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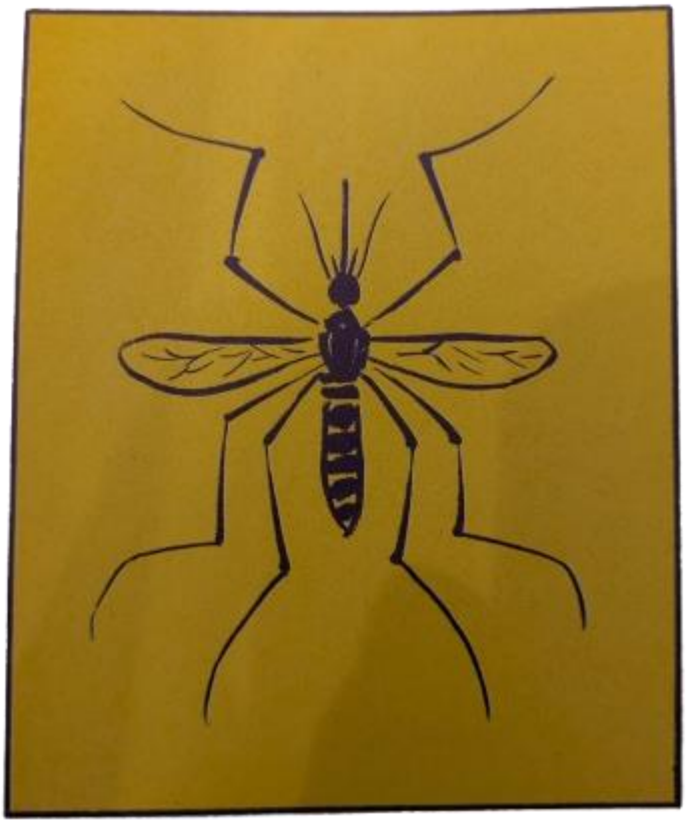

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Cover photo from the graphic novel from 2009 Asterios Polyp, by David Mazzucchelli. All rights reserved. The author creatively combines different drawing styles, panel structures and color palettes to represent different forms of diversity: opinions, perspectives, situations and temporal moments.

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# The use of informetric methods to study diversity in the scientific workforce: A literature review

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## Abstract
This literature review examines the application of informetric methods to assess diversity within the scientific workforce, focusing on recent advances in author name disambiguation, researcher profiling, and the evaluation of individual-level metrics. The study traces the evolution of quantitative approaches, from traditional productivity metrics to modern multidimensional models that incorporate contextual factors such as career trajectory, research practices, and social engagement. Emphasizing methodological innovations, the review explores the potential of advanced algorithms and new data sources (e.g., OpenAlex, ORCID) to offer a nuanced understanding of diversity in science. The review highlights gaps in the current literature, particularly the need to account for diverse individual characteristics, including gender, ethnicity, and team dynamics, and suggests pathways for future research. The findings contribute to ongoing discussions in the field of scientometrics regarding responsible research assessment and the development of equitable evaluation frameworks.

## Keywords
Diversity in scientific workforce, Scientometrics, Informetric methods, Gender and ethnicity in academia, Research evaluation

## 1 INTRODUCTION
Since Lotka's first study on productivity inequality (Lotka, 1926) and De Solla Price's law on the exponential growth of science (Price, 1963), interest in quantitatively analyzing researchers' activity has been constant (Dietz & Bozeman, 2005). This interest was originally rooted in the sociology of science and its attempts at understanding its social stratification (Cole, 1973; Crane, 1972; Merton, 1973). Soon after Garfield launched the Science Citation Index, Merton and Zuckerman saw the value of these data to empirically test many of the theoretical developments in the field (Wouters, 1999, pp. 110–111). But scientometrics shifted towards research assessment in the late 1980s (Abbott et al., 2010; Gingras, 2020). Its robustness for analyzing individual performance was often seen as limited and inadequate (Wouters et al., 2013) and historically, scientometricians have cautioned against relying only on quantitative metrics to evaluate scholars, since individual characteristics and the effect of small numbers can distort the outcomes (Moed, 2005, p. 54), the users of the metrics may ignore

the policy context in which they are applied (Robinson-Garcia & Ràfols, 2020), or may not make a responsible use of the metrics (Hammarfelt & Rushforth, 2017).

Excessive focus on performativity has led academics, practitioners and decision-makers to question efforts to quantify researchers' activity (Benedictus et al., 2016; Haddow & Hammarfelt, 2019; Pardo-Guerra, 2022), fueling a renewed debate on responsible research assessment (RRA) that criticizes prioritizing productivity over quality, social engagement, open practices, and the socio-economic impact (Pontika et al., 2022). International initiatives such as the San Francisco Declaration on Research Assessment (DORA) in 2012 or the most recent Coalition for Advancing Research Assessment (CoARA) in 2022 reflect this re-examination. According to Ràfols (2019), one reason for the misuse of quantitative metrics is the framing "in purely technical terms, paying scant attention to its context and use" (p. 8). The main concern is that indicators based on publications and citations have been inappropriate and counterproductive for the scientific community, masking the potential of scientometric methods.

Over the last decades, refinement in data processing and methodological innovation has offered new opportunities for contextualizing individual performance (Torres-Salinas et al., 2023). Advances such as machine learning algorithms, improved bibliographic metadata, and new data sources (e.g., OpenAlex, Altmetric, ORCID, Overton), have expanded the field's capabilities. Scientometric methods can now track career trajectories (Jurowetzki et al., 2021; Moed et al., 2013; Robinson-Garcia et al., 2019), study gender bias in science (H. Boekhout et al., 2021; Huang et al., 2020; Larivière et al., 2013) or analyze scholars' engagement on social media (Costas et al., 2020), among other areas. These recent developments have substantially changed the potential and relevance of scientometric and informetric methods to understand the role and importance of the individual scholar in the knowledge production enterprise. In this review we want to provide a contemporary reflection on such developments, their potential and their challenges.

## 2 OBJECTIVES AND SCOPE

This review aims at examining the recent development of author-level metrics focused on exploring the conditions under which science is produced. It covers over 250 studies from over a century from which around 80% were published in the last two decades. There are many other reviews with a similar focus, although they focus around performance and output. This review addresses multiple facets of the scientific workforce which can serve to understand and inform on the activities, roles and conditions which shape scientists' performance, key to understanding how scientometrics can contribute to our knowledge of diversity within the scientific workforce. This review aims to fill these gaps, offering a more nuanced understanding of the diversity within the scientific workforce and the tools available to study it.

To do so, we have identified the following areas of interest which structure this review: data sources and author identification, individual characteristics of researchers (e.g., gender, nationality), context (e.g., funding, trajectory) and team dynamics (e.g., collaboration, author order). Table 1 summarizes the focus areas of a selection of reviews which to some extent touch upon the use of scientometric methods applied to the scientific workforce. These reviews were identified and selected because they directly addressed either in their title or abstract, individual scientometric analysis. They focus on issues such as author-level metrics and their performative roles in measuring research productivity and impact (Alonso et al., 2009; Mering, 2017; Waltman, 2016). De Rijcke et al. (2016) and Gauffriau (2021), also consider team dynamics and collaboration patterns, although the former from a policy perspective, while the latter from a methodological viewpoint. Context is only considered by de Rijcke et al. (2016) and (Martín-Martín et al., 2018), although again from different perspectives, with the latter looking more into behavioral aspects influenced by social media. However, there remains a significant gap in addressing the role of disambiguation algorithms and the recent methodological advances for studying individual characteristics like gender and nationality, as well as contextual factors such as career trajectory and research practices.

Table 1. Comparison between bibliometric reviews related with individual-level metrics and diversity

| Reference | Author Focus | Performativity | Context | Individual characteristics | Team Dynamics | Author algorithms |
|---|---|---|---|---|---|---|
| Alonso et al., 2009 | ✓ | ✓ | | | | |
| de Rijcke et al., 2016 | ✓ | ✓ | ✓ | | ✓ | |
| Gauffriau, 2022 | ✓ | ✓ | | | ✓ | |
| Martín-Martín et al., 2018 | ✓ | ✓ | ✓ | | | |
| Mering, 2017 | ✓ | ✓ | | | | |
| Waltman, 2016 | ✓ | ✓ | | | ✓ | |
| Wildgaard et al., 2014 | ✓ | ✓ | | | ✓ | |
| Wildgaard, 2019 | ✓ | ✓ | | | | |

The review is divided into four sections. Section 3 examines changes related to data sources, which have been key for the development of the field and the exploration of new methods and venues. It focuses on two specific aspects: 1) improvements in author name disambiguation algorithms and 2) the expansion of author profiles. The next three sections look into different components which affect the conditions under which research takes place. Section 4 examines methods developed to study individual characteristics of the scientific workforce such as gender, career length or nationality. Section 5 focuses on measuring contextual variables related to individuals such as career trajectory, research practices, funding or social outreach. Section 6 examines methods to study team dynamics and the roles researchers adopt, studied scientometrically through authorship, contribution statements or collaboration patterns. We conclude by discussing the implications and opportunities these new scientometric approaches bring to the fields of sociology of science, research policy and science of science, as well as pointing to potential gaps in the literature and future lines of inquiry.

