REVIEW ARTICLE

Authorship inequality and elite dominance in management and organizational research: A review of six decades

Mehmet A. Orhan[1], Yvonne G. T. van Rossenberg[2], and P. Matthijs Bal[3]

[1]EM Normandie Business School, Paris, France
[2]Institute for Management Research, Radboud University Nijmegen, Nijmegen, The Netherlands
[3]University of Lincoln, Lincoln, UK

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ABSTRACT

Ideally, scholarly publishing should be fair, meritocratic, and inclusive of diverse groups of researchers. However, many disciplines, including management and organizational research (MOR), remain far from this ideal. We investigate the extent of authorship concentration across three closely related MOR subfields: Management (MNGT), Human Resource Management (HRM), and Industrial-Organizational Psychology (IOP), by analyzing 60-year publication trends across 42 top-tier journals, covering over 60,000 publications. The findings reveal growing authorship inequalities and a more pronounced dominance of a scientific elite. Specifically, a small group of researchers has accumulated disproportionate influence over time. IOP, in particular, exhibits more skewed disparities, with its most prolific scholars publishing significantly more than their counterparts in MNGT and HRM. Moreover, IOP shows greater recurrence of the same authors across journals' top 10 most-published lists, indicating stronger elite dominance. Network analyses further reveal that IOP is characterized by a large, densely interconnected component, with many authors linked to the same tightly knit collaborative networks, unlike MNGT and HRM, which suggests that publishing success in IOP is more strongly associated with collaboration within a small scientific elite. We conclude by proposing changes in how diversity theorized across research, policy, and practice to address rising inequalities and promote a more inclusive research environment.

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Corresponding Author:
Mehmet A. Orhan
morhan@em-normandie.fr

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1. INTRODUCTION

Authorship inequality is a worrying problem in science (Hart & Perlis, 2021; Lietz, Jadidi et al., 2024; Wellmon & Piper, 2017). Although scientific publishing is believed to be a meritocratic system, in which access should ideally be determined by the quality of ideas and research, it is well-documented that science operates as a highly stratified social system (Cole & Cole, 1973). Decades of sociological and scientometric research have revealed that certain voices are overrepresented at every stage of the research process, from authorship to citations and editorial positions. These privileges are often unevenly distributed across individuals, genders, races, institutions, and geographical locations (Aigner, