguishing between all-men, all-women or mixed-groups. A similar indicator is used by Dion et al. (2018) who also find that increasing GD in Political Science is associated with a closing of the gender citation gap. Correspondingly, Lerback et al. (2020), studying over 91,000 manuscripts submitted to the American Geophysical Union, show that teams that are diverse in gender, nationality, and age achieve superior outcomes. However, citations are slightly lower for publications cosigned by women and men, compared to mono-gender publications. Last but not least, more recently, a paper by Yang et al. (2022) also finds that mixed-gender teams produce more novel and highly cited research compared to single-gender groups. These authors, in particular, emphasize that internal gender balance (i.e., an equal share of men and women) within teams is linked to the highest levels of citation and innovation in the Medical Sciences (Yang et al., 2022). These findings support the view that diversity not only enhances the creative process but also improves the reception of scientific outputs.

The variety of fields analyzed, as well as metrics used, suggest that results are diverse and inconclusive on the role GD plays on scholarly recognition of publications. Even when the same outcome is analyzed, like for example citation scores, the metric used to measure GD differs across studies (see for exemple Nielsen and Börjeson, 2019 and Maddi and Gingras 2021). Additionally, different papers use more complex indicators of diversity, which are continuous and such indicators are then analyzed within the framework of a regression. In general, it is difficult to generalize from the bibliometric research due to data limitations, an overreliance on descriptive analysis, and contradictory reports based on specific country or field case studies. To overcome such difficulty, our paper departs from a widely used and simple, but widely applicable, indicator based on all-men, all-women or mixed-groups (as in Maddi and Gringas, 2021) and then further decompose such indicator. There are a couple of reasons why we chose such indicator: firstly, we opted for a simpler and more stable indicator, in terms of interpretability, as compared to more complex indicators. Secondly, following Maddi and Gingras (2021) and replicating their model in the Social Sciences would allow a consistent comparison with past findings and generalizations across fields of the Social Science. However, compared to Maddi and Gingras (2021), this paper develops a more structured classification framework that captures both the presence of gender diversity and its internal configuration (see Figure 1). Our approach does not only distinguish between homogeneous and heterogeneous gender compositions but it refines the analysis to account for internal asymmetries within diverse teams. Beyond these contributions, gender differences in team dynamics and contributor roles are a topic that is understudied in bibliometric studies.

3. Analytical Framework

To assess the relationship between gender composition in research teams and scientific impact, we adopt a structured classification framework that captures both the presence of gender diversity and its internal configuration. Our approach distinguishes between homogeneous and heterogeneous gender compositions and refines the analysis to account for internal asymmetries within diverse *teams.*

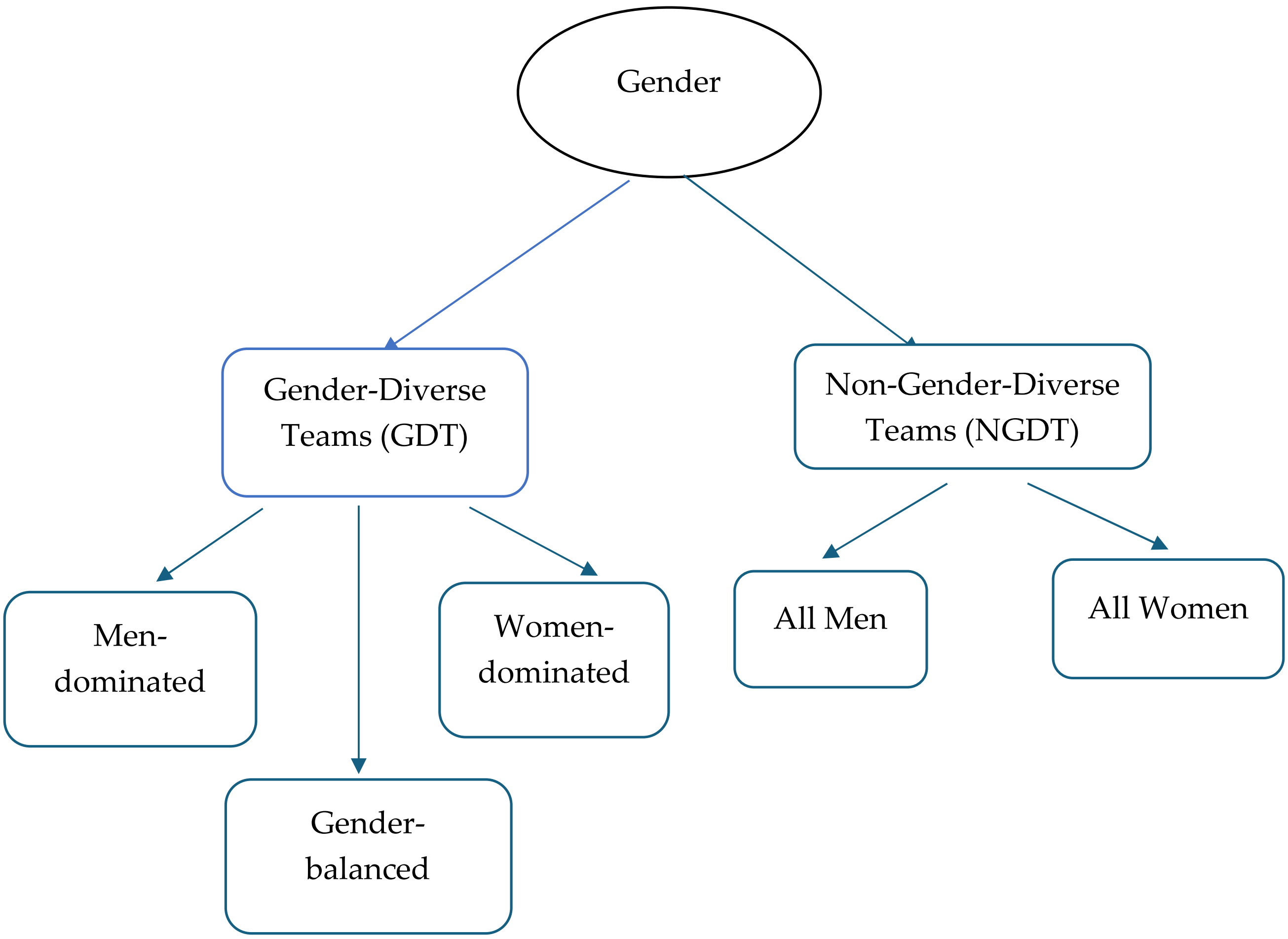
Level 1: Binary Gender Diversity Classification