# 3 DATA SOURCES

The development and implementation of individual level-metrics is linked to that of data sources. Their inclusion of metrics, the launch of author profiles and the improvement of the bibliographic metadata related to the authors of the publications have fostered the popularity of certain metrics and the possibilities for quantifying individuals' academic activities. Research on author name disambiguation has a long tradition within and beyond the field of scientometrics (e.g., Rodrigues et al., 2024). But due to the economic cost, infrastructure and expertise needed to develop them, their use has not expanded until data providers incorporated their own disambiguation algorithms and made public automatically populated researcher profiles.

The first milestone on the provision of author profiles and particularly author-level metrics was the introduction of author identifiers by the main bibliometric databases. New data providers such as Microsoft Academic[1], Dimensions (Visser et al., 2021) or OpenAlex[2] have also introduced their own unique author identifiers. Author identifiers and profiles have expanded the analytical potential of scientometric studies, as well as becoming a fundamental search tool for database users, evaluators, researcher managers and scientists. Here we review the main milestones on how data providers have contributed to expand the use (and misuse) of individual level metrics (Haddow & Hammarfelt, 2019), while at the same time increasing the opportunities for more detailed and fine-grained analyses. We observe three major developments: the introduction of author name disambiguation algorithms, the creation and expansion of author profiles and registries, and the introduction of researcher-level features.

## 3.1 Author name disambiguation

Author name disambiguation is a task that has historically been conducted by librarians through authority control for developing catalogs and creating author headings (Tillett, 2004). For instance, OCLC introduced in 2003 its Virtual International Authority File (VIAF) which aims at standardizing and linking author names across library catalogs and databases. This issue soon became a major concern in the field of scientometrics (Smalheiser & Torvik, 2009) due to the exponential increase of research publications and authors (Bornmann et al., 2021; Milojević et al., 2018). This situation required automating the disambiguation process of author names. In their seminal review, Smalheiser and Torvik (2009) already acknowledge the opportunities that a proper disambiguation approach could bring to the field, when indicating that "attaching a person to a set of documents is a key step towards a major breakthrough in information science" (p. 6-34). However, at the time the approaches proposed did not meet the optimal quality to fulfill such expectations. The main challenges can be summarized as follows:

- Lack of incentives to create a global author registry. Especially in the case of occasional and low productive authors (De Solla Price, 1980), who represent a large portion of the scientific workforce (Ioannidis et al., 2014).
- Technical and feasibility issues to manually curate author data in large bibliographic collections or databases.
- Challenges for assessing and validating unsupervised machine learning approaches.
- Limitations of the bibliographic metadata for allowing a comprehensive selection of features that could be used in the disambiguation process (e.g. classifications, author-affiliation linkages, author e-mails, etc.).

Issues such as linking affiliations with authors in bibliographic records, full indexing of references or the use of external information such as author registries can improve machine learning models when dealing with ambiguous author names. Author name disambiguation methods can be grouped into two categories (Ferreira et al., 2012): author grouping methods and author assignment methods. In most cases, these are all unsupervised methods. In author grouping (or clustering) methods, a given similarity function is calculated to a matrix of publications based on their bibliographic metadata (e.g.,

[1] Now to be replaced by OpenAlex (http://openalex.org).

[2] More in the OpenAlex online documentation at https://docs.openalex.org/api-entities/authors/author-disambiguation

author names, affiliations, references, e-mails, etc.), which are then clustered together. Each cluster of publications will represent a disambiguated 'author'.

This is the approach followed at the Centre for Science and Technology Studies (CWTS) at Leiden University (Caron & van Eck, 2014). It uses a rule-scoring approach in which publications sharing a high number of bibliographic elements are given a greater chance of belonging to the same individual. It groups metadata information into four groups: author data, article data, source data and citation data. Elements from each group receive different scores and then pairs of papers with high scores are matched together. Next, a clustering approach is followed to add new papers to the original pair, constituting an author's oeuvre. The algorithm favors precision upon recall. That is, when uncertainty exists, it will not group publications and assign publications to different 'authors', meaning that while there are no gaps in terms of coverage, author splits are quite common especially among East-Asian names and disciplines with hyper-authorship (Robinson-Garcia et al., 2019; Sugimoto et al., 2017, app. Supplementary Information). Tekles & Bornmann (2020) attempted to assess the performance of the CWTS disambiguation in comparison with three other approaches, concluding that it was the most effective of the four. In a different context, (Abramo & D'Angelo, 2023) discussed the differences between using external data to disambiguate names versus the algorithm when analyzing individuals' productivity at the institutional level.

Another example of author grouping methods is that developed for the Microsoft Academic Graph (MAG) (Sinha et al., 2015) and now continued in OpenAlex (Priem et al., 2022). In this case, they adopt a graph-based approach in which they examine the relationships between an array of features including author name, affiliated institutions, concepts tagged in their works, citations, coauthors, and third-party identifiers. As a validation method, they rely on the ORCID author registry (discussed below) as a golden set, helping to establish initial clusters and resolve ambiguities. The system continuously updates cluster information, giving preference to author clusters with higher matching scores. This dynamic process includes a safeguard against ORCID clashes within a cluster, ensuring consistency in names. According to the documentation provided by OpenAlex[3], up to July 2023, there are around 92 million author profiles currently within the OpenAlex database.

Author assignment methods use a probabilistic approach to determine authorship employing bibliographic metadata (e.g., likelihood of publishing in a topic, with a certain co-author, in a journal, etc.). It feeds from the library tradition, as observed from the approach followed for the VIAF, which uses a collaborative approach to author name disambiguation, integrating data from various national libraries and authority files. Although there is evidence that later they are also using group methods to better disambiguate authors (Hickey & Toves, 2014). The PubMed ID also applies an author assignment method by combining bibliographic metadata and heuristic techniques to uniquely identify authors within the PubMed database. The algorithm begins with the collection and preprocessing of detailed bibliographic data, including author names, titles, abstracts, co-authors, and affiliations. It then extracts features such as shared title words, journal names, medical subject headings, publication language, affiliations, and specific name attributes like middle initials and suffixes. Using these features, the algorithm applies heuristic rules to evaluate the likelihood that similar or identical names represent the same individual, considering contextual details from co-authors and affiliations (Liu et al., 2017).

[3] The information related to the author name disambiguation method deployed by OpenAlex was retrieved from https://github.com/ourresearch/openalex-name-disambiguation/tree/main/V3

Table 2. Types of author name disambiguation methods.

| **AUTHOR GROUPING METHODS** | | |
|---|---|---|
| These methods group various records believed to belong to the same author based on similarities in metadata such as name, affiliation, co-authors, and publication venues. | | |
| **Algorithms** | **Definition** | **Examples (Reference)** |
| **Rule Scoring algorithm** | Groups author records by evaluating the similarity of various attributes using scoring rules. | CWTS Author ID (Caron & van Eck, 2014) |
| **Graph-based algorithm** | Uses a network of interconnected entities to disambiguate authors by analyzing relationships within the graph. | MAG Author ID (Sinha et al., 2015)<br><br>OpenAlex ID (Priem et al., 2022) |
| **AUTHOR ASSIGNMENT METHODS** | | |
| This method assigns records to specific author profiles using rules or algorithms that consider individual attributes and relationships among records to ensure accurate author identification. | | |
| **Algorithms** | **Definition** | **Examples (Reference)** |
| **Collaborative algorithm** | Integrates data from multiple authority files to standardize and disambiguate author names. | VIAF ID (https://viaf.org/) |
| **Heuristic-based algorithm** | Applies predefined rules and heuristics to match and differentiate authors. | PubMed ID (W. Liu et al., 2014) |

## 3.2 Author profiles

Author name disambiguation algorithms have facilitated the creation and population of researcher profiles. These profiles display authors' outputs along with additional individual features and metrics. The evaluative culture around metrics and performativity has spurred their use and popularity (Hammarfelt & Rushforth, 2017; Martín-Martín et al., 2018). ORCID and Google Scholar Citations have been two major players in promoting and expanding these tools, albeit for different reasons. ORCID, due to its open nature and ability to integrate with other tools, ensures data quality and serves as a golden set to test and refine algorithms used by other platforms. Google Scholar Citations has gained immense popularity among researchers, particularly through the introduction of the h-index and other author-level metrics. A list of the main researcher profiles currently available and their characteristics are included in Table 3.

Scopus was the first database to introduce its Author ID in 2006 (Boudry & Durand-Barthez, 2020). This identifier aims to provide individual-level metrics and display researchers' academic work. Scopus employs an automatic name disambiguation algorithm which authors can curate upon request. The Author ID algorithm uses bibliographic metadata (i.e., affiliation, subject area, geographic location, co-authors, email address) to ensure accurate disambiguation of authors with similar names. This algorithm favors precision over recall (Moed et al., 2013), complemented by manual curation and tested a golden set of around 12,000 curated author profiles (Baas et al., 2020). Profiles are enriched with ORCID data, with studies reporting a 97%-98% recall rate and 99%-100% precision (Aman, 2018b; Kawashima & Tomizawa, 2015).

In 2008, Web of Science launched its ResearcherID. Initially, it invited authors to create their own profiles and suggested publication lists for manual curation (Bornmann & Williams, 2017). This approach was later combined with algorithmically generated records. In 2012, ORCID integration further enhanced ResearcherID, facilitating interoperability between platforms (Aman, 2018b). In 2017, ResearcherID merged with Publons after its acquisition (Teixeira da Silva & Al-Khatib, 2019). This integration allowed for verified peer review records and enhanced researcher profiles. Authors can manually update their profiles and correct any data, ensuring accurate representation.

The introduction of Google Scholar Citations in 2011 marked a significant milestone. This free service requires researchers to sign up to create their profiles, which they can either curate themselves or populate automatically based on Google Scholar's algorithm. While initially met with skepticism, particularly from older scientists (Ortega, 2015), Google Scholar Citations has become one of the most popular academic platforms alongside ResearchGate and Academia.edu (Martín-Martín et al., 2018). Its popularity has been somewhat controversial due to its informal misuse in research assessment (Bohannon, 2014) being a tool that lacks quality control and hence is subject to manipulation and gaming (Delgado López-Cózar et al., 2014).

ORCID ID, launched in 2012, stands out for its universal approach to researcher identification. Providing unique identifiers, ORCID integrates with multiple databases, enhancing interoperability and ensuring consistency across platforms. Researchers can manually curate their ORCID profiles, which include comprehensive information such as bio, work history, and grants. ORCID's integration with databases like CrossRef and DataCite underscores its role in the broader academic ecosystem, facilitating seamless data exchange and verification. Despite becoming pivotal as a benchmarking tool for the rest of the profiles, it is an underutilized data source in scientometric studies (Costas et al., 2024).

Dimensions Researcher ID, introduced in 2018, follows a two-step algorithm similar to the CWTS algorithm, using affiliation data, co-authorship, citation patterns, and subject area traits to cluster publications belonging to individuals (Hook et al., 2018). These clusters are connected using ORCID and DOIs, resulting in a unique researcher ID assigned to 20 million researchers. This system has successfully assigned researcher IDs to about 87% of publication-author combinations.

CRIS (Current Research Information System) author profiles, such as those from Converis and Pure, provide another approach to managing researchers' information. These systems are often used by institutions to integrate internal personnel databases with institutional repositories and other external databases (Rybinski et al., 2017). CRIS profiles typically include comprehensive information about researchers' outputs, funding, affiliations, and other activities, offering a rich dataset for analysis and reporting. For instance, the Flemish Research Information System connects around 95% of its researchers with their ORCID IDs to facilitate interoperability between systems, enhancing the accuracy and comprehensiveness of the data collected (van Leeuwen et al., 2016). CRIS profiles overcome some limitations of author name disambiguation algorithms by allowing researchers to manually curate and verify their information, although they may still contain partial or incomplete data if not fully maintained by the researchers themselves, also making it a costly system.

Table 3. Overview of the main researcher profiles available

| Researcher Profile | Year | Structure | Update method | Coverage | Owner | Individual-level features | Interoperability |
|---|---|---|---|---|---|---|---|
| ORCID ID | 2012 | Alphanumeric | Manually curated | Comprehensive | ORCID. | Bio, work history, grants, no metrics | Integrates with CrossRef, DataCite, other academic databases, export options |
| Scopus Author ID | 2006 | Numeric | Algorithmically updated | Indexed in Scopus | Elsevier | Basic bio, affiliations, h-index, citations | Limited integration with ORCID, export options |
| Web of Science Researcher ID | 2008 | Alphanumeric | Supervised automated | Indexed in Web of Science | Clarivate | Bio, work history, publications, h-index, citations | Integrates with Publons, export options |
| Dimensions Researcher ID | 2018 | Alphanumeric | Algorithmically updated | Indexed in Dimensions | Digital Science | Basic bio, affiliations, citations, altmetrics | Integrates with ORCID, export options |
| Google Scholar Profile | 2011 | Alphanumeric | Supervised automated | Comprehensive | Google | Bio, work history, research interests, h-index, citations | Limited integration, export options |
| ResearchGate ID | 2008 | Alphanumeric | Supervised automated | Comprehensive | ResearchGate GmbH | Bio, work history, publications, research interests, RG Score, citations | Limited integration, export options |
| Academia.edu ID | 2008 | Alphanumeric | Manually curated | Comprehensive | Academia.edu | Bio, work history, publications, research interests, no metrics | Limited integration, export options |
| CRIS Profiles (e.g., Converis, Pure) | -- | Alphanumeric | Institutional | Manually curated and supervised | Institutional databases | Various (e.g., Clarivate, Elsevier) | Comprehensive bio, work history, funding, publications |

The rise of academic social networks like ResearchGate and Academia.edu has further expanded the landscape of researcher profiles. These platforms offer venues for researchers to display their work, engage with peers, and enhance their visibility. However, they also present challenges regarding data reliability and privacy (Gumpenberger et al., 2016; Thelwall & Kousha, 2015).

Each of these profiles—Scopus Author ID, Web of Science Researcher ID, Google Scholar Citations, ORCID ID, Dimensions Researcher ID, ResearchGate, and Academia.edu—has unique features and limitations. Scopus and Web of Science provide robust, proprietary systems with varying degrees of researcher control. Google Scholar and ORCID offer open, researcher-managed profiles with broad adoption and interoperability. Dimensions combines automated updates with comprehensive metrics, while academic social networks like ResearchGate and Academia.edu focus on community engagement and visibility. Together, these profiles enhance the evaluation of scientific performance by providing diverse tools and platforms that cater to diverse needs and preferences within the academic community. However, concerns about the “self-quantification” and “gamification” that these tools may pose (Hammarfelt et al., 2016), particularly those that aim at reducing the reputation and contribution of scientists to a single number (e.g. ResearchGate) are also important to keep in mind, and arguably they should be weighed against other values such as inclusivity, visibility or scholarly “citizenship” (Porter, 2022).

# 4 INDIVIDUAL CHARACTERISTICS

This section examines the various personal traits and categories that influence individual-level performance in academia. Studies from fields such as science policy and evaluation, sociology of science, and economics of science (Bozeman et al., 2001; Franzoni et al., 2018; Gläser & Laudel, 2015; Levin & Stephan, 1989) indicate that personal characteristics significantly impact research outcomes, agendas, scientific and societal impact, and innovation. Recent research highlights substantial disparities in citations, productivity, collaboration, and visibility based on gender and race (Kozlowski et al., 2022; Sugimoto & Larivière, 2023) , which have implications for career prospects (Hopkins et al., 2013; Jr et al., 2014; Robinson-Garcia et al., 2020). We identify three specific categories of individual characteristics that merit closer examination: career length, gender, and ethnic background.

## 4.1 Career length

Biological age, academic age or career length are historically considered crucial components of the scientific structure, being a key determinant of researchers’ creativity and performance[4]. Early studies assumed that biological age and performance were negatively correlated, suggesting that younger scientists were more likely to make breakthroughs (Zuckerman & Merton, 1972). These studies were based on partial data of lists of prominent scientists and their biological age at the time of discovery. The introduction of scientometric approaches was key to challenge such assumptions (S. Cole, 1979). Still today, studies report contradicting results on the relationship between biological age and performance, in many cases due either to methodological or population differences. For instance, we find contradicting findings between Abramo et al. (2016) and Sugimoto et al. (2016). While Costas et al. (2010) report different productivity patterns by discipline in Spain. In the case of Mexican researchers, the productivity peak was around 53 years old, showing a quadratic relationship with productivity (Gonzalez-Brambila & Veloso, 2007).