At the most basic level, we classify author teams into two categories: **Gender-Diverse Teams (GDT):** Teams that include at least one member of a different gender. For instance, a predominantly men team with at least one woman, or vice versa. **Non-Gender-Diverse Teams (NGDT):** Teams composed exclusively of authors of the same gender, either all-men or all-women. This binary classification serves to identify whether the **mere presence of gender diversity** within a team is associated with differences in scientific recognition, measured via normalized citation counts.

Level 2: Full 5-Category Typology

To move beyond the binary view and capture structural asymmetries within gender-diverse teams, we construct a five-category typology based on the **share of** men **authors** in each publication: **All-**men **Teams** – Teams composed entirely of men authors (NGDT). **All-**women **Teams** – Teams composed entirely of women authors (NGDT). men**-Dominated Teams** – Mixed-gender teams in which men authors constitute more than 50% of the team. Women**-Dominated Teams** – Mixed-gender teams in which women authors constitute more than 50% of the team. **Gender-Balanced Teams** – Teams in which men and women authors are equally represented (50%-50%).

Figure 1. *A Framework for GD*



This typology allows us to assess whether different configurations of GD—not only its presence—are associated with systematic variation in scholarly impact. By disaggregating mixed-gender teams, we are able to test whether gender-balanced teams are particularly effective, or whether citation advantages are skewed toward men-dominated team structures. This framework provides the conceptual basis for both the descriptive statistics and the regression models presented in the following sections, where we control for confounding factors such as year of publication and research topic.

4. Data analysis and descriptive statistics

4.1. Dataset and variables

To build our dataset, we downloaded bibliographic metadata from Scopus, selecting peer-reviewed articles published between 2010 and 2025 in the field of social sciences. The search was limited to publications in English and published in scientific journals (excluding conferences, proceedings, and other types of documents) in order to ensure the homogeneity and quality of the data. We only included articles in the final stage of publication, i.e., those already assigned to a volume and issue number.

To narrow down the geographical context, we filtered the results based on the authors' country of affiliation, including all European Union member states. Overall, the query returned 145,000 peer-reviewed articles that met all of the above criteria.

The primary aim of this study is to investigate whether research teams composed of only men, only women, or mixed-gender groups are more likely to produce publications that receive a higher number of citations. A greater *Citation count* is interpreted as a proxy for higher scientific quality and impact. To identify the gender of the authors, we relied on the World Gender Name Dictionary (WGND 2.0) developed by Raffo (2021) and hosted on Harvard Dataverse. The WGND 2.0 links more than 26 million given names to gender information across 195 countries and territories, providing an internationally comprehensive dataset specifically designed for research applications. Based on this resource, we assigned gender to each author name in our dataset and constructed a set of dummy variables to capture team gender composition.