[4] Biological age refers to that based on the birth date of an individual. Conversely academic age is normally used as the years passed since a researcher published their first paper. Career length has to do with their work experience beyond their publication record and may not necessarily be reflected by their academic age.

Age and academic status are in many cases treated indistinctly, and hence not only productivity, but role expectations and behavioral patterns are expected to change over time (Zuckerman & Merton, 1972). This sensibility to academic status is reflected in authorship, where there is a relation between career length and author order. Younger scientists will tend to occupy first positions and more senior scientists will occupy last positions in the author byline of publications (Costas & Bordons, 2011). This relation with author order is extensive to the way in which researchers distribute tasks (Escabias & Robinson-Garcia, 2022). Furthermore, there is a relation between task specialization at early career stages and the prospects of a longer academic career (Robinson-Garcia et al., 2020).

Collaboration patterns are also influenced by academic age. Researchers tend to collaborate more as they gain experience (Sugimoto et al., 2016), often opting for peers at similar career stages (Wang et al., 2017). Senior researchers tend to have more stable collaboration partners and tend to collaborate more with more junior colleagues, while middle-career researchers show higher churns in their collaboration networks (Wang et al., 2017). Collaboration seems to be field-dependent, observing notable differences by discipline (Sugimoto et al., 2016; Wang et al., 2017).

Younger scholars are more likely to change their publication patterns due to evaluation policies (Hammarfelt & de Rijcke, 2015). This is something especially notable in the humanities, where scholars have been pressured by a journal-centric evaluation system to abandon traditional venues such as books and book chapters (Arroyo-Machado et al., 2024). Disregarding academic age or trajectory in evaluation exercises can be detrimental to younger scholars (CoARA, 2022; Liao, 2021) and may have systemic effects on the global aging of the scientific workforce (Halevi et al., 2023).

From a methodological perspective, different approaches have been applied to compute career length or academic age. Table 4 enumerates eight ways for calculating an academic's experience. As observed, some rely on external data, mainly CV data, sometimes also obtained through surveys and questionnaires. Scientometric approaches mimic them to some extent, using CV information to validate their measures (Cortes et al., 2024; Nane et al., 2017). They rely on researcher identifiers, combining the bibliographic metadata of their publications to compute their career length. Most individual-level analyses use the year of researchers' first publication as a proxy for their academic age, that is, their length academic career (Milojević, 2012; Radicchi & Castellano, 2013). However, it must be noted that its reliance varies by field. Nane et al. (2017) reported an error below 4 years when compared with the birth and PhD age of a set of Québec researchers. However, Kwiek and Roszka (2022) found that these correlations were much lower in the case of the social sciences and humanities. Cortes et al. (2024) explored alternative methods or academic ages based on the date in which Colombian researchers first undertook a given activity (i.e., teaching, publishing, knowledge appropriation), showing significant differences depending on the chosen proxy. This latter result shows that national scientific development will also influence the appropriateness of the first publication year as a proxy for academic age.

Table 4. List of operational definitions of career length or academic age

| **Operationalization/Indicator** | **Definition** | **Reference** |
|---|---|---|
| **CV-BASED APPROACHES** | | |
| Academic Rank | The current academic rank or position held by the researcher, such as assistant, associate, or full professor. | (Gaughan & Bozeman, 2002; Sugimoto et al., 2016) |
| Career Stage Based on Job History | The stage of a researcher's career based on their job history and promotions. | (Cañibano & Bozeman, 2009) |
| Years in Academia | The total number of years a researcher has been working in academia. | (Heijstra et al., 2017) |

| SCIENTOMETRIC APPROACHES | | |
|---|---|---|
| First Publication Year | The number of years since a researcher's first publication. | Milojević (2012); Radicchi & Castellano (2013) |
| Years Since PhD | The number of years since a researcher obtained their PhD degree. | Ioannidis et al. (2014) |
| Publication Career Length | The span of years between a researcher's first and most recent publication. | (Nane et al., 2017) |
| Age at First Major Grant | The age of a researcher when they receive their first major research grant. | (Franzoni et al., 2018) |
| Activity-Based Career Age | The number of years since a researcher first undertook a given academic activity (e.g., teaching, publishing). | (Cortes et al., 2024) |

By using the year of first publication as a proxy for academic age we ignore career breaks. This is critical, as only a small fraction of authors publish continuously and uninterrupted (Ioannidis et al., 2014). There is little evidence of the preponderance of career breaks in publishing. Although some studies do consider these gaps (e.g., Sanliturk et al., 2023), they do it only for methodological reasons and arbitrarily. Career breaks impact directly on productivity measurements especially by gender (Ketsche et al., 2003), as women tend to take longer parental leaves than men, negatively affecting their productivity (Derrick et al., 2022). The difficulty in computing career length does not only lie in the methodological decisions used, but in contextual factors which will decide which method to adopt. For instance, while the first publication may be a good proxy in certain countries and fields due to its high correlation with PhD year, it may not work in fields in which first publication is expected before or much after defending a PhD. Furthermore, it may not make sense in countries in which having a PhD may not be that common within the scientific workforce, as in the case of Colombia (Cortes et al., 2024).

## 4.2 Gender

Gender plays a significant role in shaping the academic experiences and career trajectories of researchers. Gender disparities in science are well-documented, highlighting that women face more barriers and biases than men. The perception and treatment of women in academia are influenced by deeply ingrained social norms and stereotypes (Sugimoto & Larivière, 2023; Zippel, 2017). Studies show that women are underrepresented in senior academic positions, receive less recognition for their contributions, and have fewer opportunities for career advancement (Boekhout et al., 2021; González-Salmón et al., 2024; Huang et al., 2020). These issues are compounded by the tendency of research institutions to overlook or undervalue the work done by women, especially in leadership roles or high-impact research activities. Gender inequality is reflected in the distribution of research funding (Larivière et al., 2021), collaboration opportunities (Fox, 2020) and productivity (Huang et al., 2020; Torres-Salinas et al., 2011; van den Besselaar & Sandström, 2017). Women are less likely to be first authors or corresponding authors in publications, which can negatively affect their visibility and recognition within the scientific community (Chinchilla-Rodríguez et al., 2024; Holman et al., 2018). Additionally, women are more likely to experience career interruptions due to family responsibilities, which can hinder their academic productivity and progression (Derrick et al., 2022).

According to González-Salmón et al. (2024), the literature identifies three main aspects contributing to these differences: gendered behavioral patterns and preferences, gender roles in science, and gendered impacts of the COVID-19 pandemic. Gendered behavioral patterns and preferences, such as gender homophily, significantly influence collaborative choices, quality perceptions, and evaluation processes. For instance, men and women tend to prefer collaborating within their own gender, impacting the composition and dynamics of research teams (Holman & Morandin, 2019; Jadidi et al., 2018; Kwiek & Roszka, 2021). Moreover, studies show that both men and women rate work conducted by colleagues of their own gender more favorably (Helmer et al., 2017; Murray et al., 2019). In the absence of gender homophily, men are often preferred over women due to perceptions of higher quality in men's work (Ellemers et al., 2004; Krawczyk, 2017).

Gender roles in science highlight disparities in research strategies, workload distribution, and work-life balance. Women are often directed towards teaching and administrative tasks, while men focus more on research, which is more highly valued in evaluations (Filandri & Pasqua, 2021; MacNell et al., 2015; Mengel et al., 2019; Miller & Chamberlin, 2000). Additionally, women face greater domestic responsibilities, leading to a "parenting penalty" that hinders their academic productivity and career progression (Derrick et al., 2022; Hunter & Leahey, 2010; Jiménez-Contreras et al., 2024). Lastly, the COVID-19 pandemic has exacerbated these gender disparities. The pandemic increased the domestic workload for women, reduced their productivity, and limited their contributions to COVID-19 research (Andersen et al., 2020). These factors collectively illustrate the multifaceted nature of gender inequity in academia, necessitating targeted interventions to address these systemic issues.