The analysis is based on five mutually exclusive categories of team composition: *Gender-balanced*, *Women-dominated*, *Men-dominated*, *All-women*, and *All-men* teams. This classification makes it possible to move beyond a generic view of diversity and to observe how different internal structures are associated with distinct patterns of scholarly visibility. Gender-balanced groups represent the ideal of parity but remain a minority in the dataset. Women-dominated and all-women teams, although present, tend to be associated with lower citation performance, pointing to persistent structural disadvantages. By contrast, men-dominated and all-men teams are not only more frequent but also systematically linked to higher citation counts, suggesting that academic recognition continues to be shaped by men's prevalence within collaborative settings.

To control for the quality and visibility of the journals in which the authors publish, the dataset was further enriched by merging the Scopus database with the SCImago Journal & Country Rank (SJR) dataset. This integration provides widely recognized journal-level indicators, such as the SCImago Journal Rank (SJR) score, as well as country-level metrics of scientific output. Incorporating these variables allows us to account for structural factors that may systematically affect citation outcomes, such as journal prestige, impact, and accessibility. *Open access* identifies publications that are freely available without paywalls, an aspect that can substantially enhance their visibility and, consequently, their likelihood of being cited. We also control for the prestige of the publishing outlet by including the SCImago Journal Rank (SJR) quartiles. Journals in the top quartile (*Q1*) serve as the reference category, while separate indicators capture publications appearing in *Q2*, *Q3*, and *Q4* journals. This design reflects the well-documented hierarchy of journal visibility and impact, whereby articles in lower-quartile journals generally receive fewer citations than those published in top-ranked outlets.

An additional factor that may influence citation performance is the research topic itself. Certain areas of inquiry are structurally more visible or “trendy” within the academic community and therefore attract a higher number of citations, regardless of the intrinsic quality of the work. Conversely, topics that are more specialized or peripheral to mainstream debates often receive less attention. To account for this, we examine whether all-men, all-women, or mixed-gender teams tend to focus on different research topics, which may in turn affect their citation performance.

The first part of the analysis focuses on identifying the most frequent topic in article titles. These topics serve as the basis for examining the relationship between research topics, citation performance, and the teams gender composition. The first step of the analysis is the identification of thematic structure. To this end, we applied a series of standard natural language processing (NLP) techniques to clean and prepare the textual data. Specifically, we focused on tokenizing (i.e., breaking down text into individual words or terms to enable structured analysis of language patterns and thematic content) and filtering the document titles in order to construct a high-quality document-term matrix suitable for topic modeling. The dataset was filtered to retain only entries with non-missing and non-empty titles. A corpus object was created from the cleaned titles using the quanteda package in R. The text was tokenized with punctuation and numeric characters removed. We then applied stop word removal using the standard English stop word list, excluding commonly used functional words (e.g., 'the', 'and', 'is') that do not carry topical meaning. To further refine the corpus, we manually excluded a list of high-frequency but domain-generic words such as 'study', 'analysis', 'results', 'impact', and 'model'.

These terms were deemed uninformative for distinguishing between thematic clusters, as they tend to appear ubiquitously across scientific publications regardless of topic. The resulting tokenized corpus was converted into a document-feature matrix (DFM). To reduce noise and ensure model interpretability, we applied a sparsity filter: only terms with a minimum frequency of five occurrences across the entire corpus were retained. This trimming step removed rare or idiosyncratic terms that are unlikely to contribute meaningfully to topic differentiation. Following the preprocessing phase, we applied Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to the document-term matrix constructed from the cleaned publication titles, with the goal of uncovering latent thematic structures across the corpus. LDA is an unsupervised probabilistic topic modeling algorithm that represents each document as a combination of multiple topics, and each topic as a probability distribution over words. This approach enables the discovery of hidden semantic patterns in text without prior labeling. We set the number of topics to k = 5**,** a parameter chosen based on interpretability and coherence of the resulting themes. The model estimation was conducted using Gibbs sampling, a Markov Chain Monte Carlo (MCMC) technique, with a fixed random seed to ensure reproducibility of results. For each document, LDA outputs a posterior distribution over topics (commonly referred to as the gamma vector), which quantifies the extent to which each topic is represented in that document. To assign a dominant topic label, we selected the topic with the highest gamma value, effectively classifying each document according to its most prominent theme. To facilitate interpretation of the latent topics, we extracted the top 10 terms with the highest beta values within each topic. These beta values represent the probability of a term appearing in a given topic. By analyzing these top-ranked terms, we qualitatively labeled each topic to reflect its underlying semantic content. The resulting topic labels were assigned based on the interpretative coherence of the most representative terms. The results are shown in Table 1.

Table 1. *Top 10 Terms per Topic Identified via LDA*

Topic 1 Education and Local Environmental Management	**Topic 2 Educational Systems and Organizational Sustainability**	**Topic 3 Environmental Governance and Regional Development**	**Topic 4 Urban Environment, Risk, and Public Policy**	**Topic 5 Socioeconomic Inequalities and Territorial Well-being**
data	European	development	urban	education
social	social	public	environmental	economic
learning	management	students	social	European
students	education	climate	policy	land
change	performance	performance	learning	social
water	quality	change	water	learning
energy	sustainable	environmental	research	health
local	learning	Italy	risk	policy
management	design	perspective	teachers	energy
development	development	models	age	conditions

4.2. Descriptive statistics

At this stage, we aim to investigate whether there is a gender preference in relation to the topics studied. Table 2 reports the share of all-men, all-women, and mixed-gender author groups by topic.

Table 2: *Distribution of Gender Group Typologies Across Topics*

Topic	Group typology	Share by group typology (%)
1	Mixed-gender	54.2
1	All-women	12.9
1	All-men	32.9
2	Mixed-gender	54.3
2	All-women	13
2	All-men	32.7
3	Mixed-gender	56.5
3	All-women	12.6
3	All-men	30.9
4	Mixed-gender	53.8
4	All-women	14.3
4	All-men	31.9
5	Mixed-gender	54.1
5	All-women	13.3
5	All-men	32.5

As shown in Table 2, the share of papers authored by all-men groups ranges from 31% to 33%, while the share of all-women groups ranges from 12.6% to 14.3%. Approximately half of the publications are authored by mixed-gender teams, but the proportion of single-gender groups is significantly higher in the case of men. Table 2 also reports the share of each topic by GD indicator, i.e. Topic 1 is represented in papers that are 54.2% of the cases of mixed gender, while in 12.9% of the cases in all-women etc. The relative proportion is qualitatively comparable across topics, suggesting that topics are not specific to any gender group.

Finally, Table 3 reports the average number of citations by group typology and topic. It presents the average number of citations received by publications, disaggregated by topic and the gender composition of the authoring teams (all-women, all-men, or mixed-gender).

Table 3. *Mean Number of Citations by Topic and Gender Composition of Research Teams*

Topic	Group typology	Mean Number of Citations
1	Mixed-gender	24.1
1	All-women	19.1
1	All-men	25.3
2	Mixed-gender	24.3

2	All-women	20.5
2	All-men	26.8
3	Mixed-gender	24.7
3	All-women	19.3
3	All-men	27.2
4	Mixed-gender	24.8
4	All-women	20.1
4	All-men	27.6
5	Mixed-gender	22.8
5	All-women	18.1
5	All-men	25.5

Across all five topics, all-men teams consistently receive the highest mean citation counts, followed by mixed-gender teams, while all-women teams receive the lowest. This pattern suggests a systematic citation gap that persists across different research themes, indicating that gender composition may interact with citation dynamics beyond topic choice alone. Notably, the difference in citation averages between all-women and all-men teams is particularly pronounced in Topics 3 and 4, where the gap exceeds 7 citations on average.

To gain a more granular understanding of gender composition within authorship teams, we further disaggregated the "mixed-gender" category into three subtypes: gender-balanced (approximately equal representation of men and women), women-dominated (more than 50% women), and men-dominated (more than 50% men). While mixed-gender teams account for the largest share across all topics (ranging from 53.8% to 56.5%), this aggregate category conceals important internal heterogeneity. The results are depicted in Table 4.

Table 4: *Detailed Distribution of Author Gender Composition by Topic, Including Mixed-Gender Subtypes (%)*

Topic	**Group typology**	**Share by group typology**
1	Gender balanced	14.96
1	Women dominate	13.25
1	Men dominate	24.9
1	All-women	13.18
1	All-men	33.72
2	Gender balanced	14.98
2	Women dominate	13.62
2	Men dominate	24.58
2	All-women	13.3
2	All-men	33.52
3	Gender balanced	14.77
3	Women dominate	14.87
3	Men dominate	25.78

3	All-women	12.92
3	All-men	31.65
4	Gender balanced	15.55
4	Women dominate	13.94
4	Men dominate	23.24
4	All-women	14.65
4	All-men	32.63
5	Gender balanced	14.75
5	Women dominate	14.44
5	Men dominate	23.84
5	All-women	13.64
5	All-men	33.33