The scientometric community has devoted many efforts to analyze these differences at a large scale through the development of various methodologies (González-Salmón et al., 2024; Halevi, 2019). These are summarized in Table 5. Addressing gender inequality involves several methodological challenges, such as identifying gender based on metadata, selecting appropriate units of analysis, and designing robust explanatory studies.

A key aspect is the assignment of gender to researcher profiles. The most common approach is to infer gender from author names and affiliations, as explicit gender data is typically unavailable in the bibliographic metadata. Algorithmic approaches match names against gendered databases, incorporating geographical and temporal contexts to enhance accuracy (Blevins & Mullen, 2015). However, these methods usually assume a binary gender model (Andersen et al., 2019; Larivière et al., 2013) and cultural biases (Lindqvist et al., 2021) confusing the concepts of 'biological sex' and gender identity. Advanced approaches have integrated geographic and temporal data to improve the accuracy of gender assignments. For example, incorporating different gender identification models for each language (Karimi et al., 2016), introducing preferred pronouns from external data sources (Azoulay & Lynn, 2020; Maliniak et al., 2013) or surveying authors (Amering et al., 2011; Zheng et al., 2022). Still, the most common approach is to use third-party sources (e.g., Genderize, GenderAPI). However, the lack of transparency of these sources prevents assessing their accuracy and potential geographic biases (González-Salmón & Robinson-Garcia, 2024).

Table 5. Summary of gender assignment methods reviewed in the literature

| Method | Definition | Reference |
|---:|---|:---:|
| **ALGORITHMIC APPROACHES** | | |
| Name-based databases | Use of external databases such as Wikidata or the World Gender Name Dictionary | González-Salmón, 2024; Bérubé et al., 2020 |
| Incorporation of geographic and temporal data | Use of name-databases enriched with geographic and temporal variations in the assignment of gender to names | González-Salmón, 2024; Karimi et ., 2016 |
| Language-specific modelss | Using different gender assignment models tailored for each language | Karimi et al., 2016 |
| **EXTERNAL DATA** | | |

| | | |
|---|---|---|
| Preferred nouns from external sources | Extracting pronouns from external sources to determine gender | Azoulay & Lynn, 2020; Maliniak et al., 2013 |
| Survey data | Directly requesting gender information through surveys | Amering et al., 2011; Zheng et al., 2022 |
| **THIRD-PARTY SOURCES** | | |
| Non-transparent third-party services | Use of proprietary APIs and tools such as Genderize, ChatGPT or GenderAPI to infer names | González-Salmón & Robinson-Garcia, 2024 |

Gender has been studied from various perspectives, which are not always explicit but ingrained on the selection of the unit of analysis. This methodological choice will influence findings, yielding varying results (Nygaard et al., 2022). Common units include publications, authorship, individual researchers, and citations. Some studies classify papers by the gender of the first author (Caplar et al., 2017), while others analyze the gender contribution of all authors (Kong et al., 2022). Authorship analysis helps construct indicators of gender diversity at institutions (e.g., Leiden Ranking's gender indicator). Individual researcher analysis involves disambiguating authors' names to assess productivity differences (Cameron et al., 2016). Lastly, citation analysis examines the gender of cited authors to investigate citation patterns (Dion et al., 2018; X. Wang et al., 2021).

Descriptive and causal approaches are often combined to uncover underlying disparities. Methodologies such as regression analyses (Aksnes et al., 2019) or survival analysis (Hart et al., 2019) aim to isolate gender differences by controlling for various factors. However, this can sometimes obscure the mechanisms behind disparities (West et al., 2013). Traag & Waltman (2022) highlight the importance of distinguishing between genuine differences and those arising from biases, noting that not all observed disparities necessarily indicate unfairness. Thus, to effectively address gender inequities in academia, it is crucial to consider how changes in social structures can alter these conditions, reducing both biases and structural barriers.

## 4.3 Nationality and/or ethnic background

Country and institution are considered important confounders of citation impact due to a relation between citations and international collaboration (Van Raan, 1998), as well the existence of an 'halo effect' affecting scientists' recognition and status based on their location (Crane, 1967). This effect extends to individuals' country of origin, as it may lead to nationality or ethnic discrimination in academia. The need to conceive science from an intersectional framework has gained greater relevance (Larivière et al., 2013). Gök et al. (2024a) propose the concept of superdiversity as a complementary perspective on intersectionality. More worrisome is the critical point made by Kozlowski et al. (2022), who stated that "there is a privilege of choice in scientific knowledge production, wherein research on a particular topic is influenced by scientist's race and gender" (p. 6). Minorities will suffer from this lack of privilege, being involved in topics which are systematically understudied, and even then, will receive less credit than other authors.

The aim is to build a more diverse scientific space that also affects the quality of scientific outcomes (Freeman & Huang, 2014; Hofstra et al., 2020; Nielsen et al., 2018). However, conceptual distinctions between ethnicity, nationality or cultural background are sometimes overlooked in the literature or operationalized in similar ways. Gök et al. (2024b) suggest distinguishing between three dimensions associated with these concepts: lived experience, social group identity and broader concepts.

For instance, studies combining affiliation and surname data to link it to given countries or ethnicities will differ on the grouping but use similar approaches (Freeman & Huang, 2015; Robinson-Garcia et al., 2015). These approaches are based on the assumption that the combination of surname and affiliation data can serve as an appropriate proxy to reflect national background and heritage, at least at a macro-level (Hofstra et al., 2020). This is not exempt from limitations. Given the complexity and personal nature of race and ethnicity as socially made constructs, it is essential to acknowledge their intricacies in scientometric analysis, but a detailed exploration of these aspects is beyond the scope of this review. A more nuanced approach is that by Mulders et al. (2024) who focus on a single country and track the origin of surnames to group individuals into ethnic minorities within the Netherlands.

A key component of these studies is the use of data sources for assigning ethnic origin. Here we find two approaches: 1) relying entirely on scientometric data, and 2) using external sources to validate methods assigning an ethnic origin. Studies based on scientometric data use unsupervised methods to infer nationality or ethnicity, while the latter link bibliographic data with lists of surnames assigned to countries or ethnicities. The first study to propose a scientometric approach to study the ethnic origin of researchers dates to the early 2000s (Webster, 2004). It assigned ethnic origin by confronting the distribution of surnames extracted from a list of national scientific publications with the density distribution of surnames in foreign countries and complemented with experts' judgment. Since then, more advanced approaches have been proposed. Karaulova et al. (2019) combined information from public surname lists and lexical information to develop a method of heritage identification for Russian authors. Other examples looking into geographical concentration of surnames were the analysis on surname uniqueness conducted by Thelwall, (2023) or the use of inequality index and informetric theory measures proposed by Robinson-Garcia et al. (2015).

Studies using external data sources tend to rely on governmental sources including ethnicity data. This will determine the scope of the studies, as inferring from such sources to third countries would not be advisable. Most studies have focused on the United States, which has governmental databases containing information on race (i.e., Hofstra et al., 2020). Data sources include the U.S. Social Security Administration (Conklin et al., 2023), National Science Foundation (NSF) racial/ethnic data (Leggon, 2006) or the U.S. Census and mortgage applications (Kissin, 2011; Kozlowski et al., 2021). We find less studies of this nature in Europe due to the lack of data availability. Some examples can be found in the United Kingdom (Webster, 2004) or Germany (Razum et al., 2001) using census data and ethnic monitoring. But these sources have their own limitations with regard to data quality completeness and update frequency (Chintalapati et al., 2018). Additionally, they may underestimate minority groups when conducting longitudinal analyses (Cook et al., 2014). For instance, it is common to aggregate them into broader categories such as white, Asian, and underrepresented minorities (Hofstra et al., 2020). However, assigning individuals to the "other" category leaves room for considerable discretion. Kozlowski et al. (2021) warn about the risk of underestimating minority groups when using a threshold, as well as overestimating white authors.

# 5 CONTEXT

The context surrounding the individual researcher should be considered to offer a more holistic view of the individual level performance (Ràfols, 2019). Scientometric indicators have been historically considered universal, both in their interpretation as well as their application. However, the 'mirages of universality' as defined by Zitt and Bassecoulard (2008, p.53), do not always work because of the diversity of communities and its consequences on scientometrics indicators. This is partly because they tend to be used without an evaluative framework which can help users interpret them (Moed, 2017). The concept of *context* has been used differently in the last decade to surpass such limitations. For instance, Waltman (2019) refers to 'contextualized scientometrics' as that which aims at providing "transparent and understandable metrics that support responsible evaluation practices based on qualitative and quantitative information from a broad range of sources". In other words, reporting metrics in ways that are comprehensible by non-experts. Another meaning of context is that provided by Moed, who uses the concept of *'policy context'* (Moed, 2017, p. 119-127). Here, it is understood as that which relates to the purpose of the assessment and exogenous factors to performance (Robinson-Garcia & Ràfols, 2020). Here context refers to the underlying conditions and setting in which an evaluation takes place. We define context as those factors influencing the production, visibility and impact of scientific knowledge.