Table 4 presents the detailed distribution of author gender composition across the five identified research topics, disaggregating the mixed-gender category into three subtypes: gender-balanced, women-dominated, and men-dominated, alongside the traditional all-women and all-men configurations. Across all topics, all-men teams consistently account for the largest share, ranging from 31.65% to 33.72%, followed by men-dominated mixed-gender teams (23–26%). Gender-balanced teams represent a stable but comparatively smaller share (approximately 14.7%–15.6%), and women-dominated teams remain the least common subtype within the mixed-gender category, hovering between 13.2% and 14.9%. The share of all-women teams is also limited, varying from 12.9% to 14.7% across topics. This distribution reveals a persistent asymmetry in team composition, with men-prevalent configurations—either exclusively men or men-dominated—constituting the majority of author groups**.** By contrast, gender-balanced and women-majority teams are underrepresented across all thematic clusters. These patterns underscore the importance of moving beyond binary gender classifications when analyzing collaboration structures, as aggregate categories like "mixed gender" may mask significant gender imbalances within teams.

Table 5: *Mean Number of Citations by Topic and Gender Composition of Research Teams*

Topic	**Group typology**	**Number of Citations**
1	Gender balanced	25.3
1	Women dominate	19.4
1	Men dominate	25.9
1	All-women	19.1
1	All-men	25.3
2	Gender balanced	24.5
2	Women dominate	19.9
2	Men dominate	26.7

2	All-women	20.5
2	All-men	26.8
3	Gender balanced	23.3
3	Women dominate	19.2
3	Men dominate	28.6
3	All-women	19.3
3	All-men	27.2
4	Gender balanced	25.4
4	Women dominate	19.5
4	Men dominate	27.5
4	All-women	20.1
4	All-men	27.6
5	Gender balanced	22.3
5	Women dominate	18.6
5	Men dominate	25.7
5	All-women	18.1
5	All-men	25.5

To deepen our understanding of how team gender composition relates to citation impact, we compare two levels of aggregation: a tripartite classification distinguishing all-women, all-men, and mixed-gender teams (Table 3), and a more refined typology that disaggregates the mixed-gender category into gender-balanced, women-dominated, and men-dominated teams (Table 5). Across all topics, the tripartite classification in Table 3 reveals a consistent pattern: all-men teams receive the highest mean number of citations, followed closely by mixed-gender teams, while all-women teams consistently receive the fewest citations. However, this aggregated view obscures substantial internal variation within mixed-gender configurations. The extended classification in Table 5 shows that, within the mixed-gender group, men-dominated teams systematically outperform other subtypes, with mean citation counts often exceeding those of gender-balanced teams and consistently surpassing women-dominated ones. For instance, in Topic 3, men-dominated teams average 28.6 citations, compared to 23.3 for gender-balanced and 19.2 for women-dominated teams. Similar gaps are observed in all other topics. Gender-balanced teams generally perform better than women-dominated ones, and in some cases (e.g., Topic 1), they match or exceed the performance of all-men teams. However, their citation levels remain lower than those of men-dominated teams across all topics, highlighting a subtle but persistent citation advantage associated with men's prevalence in team composition. These findings suggest that the apparent advantage of mixed-gender teams reported in aggregate analyses is largely driven by men-dominated configurations, while women-majority teams, whether all-women or mixed, continue to be associated with lower citation counts. This underscores the importance of using fine-grained gender typologies in scient metric research, as aggregated categories may conceal meaningful inequalities and obscure the structural dynamics that shape academic visibility and impact.

5. Empirical Investigation

To investigate the relationship between team gender composition, research topic, and citation performance, we first addressed the temporal bias introduced by publication year. Newer articles typically have fewer citations due to limited exposure time. Therefore, citation counts are inherently influenced by the time elapsed since publication: older articles generally accumulate more citations simply because they have been available longer. Consequently, comparing raw citation counts across publications from different years introduces a systematic temporal bias that can confound estimates of scholarly impact. To address this issue, we implemented a normalization procedure designed to isolate citation performance net of time effects. Specifically, we first estimated a linear regression model with the number of citations as the dependent variable and the publication year as the independent variable. The residuals from this model represent the portion of citation variation not explained by the time factor**,** thus capturing time-adjusted deviations from expected citation levels. To facilitate comparability across publications, these residuals were then standardized into z-scores**,** yielding a normalized citation metric with mean zero and unit variance. This transformation allows us to interpret citation performance in relative terms, independent of publication year, and ensures a common scale across all observations. By using this normalized citation score as the dependent variable in subsequent analyses, we can more accurately assess the association between citation outcomes and key explanatory variables such as team gender composition and research topic, without conflating these relationships with age-related citation dynamics.

$$Citation_i = \alpha + \beta_i year_i + \varepsilon_i \qquad (1)$$

where $citation_i$ is the number of citations received by publication i, $year_i$ is the publication year. To remove the linear effect of publication year on citation counts we normalize the citations:

$$Citation\_normalized_i = \widehat{\varepsilon_i} = Citation_i - \left(\hat{\alpha} - \widehat{\beta_i} year_i\right) \qquad (2)$$

To ensure that the adjusted citation metric has a mean of 0 and a standard deviation of 1, allowing for comparison across publication years we standardize the normalized citation score:

$$Citation\_zscore_i = \frac{Citation\_normalized_i - \mu}{\sigma} \qquad (3)$$

where μ is the mean of the normalized citation values and σ is the standard deviation of the normalized citation values. This transformation ensures that the adjusted citation metric has a mean of 0 and a standard deviation of 1, allowing for comparison across publication years.

Our estimation strategy has two steps. In the first stage of our analysis, we modeled the normalized citation score as a function of research topic and group typology, using a three-category classification: all-women, all-men, and mixed-gender teams. The first one aims to investigate the relationship between the citation score obtained using equation (3), the different topics using Topic 1 as baseline, and the thee groups: mixed-gender, all men and all women, the latter used as baseline:

$$Citation_{zscore_i} = \alpha + \beta_1 Topic_2 + \beta_2 Topic_3 + \beta_3 Topic_4 + \beta_4 Topic_5 + \beta_5 All\_men + \beta_6 Mixed\_gender + \varepsilon_i$$

6. Results

Descriptive statistics for all variables included in the study are reported in Table 6, which provides an overview of their distribution and key summary measures.

Table 6 summarizes the result of the empirical estimation.

Table 6. *Empirical estimation results*

Dependent variable: normalized citation metric	
Intercept	-0.085825*** (0.009037)
Topic 2	0.024969** (0.008461)
Topic 3	0.010937 (0.008432)
Topic 4	0.022107** (0.008434)
Topic 5	-0.020607* (0.008456)
Mixed-gender	0.104210*** (0.008108)
All-men	0.075799*** (0.008603)
Standard error in parenthesis	
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’	
Table 5: Linear Regression Results: Association Between Citation Performance, Research Topic, and Basic Gender Composition of Author Teams	

The regression analysis reveals that the gender composition of author teams has a strong and statistically significant association with a paper’s normalized citation impact. In Table 6, papers authored by mixed-gender teams show a coefficient of +0.104 (with p<0.001), while all-men teams have a coefficient of +0.0758 (p<0.001), both measured in relative to the all-women team baseline. These positive coefficients indicate that, holding other factors constant, publications written by mixed-gender or all-men groups tend to receive higher citation counts than those written by all-women teams. In fact, the mixed-gender effect is the largest, suggesting that gender-diverse teams achieve the highest citation impact on average. This finding is in line with prior studies showing that gender-diverse research teams produce more highly cited papers than either all-women or all-men teams. Conversely, the significantly negative baseline (intercept = –0.0858*** for an all-women team in Topic 1) underscores a known citation gap: papers with exclusively women authors generally garner fewer citations on average than those with men authors involved. Overall, the magnitude of the team composition effects (on the order of 0.08–0.10 in normalized citation units) is substantial – far exceeding any single topic's influence – highlighting that who composes the author team is a key predictor of research impact in this dataset. Table 6 also shows that the research topic (thematic area of the paper) significantly affects citation performance. Using Topic 1 as the reference category, two topic dummies exhibit positive and significant coefficients. Topic 2 has a coefficient around +0.02497 ($p<0.01$) and Topic 4 about +0.02211 ($p<0.01$). This means papers classified under Topic 2 or Topic 4 tend to receive moderately higher citations compared to Topic 1, all else being equal. By contrast, Topic 5 shows a negative coefficient of roughly –0.02061 ($p<0.05$), indicating a slight citation disadvantage for papers in that topical category relative to Topic 1. Topic 3 has a small positive coefficient (+0.01094) that is not statistically significant, suggesting its citation impact is on par with the reference topic. These results demonstrate that not all research areas receive the same citation attention – some topics yield systematically higher citation counts, while others may lag behind. This pattern is consistent with evidence that publications in certain fast-growing or popular research topics enjoy a citation advantage over those in slower-growing areas. In summary, even after normalizing for overall field differences, there remain discernible citation disparities across topics, underscoring the importance of controlling for subject area in citation impact analyses.

The second step of our analysis explores whether the gender composition of research teams is associated with differential citation outcomes, once we account for topical variation and publication year. We extend the conventional binary classification of gendered authorship (men-only vs. women-only vs. mixed) by introducing a finer-grained taxonomy: mixed-gender teams are now disaggregated into *men-dominated* (more than 50% men), *women-dominated* (less than 50% men), and *gender-balanced* (exactly 50% men and women). This allows us to distinguish whether the relative share of men and women contributors within a team is linked to differential scholarly recognition (Table 7).