Figure 1. Contextual factors affecting individuals' performance

Contextual factors influencing the production of knowledge can be key for understanding academic success as well as providing the optimal conditions for academic development. These have been explored by large in fields closely related to scientometrics such as sociology of science, science policy or management (D'Este & Robinson-García, 2023; El-Ouahi et al., 2021; Franzoni et al., 2018; Latour & Woolgar, 1979; Robinson-Garcia et al., 2018). In this stream of literature we find studies on the effect on productivity of intersectoral job changes (Dietz & Bozeman, 2005), contextual factors leading to international mobility and performance (Franzoni et al., 2018), institutional factors and logics affecting performance (Sauermann & Stephan, 2012) or the relation between interdisciplinary research and societal relevance (D'Este & Robinson-García, 2023) among others.

Figure 1 resumes the four types of contextual factors that can affect individual performance. These are related to past trajectory, practices, funding conditions and societal relevance of research outcomes. Scientometric measures at the individual level have been developed unevenly for each of them, being the past trajectory the one that has received most of the attention.

## 5.1 Trajectory and career

Career trajectories have been studied in scientometric by profiling scholars' experience throughout their career length by looking into affiliation changes. This allows tracking and studying career changes. Career trajectory has also been studied to analyze academic success or identify systemic constraints affecting individual career prospects. An example is the effect that author position, – a longstanding proxy for leadership in evaluation processes (Chinchilla-Rodríguez et al., 2019), – has on individuals' chances to have a long academic career (Milojević et al., 2018), or how task specialization may affect such career length (Robinson-Garcia et al., 2020).

Laudel (2003) was among the first to suggest using bibliographic data to reconstruct career trajectories. She saw the potential of scientometrics, not only to look into institutional mobility, but also to reconstruct 'cognitive careers' or 'research trails', i.e., "successive stages of knowledge production building on each other" (Gläser & Laudel, 2015, p. 301). However, it is the introduction of author profiles and author name disambiguation algorithms that made this type of approach finally possible at a large scale.

The first large-scale scientometric studies analyzing career trajectories focused on geographical mobility (Moed et al., 2013; Moed & Halevi, 2014; Robinson-Garcia et al., 2016; Sugimoto, Robinson-Garcia, et al., 2017). Since then, studies on the international movement of scholars using scientometric methods have increased. Here the range of studies goes from methodological approaches (Aman, 2018a; Robinson-Garcia et al., 2019) to investigating international trends (Chinchilla-Rodríguez et al., 2018; Murray et al., 2023; Sanliturk et al., 2023) or focusing on specific regional dynamics (El-Ouahi et al., 2021; Miranda-González et al., 2020; Subbotin & Aref, 2021; J. Wang et al., 2019). We also find studies analyzing the interplay between specific individual traits or team dynamics and mobility. These studies have serve to confirm gender differences in terms of international mobility (Momeni et al., 2022; Zhao et al., 2023), analyze the role of mobility on collaboration patterns (Wang et al., 2019) as a reinforcing mechanism (Boekhout et al., 2021), or understand how institutional and geographic constraints affect career trajectories (Vaccario et al., 2020). Also looking into mobility, but in this case, inter-sectoral mobility, Yegros-Yegros et al. (2021) explored the role researchers holding multiple affiliations play in bridging between institutions. They reported that researchers holding multiple affiliations within a country bridge between sectors, while those with international multiple affiliations will bridge between universities. Using a similar approach, Jurowetzki et al., (2021) looked into the phenomenon of scientific brain drain from academia to the public sector in the field of AI.

Beyond geographical mobility, trajectories have also been studied in terms of production and institutional changes (Petersen et al., 2012), tenure track (Tripodi et al., 2024) or career progression (Kwiek & Szymula, 2024).

## 5.2 Research dissemination practices

Building upon previous research (Robinson-Garcia et al., 2023), we define research dissemination practices activities, workflows and routines which may or may not be influenced by cultural, disciplinary or institutional logics and which define ways of operating external to the quality or productivity of scholars (i.e., researchers conducting fieldwork may publish less than those focused on meta-analyses, and their number of papers may not necessarily reflect their productivity as scientists). These practices include but can go beyond open scholarship or responsible practices (Moher et al., 2020). Scientometric attempts have focused on the characterization and profiling of researchers based on their research practices. In some cases, this is done by combining scientometric data with other data sources such as survey data (e.g., D'Este & Robinson-García, 2023; Ramos-Vielba et al., 2022).

For instance, we observe author-level analyses on publication patterns which aim at identifying distinct profiles of researchers by their use of different communication channels (Arroyo-Machado & Robinson-Garcia, 2023; Verleysen & Ossenblok, 2017). Language has also become an object of study in order to understand the caveats and potentials of multilingualism in science. Hence, there is overwhelming evidence on the impact and visibility bias towards English written literature (van Leeuwen et al., 2001). This has led scholars to develop the 'Helsinki Initiative on Multilingualism in Scholarly Communication (Federation of Finnish Learned Societies et al., 2019) to support the dissemination, promotion and protection of multilingualism in science. Even within scientific journals, there will be a variety of factors which will determine the choice of the publication venue, especially in non-English speaking countries (Chavarro, Tang & Ràfols, 2017).

Other attempts relate to capturing specific activities which are not present in bibliographic databases. An example can be found in the work by Mongeon et al. (2017) who link authorships of datasets with publications in order to explore data sharing practices among scholars. With regard to data sharing, we find several attempts at developing author level metrics, due to the interest in promoting transparency (Bierer et al., 2017). Sixto-Costoya et al. (2021) investigated ORCID as a potential tool to investigate data sharing practices at the author level. While Hood & Sutherland (2021) suggested different metrics to encourage data sharing and data citation.

## 5.3 Funding

The role funding plays has also been studied through scientometric means, in this case looking into questions such as its effect on career advancement (Bol et al., 2018) or the pertinence of funding schemes (Fedderke & Goldschmidt, 2015). However, these studies tend to combine scientometric data with other sources, as linking authorship with funding sources is not always feasible. This explains the lack of research in this area. The indexation of funding acknowledgements by bibliographic databases (Costas & van Leeuwen, 2012) has opened the possibility to explore the role of funding in science. Still, technical issues linking authors to funding schemes , along with the omission of funding bodies in many publications impede their use at the individual level (Álvarez-Bornstein & Montesi, 2021). In this regard, author name disambiguation algorithms may not be the answer to solve this issue, but the expansion in the use and integration of author registries like ORCID or other CV-based applications, in which these other activities can be included and easily linked to other activities and outputs of individual researchers (Costas et al., 2024).

## 5.4 Social media outreach

The attention gathered around the irruption of social media (Sugimoto, Work, et al., 2017) has also included the study of individual's behavior within altmetric studies. In this regard efforts have been directed in four directions.

First, trying to identify and describe researchers' presence on different social media platforms (Martín-Martín et al., 2018; Torres-Salinas & Milanés-Guisado, 2014). These studies tend to depart from a list of researchers for which then an online presence in different platforms is tracked in order to estimate the usage scientists make of these tools. Then, they follow up by looking at their levels of activity and interaction through the formulation of various metrics. Second, we find studies characterizing and profiling researchers who actively use social media tools to promote their research or interact with other audiences (Bruns et al., 2014; Díaz-Faes et al., 2019; Holmberg et al., 2014; Robinson-Garcia et al., 2018). Their aim is to understand how they use these tools rather than to observe if they do use them. In this regard, they focus on interactions with other users or self-depictions on these platforms.

The third stream of literature relates to the development of methodological solutions to monitor researchers' activities on social media platforms. The goal is to find ways in which social media accounts can be linked to researcher profiles or at least tagged as academic accounts. To do so, two approaches have been observed. The first one relies solely on the information depicted by the descriptions included in social media lists (Ke et al., 2017). The second approach consists of matching social media information with publication data via author profiles in order to identify those researchers who also have an online presence (Costas et al., 2020; Mongeon et al., 2023).

The last group of studies relates to performativity and social visibility. Here, altmetric indicators are grouped at the author level by using author identifiers and then scholars are profiled or compared based on the social media activity surrounding their publications. For example, Ramos-Vielba et al. (2022), combine scientometric and survey data to propose a value creation model of science-society interactions. Within the same project and using the same dataset, D'Este & Robinson-García (2023) explore the relation between interdisciplinary research and societal visibility. Finally, Arroyo-Machado

& Torres-Salinas (2023) propose developing altmetric profiles at the author level focusing on different aspects or dimensions of societal visibility.

# 6 TEAM DYNAMICS

A weakness in research evaluation is its difficulty in reconciling the notion of individual evaluation in the context of collaboration and teamwork (Walsh et al., 2019). In a setting in which teams in science become the norm (Mongeon, Smith, et al., 2017; Wuchty et al., 2007), many studies on research careers point towards an excessive focus on promoting scientific leadership to the detriment of authors who are team members (Chinchilla-Rodríguez et al., 2024; Milojević et al., 2018; Robinson-Garcia et al., 2020). The rise of teams leads to further diversity in the way researchers collaborate, distribute work and specialize, always mediated by disciplinary differences and characteristics. The literature on research collaboration and team dynamics is vast, both in sociology of science as well as in scientometrics. However, there are important differences in the approaches and findings reported in each field. Sociologists of science have focused on the internal mechanics of scientific teams such as power dynamics, social interactions, cultural norms or internal structure (Knorr-Cetina, 1982; Latour & Woolgar, 1979; Walsh & Lee, 2015; Whitley, 2000). Scientometricians and scientists of science, on the other hand, have looked into quantifiable aspects of scientific collaboration, such as co-authorship networks, large-scale analyses on scientific communities and network structure (Börner et al., 2010; Calero et al., 2006; Newman, 2004; Raan, 2008). Furthermore, their operational definition of teams also varies with research teams being defined through co-authorship (e.g., Xu et al., 2022), departmental units (e.g., Engels et al., 2013) or project-based teams (e.g., Bone et al., 2020).

At the individual level, we can group scientometric studies on team dynamics into three groups: 1) studies analyzing order and hierarchy in the author byline of publications, 2) studies profiling researchers based on their co-authorship patterns and networks, and 3) more recently, studies looking into contribution statements and specialization.

## 6.1 Author order

Authorship plays an essential role in academic career progression, as it is used as a source of recognition or credit, being the entry point into what is known as the 'reward system' of science (Biagioli, 2003; Merton, 1968). However, collaborative research challenges how credit should be distributed. For instance, in a multi-authored paper, the more prestigious authors will gather more recognition than those less known (Merton, 1968).

Different fields have responded differently to such challenges. While in some cases, authors are listed alphabetically, in most, credit is distributed unequally on the author byline of papers. That is, adhering to different levels of prestige, depending on authors' position (Frandsen & Nicolaisen, 2010; Marušić et al., 2011). Some disciplines order authors by decreasing order of contribution (Bu et al., 2020; Grando & Bernhard, 2003), whereas most lab-based disciplines exhibit an inverted U-shape, with first authors and last authors having performed the most contributions (Larivière et al., 2021). There are exceptions to those dominant trends—such as economics, mathematics and business, management and accounting—where researchers show a strong trend to sign in alphabetical order (Fernandes & Cortez, 2020; Waltman, 2012; Wohlrabe & Bornmann, 2022).

When comparing author position with contribution statements, we observe that first authors will be the most invested researchers in a given study, last position will be hold by those responsible of coordinating, supervising or acquiring funding, while middle positions will be reserved to less involved authors, normally those contributing with technical or field work (Escabias & Robinson-Garcia, 2022; Sauermann & Haeussler, 2017). However, this alignment might change based on disciplinary differences, institutional policies or misconduct, conflict or fraud in authorship (Biagioli, 2003; Frandsen & Nicolaisen, 2010; Walsh et al., 2019).

As authorship plays an important role in career progression from undergraduate to professorship, the position of authors in byline publications is usually used in the assessment of researcher' scientific contributions (Bhandari et al., 2004; Hess et al., 2015; Perneger et al., 2017). This naturally leads to a relation between authorship order and career length, especially when looking at first and last author positions (Escabias & Robinson-Garcia, 2022; Robinson-Garcia et al., 2020). But also leads to unequal power dynamics (Xu et al., 2024), which in the context of evaluation, can lead to malpractices such as the inclusion of non-contributing authors (known as "honorary" or "guest" authors) or the exclusion of qualifying authors (known as "ghost" authors), gaming and limiting the potential of scientometric methods to capture credit through authorship (Cronin, 2001) in an ever more team-based science (Greenland & Fontanarosa, 2012; Jabbehdari & Walsh, 2017).

The scientometric community has devised a variety of counting methods to distribute credit among members of multi-authored papers (Gauffriau, 2021). These range from full counting, – that is, giving full credit to all authors of a given publication –, to fractional counting, – distributing credit equally by the number of authors of a publication. In between there is a large range of different weighting systems which aim at distributing credit unequally among authors on the basis that position order reflects their level of involvement in a given publication. Some examples are harmonic (Hagen, 2008) or geometric (Liu & Fang, 2023) allocation of credit among others. However, all these methods are somewhat arbitrary and unsubstantiated, as the true contribution of each author can vary significantly and is not always accurately reflected by their position in the author list. This inherent arbitrariness raises questions about the fairness and accuracy of these credit distribution methods (Kim & Kim, 2015).

## 6.2 Contribution statements

To reduce the arbitrariness of credit distribution methods based on author counting, the introduction of contribution statements in publication records has greatly improved opportunities to scientometrically study author roles in multi-authored publications (Allen et al., 2014). Contributorship statements emerged in the late 1990s, primarily in biomedical journals, to address these challenges (Rennie et al., 1997; Smith, 1997). Contribution disclosures show that first authors are more likely to have conceived research, analyzed data, and written the paper, as well as performed research and analyzed the data than middle and last authors. Last authors are more likely to have conceived research and written the paper than first or middle authors (Larivière et al., 2016; Perneger et al., 2017).

Also, the number of contributions conducted by each author seems to be informed by their author byline. Lu et al. (2020) identified three types of authors based on the distribution of tasks among co-authors. They differentiated between those who contribute to a task by themselves (specialists), those who share the burden on most tasks (team players), and those who combine both roles (versatile). These types seemed to be associated with specific groupings of tasks. Team players would be involved equally in the most common tasks across studies (i.e., data analysis, writing the draft, conceiving and designing the study, performing experiments). Versatile authors have a similar profile, although more focused on performing experiments. But specialists would tend to contribute to lesser common tasks such as contributing with tools. These roles were found across fields and were normally associated with author position, although they were less clearly identifiable in large teams (Lu et al., 2022).

More specifically, Robinson-Garcia et al. (2020), identified three types of researchers based on their different forms of contributorships. The methodological approach to define these typologies is different from that followed by Lu et al. (2019). They apply an archetypal analysis to identify extreme combinations of contributions at the author level. However, there are similarities between the findings of both studies. Robinson-Garcia et al. (2020) refers to leaders as those “characterized by high coefficient values for all contributions” (p. 9), specialists as those “characterized by high coefficient values for PE and AD” (p., 9), - where PE refers to performing experiments and AD to analyzing data-, and supporting authors as those “characterized by generally low values for all contributorships” (p. 9). These types hold a great resemblance with what Lu et al. (2019) refer to as team players, versatile and specialists, accordingly. A study by Zhao et al. (2024) further explores this by examining the impact of the number of thought leaders (as defined by those contributing through conceptualization tasks) on team performance. They reported that teams with more thought leaders tend to produce more cited outputs but were less disruptive. This nuanced understanding helps refine how credit is attributed and how team dynamics affect research outcomes.

Inferring contributions based solely on author order can be highly problematic, especially in an evaluative context, as these are major trends rather than common and cross-disciplinary practice (Sauermann & Haeussler, 2017). Still, understanding team dynamics and distribution of labor can help understand and improve biases when attributing credit and designing science policies promoting a healthy and sustainable scientific ecosystem (Brand et al., 2015; Milojević et al., 2018). The Contributor Roles Taxonomy or CRediT aims at providing a universal contribution taxonomy that allows cross-comparison between journals, fields and organization, thus contributing to such understanding (Allen et al., 2014; Larivière et al., 2021). Beyond understanding team dynamics, this information can also help understand biases in science such as gender biases (Larivière et al., 2021; Robinson-Garcia et al., 2020) or geographical biases (van Schalkwyk, 2023).