Table 7. *Linear Regression Results: Association Between Citation Performance, Research Topic, and Basic Gender Composition of Author Teams*

Dependent variable: normalized citation metric	
Intercept	-0.00372
	(0.008725)

Topic 2	0.025296**
	(0.008457)
Topic 3	0.01135
	(0.008429)
Topic 4	0.023286**
	(0.008432)
Topic 5	-0.019597*
	(0.008453)
Women dominated	-0.029158**
	(0.008735)
Men dominated	0.063759***
	(0.008735)
All women	-0.082713***
	(0.009985)
All Men	-0.0069
	(0.008295)
Standard error in parenthesis	
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’	

The regression results presented in Table 7 provide statistically robust evidence that both research topic and the detailed gender composition of research teams are systematically associated with variation in citation outcomes, even after adjusting for publication year. Using gender-balanced teams as the reference category, the model reveals a clear and consistent pattern of association between gender configuration and normalized citation performance. Men-dominated teams are associated with a statistically significant increase in standardized citation scores (+0.064, $p < 0.001$), whereas women-dominated and all-women teams are significantly penalized (−0.029, $p < 0.01$; and −0.083, $p < 0.001$, respectively). In contrast, all-men teams do not differ significantly from gender-balanced teams (coefficient = −0.0069, $p > 0.1$), suggesting that the citation advantage is specific to men-dominated mixed-gender teams, rather than to men-only authorship per se. The size of the coefficients reinforces the substantive relevance of these effects. The citation disadvantage for all-women teams is not only statistically significant but also nearly equivalent in magnitude—though in the opposite direction—to the advantage observed for men-dominated teams (+0.064 SD). The difference between these two configurations amounts to over 0.14 standard deviations, reflecting a nontrivial gap in citation performance associated with team gender structure.

Topic effects are also statistically significant in three of the four topic dummies. Compared to Topic 1 (the reference), papers classified under Topic 2 and Topic 4 show small but significant positive effects (+0.025 and +0.023, respectively, $p < 0.01$), while Topic 5 is associated with a modest negative citation effect (−0.020, $p < 0.05$). Topic 3 shows a positive but non-significant coefficient (+0.011, $p > 0.1$), suggesting that its citation performance does not statistically differ from Topic 1 after controlling for author gender composition and publication year. The intercept, which captures the expected normalized citation score for an all-women team publishing in Topic 1, is near zero and statistically non-significant (−0.0037, $p > 0.1$), indicating that deviations from this baseline are fully accounted for by the included predictors.

While this model highlights relevant disparities in citation outcomes across gendered team configurations and research fields, it does not yet account for critical journal-level characteristics that may systematically influence citation performance. In particular, journal prestige and accessibility are two well-established drivers of academic visibility and citation frequency (Larivière et al., 2015; Wang et al., 2016). Ignoring these structural attributes may obscure or inflate the observed effects of gender composition, especially if certain team types are disproportionately published in lower-impact or pay-walled venues. To address this issue, we expand our model by incorporating two additional covariates. The first one is the SJR quartile rank**,** a widely recognized proxy for journal prestige and disciplinary influence, and the second one is a binary indicator for Open Access availability**,** which captures whether articles are freely accessible to readers without paywalls. The inclusion of these controls allows us to assess whether gender-based citation gaps persist once journal visibility and dissemination mode are taken into account. From a theoretical standpoint, this adjustment is essential: if women or mixed-gender teams are systematically underrepresented in high-impact or open-access journals, failure to control for these dimensions could conflate structural barriers with behavioral outcomes. Moreover, from a policy perspective, accounting for journal-level factors enables a more precise identification of where inequities arise—whether at the level of collaborative team dynamics, institutional publishing practices, or structural dissemination constraints. By integrating these variables, we move closer to an analytically robust understanding of how gender, research content, and publishing context interact to shape academic recognition. This refined model provides a firmer foundation for evaluating whether observed gender disparities in citation outcomes reflect differences in research quality and visibility—or whether they instead point to underlying biases in the academic reward system. The results are depicted in Table 8:

Table 8. *Results of the adjusted model*

Dependent variable: normalized citation metric		
	Model 1	Model 2

Intercept	0.238074*** (0.010064)	0.266304*** (0.008474)
Topic 2	0.010548 (0.008296)	0.01788* (0.008301)
Topic 3	0.013303 (0.00827)	0.013447 (0.008272)
Topic 4	0.005928 (0.008277)	0.006595 (0.008279)
Topic 5	-0.00872 (0.008295)	-0.01343 (0.008296)
Women dominated	-0.00118 (0.009731)	
Men dominate	0.064664*** (0.008579)	
All women	-0.056203*** (0.009806)	-0.085295*** (0.007972)
All Men	-0.01113 (0.008144)	-0.040409*** (0.005813)
Open Access -	0.101641*** (0.0054)	0.102207*** (0.005397)
Q4	-0.519515*** (0.007458)	-0.519993*** (0.007457)
Q3	-0.421121*** (0.007558)	-0.422664*** (0.007547)
Q2	-0.252563*** (0.007427)	-0.519993*** (0.007457)
Standard error in parenthesis		
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’		