## 6.3 Collaboration patterns

Scientific collaboration is a critical dimension in analyzing researchers’ activities and performance (Bozeman & Corley, 2004; Perkmann et al., 2013). It also plays a vital role in promoting diversity within the scientific workforce by fostering inclusive research environments (Freeman & Huang, 2014). Beyond author order, there is a vast number of studies examining co-authorship patterns, types of collaboration and size of collaborating networks (Guimerà et al., 2005; Heinze & Bauer, 2007; Newman, 2001). These studies tend to characterize collaboration patterns and tie them with performance or outcomes.

Over 50 years ago, De Solla Price & Beaver (1966) highlighted that differences in productivity among authors are linked to collaboration. Since then, we have learned that collaboration is structured in a small world (Newman, 2001) and self-organized networks in which co-authorships are determined through preferential attachment and Matthew Effect (Wagner & Leydesdorff, 2005). These networks often facilitate diverse collaborations, which can bring together a variety of perspectives and expertise (Bu et al., 2019). Furthermore, external factors affect the dynamics of collaboration, including structural, climate-related, and institutional aspects (Adams et al., 2014; Chinchilla-Rodríguez et al., 2018; Luukkonen et al., 1993). Citation impact increases exponentially with the number of collaborating authors from the same institution and linearly with the number of domestic and foreign institutions (Gazni et al., 2012; Katz & Hicks, 1997).

In terms of methodological approaches, Social Network Analysis techniques are dominant within these studies, applied to scientometric data (Otte & Rousseau, 2002). These techniques can also be used to analyze the diversity of collaboration networks and their impact on research outcomes. Survey or CV data are used in many cases either substituting or complementing bibliographic data (Bozeman & Gaughan, 2011; Gaughan & Bozeman, 2002). The distinction between collaboration types is essential in order to identify and understand the type and impact of outcomes produced. Bozeman & Boardman (2014) suggest distinguishing between "knowledge-based collaborations" which enhance research productivity and "property-based collaborations" which affect economic development and wealth. This can be operationalized by looking into inter-sectoral co-authorship (Yegros-Yegros et al., 2016) as a proxy to identify entrepreneurial authors. But not only industry collaboration can be identified through co-authorship, but through a combination of altmetric (Robinson-Garcia et al., 2018), scientometric and survey methods (D'Este & Robinson-García, 2023), it is possible to profile researchers based on their societal engagement, linking these profiles with research outputs, interdisciplinary metrics and citation impact measures. The combination of scientometric approaches with other data collection methods seems to be desirable, given that co-authorship, as collaboration is normally operationalized, tends to make visible only certain types of collaborations (Laudel, 2002).

# 7 DISCUSSION

The scientometric toolbox has greatly expanded in the last decades, allowing for contextualized approaches at the individual level which do not only benchmark but also explain and describe its diversity. These developments expand the opportunities to learn and explain scientific performance, productivity and impact beyond outdated and simplistic notions of meritocracy and excellence (Moed & Halevi, 2015; Moravcsik, 1984). The integration of machine learning algorithms, the improved quality of bibliographic metadata, and new data sources such as OpenAlex and ORCID, have allowed for more nuanced and detailed analyses. These advancements enable researchers to track career trajectories, study gender bias, and examine scholars' engagement in social media, bridging the gap between performative and sociological approaches. Still, it is important to note that there are many other types of diversity at the individual level that cannot be currently accounted for using scientometrics, such as cognitive and physical diversity, socioeconomic diversity, sexual orientation diversity or neurodiversity among others.

By incorporating a variety of metrics beyond simple publication and citation counts, such as funding acknowledgments, author contributions, and social media activity, scientometric methods can provide a more holistic understanding of researchers' activities and their contexts. This approach helps to illuminate the diverse conditions under which science is produced, offering valuable insights into how individual characteristics, team dynamics, and contextual factors shape scientific performance. Table 4 summarizes the main opportunities and gaps identified in this review in order to inspire and set future research goals and agendas.

Table 6. Summary of the main opportunities and limitations identified in the literature about the use of scientometric methods to study diversity within the scientific workforce

| Section | Subsection | Opportunities | Limitations |
|---|---|---|---|
| **Data sources** | Author name disambiguation | Improved accuracy with machine learning algorithms | High economic cost and infrastructure requirements |
| | Author profiles | Enhanced researcher profiles with ORCID and other tools | Variability in data quality and coverage |

| | | | |
|---|---|---|---|
| **Individual characteristics** | Career length | Tracking career trajectories using bibliographic metadata | Methodological differences and lack of consideration for career breaks |
| | Gender | Improving our understanding on gender inequity in academia | Reliance on binary gender models and potential biases |
| | National and/or ethnic background | Combination of surname data with affiliation for ethnic classification | Limitations in data sources and potential misclassification |
| **Context** | Trajectory and career | Reconstructing career paths using author profiles | Difficulty in capturing full career trajectories accurately |
| | Dissemination practices | Profiling researchers based on publication patterns and other activities | Limited by data availability |
| | Funding | Linking research investment and policies to outputs | Challenges in accurately matching authorship with funding sources |
| | Social outreach | Studying researchers' engagement beyond academia | Limited to social media and data reliability issues |
| **Team dynamics** | Author order | Credit distribution in multi-authored papers | Potential reinforcement of existing inequalities through author order |
| | Contribution statements | Detailed insights into individual contributions to research | Variability in reporting practices and contribution accuracy |
| | Collaboration patterns | Characterizing collaboration networks and their impact | Limited visibility of certain types of collaborations |

Despite these advancements, significant challenges remain. Scientometric methods have historically faced criticism for their over-reliance and presumptions added to quantitative metrics based on secondary (i.e., publications) data, which can sometimes obscure the qualitative aspects of research performance. Traditional metrics such as publication and citation counts may not adequately capture the diverse contributions of researchers, particularly those from underrepresented groups. The inherent biases in these metrics can reinforce existing inequalities and fail to account for the varied roles and responsibilities within research teams. Some of these biases have been long acquainted and denounced, such as language, geographic and disciplinary biases (Alperin, 2013; van Leeuwen, 2013). However, the introduction of author-level indicators which largely relies on algorithms, reinforces some of these biases. For instance, author name disambiguation algorithms tend to perform worst for Asian authors (Sugimoto et al., 2017, supplementary information), while gender assignment algorithms underperform for authors coming from Asian and Sub-Saharan African countries, or Brazil (Andersen et al., 2019; Larivière et al., 2013). This means that these geographic areas are worst covered by our analyses and findings derived from any analysis using these variables will be limited.

Methodological challenges in accurately identifying and analyzing individual characteristics such as gender and ethnicity persist. The assignment of gender based on author names and the classification of ethnic origin using surnames, while common, can introduce errors and biases. These methods often rely on binary gender models and may not accurately reflect the complex, socially constructed nature of race and ethnicity. Additionally, the lack of comprehensive and reliable data on these characteristics can hinder efforts to study diversity at a large scale. In this sense, studies using these data should introduce methods and algorithmic approaches which are transparent and/or replicable (González-Salmón & Robinson-Garcia, 2024). When this is not possible due to limited data accessibility or resources, including measures of errors and uncertainty measures (Erman & Todorovski, 2015; Herman, 2024; Robinson-Garcia et al., 2024) could also help acknowledge and account for these limitations.

The context in which research is conducted also plays a crucial role in shaping individuals' scientific performance. Factors such as career trajectory, research practices, funding conditions, and social outreach influence the production and visibility of scientific knowledge. Scientometric indicators have traditionally been used without adequate consideration of these contextual factors, limiting their ability to provide a complete picture of researchers' activities and achievements. Recent efforts to contextualize these indicators, by incorporating information from a broad range of sources and reporting metrics in ways that are comprehensible to non-experts, represent a step forward. However, more work is needed to develop robust frameworks that can account for the diverse contexts in which science is produced.

The study of diversity within the scientific workforce using scientometric methods offers both opportunities and challenges. Advances in data processing and methodological innovations have expanded the analytical potential of these methods, allowing for more detailed and nuanced analyses of researchers' activities and performance. However, significant challenges remain, particularly related to the inherent biases in traditional metrics and the methodological difficulties in accurately identifying and analyzing individual characteristics and contextual factors. Addressing these challenges requires a critical and nuanced approach to the use of scientometric methods. By integrating diverse data sources, developing more inclusive metrics, and considering the context in which research is conducted, future research can provide a more comprehensive and equitable understanding of diversity in the scientific workforce. This will not only enhance our understanding of how science is produced but also inform policies and practices aimed at promoting diversity and inclusion in academia.

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