Table 8 compares two linear regression models aimed at explaining variation in normalized citation scores across articles. Both models control for research topic, Open Access status, and journal quality (proxied by SJR quartile rank), but differ in how they classify the gender composition of research teams. Model 2 uses a three-category typology: all-women, all-men, and mixed-gender teams while Model 1 adopts a finer-grained five-category typology: all-women, all-men, women-dominated, men-dominated, and gender-balanced teams. This design allows us to assess whether more detailed classifications offer additional explanatory insight into gendered citation dynamics. The results show that Open Access publication is robustly associated with higher citation scores (+0.102, $p < 0.001$), reaffirming the role of dissemination mode in amplifying research visibility. Journal SJR quartile exerts a powerful effect: relative to Q1 journals (baseline), publishing in Q2, Q3, or Q4 is associated with a stepwise decline in citation performance, with Q4 articles experiencing the steepest drop

(−0.520, $p < 0.001$). This gradient reflects the well-documented influence of journal prestige on citation accumulation. The comparison of the two models provides compelling evidence that the structure of gender composition within research teams meaningfully shapes scholarly visibility, even after adjusting for topical content and journal characteristics. The stronger explanatory power and sharper distinctions obtained in the five-group specification support the adoption of more nuanced gender taxonomies in bibliometric research. Notably, the citation penalty for all-women teams persists and even deepens in the five-group model, while the advantage is concentrated in men-dominated, not all-men, teams, suggesting that citation dynamics may be influenced not only by gender representation per se, but also by gendered power configurations within collaborative teams. These findings underscore the need for more fine-grained, intersectional metrics in scientometrics and for greater attention to how gendered team structures interact with structural factors like journal prestige and accessibility to shape academic recognition.

7. Conclusion

This study contributes to the growing body of research examining gender disparities in academic publishing by focusing on how the gender composition of research teams influences scientific visibility, measured through normalized citation performance. Using topic modeling to control for thematic differences and z-score transformation to account for temporal citation trends, we introduced a refined typology of team composition. By disaggregating the "mixed-gender" category into men-dominated, women-dominated, and gender-balanced configurations, we provide a more nuanced perspective on how gendered team dynamics shape recognition in science.

Our results show that both research topic and team gender composition significantly predict normalized citation outcomes. Specifically, men-dominated teams enjoy a clear citation advantage, while women-dominated and all-women teams face consistent disadvantages, even after adjusting for publication year and subject area. Interestingly, all-men teams do not significantly differ from gender-balanced teams, suggesting that it is not men's exclusivity, but rather men's dominance in team dynamics, that drives citation advantage.

These findings reinforce prior evidence of gender-based disparities in scholarly recognition (Larivière et al., 2013; Caplar et al., 2017; Wang et al., 2021), and extend it by demonstrating that not all forms of gender diversity function equivalently. Moreover, by employing a methodological framework that integrates topic modeling, normalized citation metrics, and a granular classification of gendered collaboration, this study overcomes key limitations of previous research relying on raw citation counts and binary gender metrics. In line with recent work on gendered credit attribution in team science (Murray et al., 2019; Ross et al., 2022), our results highlight the importance of internal compositional asymmetries—not just gender presence, but power distribution within teams.

Broadly, this study supports the view that structural and cultural forces within academia continue to shape recognition and reward mechanisms in gendered ways. As Holman et al. (2018) note, *“gender equity in science remains elusive and progress is glacial”* (p. 12). The observed disadvantages experienced by women-dominated teams suggest that visibility in science is not only a matter of producing high-quality research, but also of navigating power-laden collaboration structures where masculine-coded team configurations are more likely to be perceived as authoritative and citable.

Therefore, addressing gender inequalities in scientific publishing must involve more than increasing women representation in authorship. It requires a critical examination of how gender hierarchies are reproduced within collaborative contexts and how current recognition systems (e.g., citations, authorship credit, reviewer perceptions) systematically reward men-dominated formations. Without such structural interrogation, academic meritocracy risks perpetuating the very inequities it claims to transcend.

In conclusion, this research underscores the need for interventions that are not merely inclusionary but transformative—ones that rethink collaborative norms, dismantle internal hierarchies, and promote epistemic justice in how scholarly impact is assessed and rewarded.

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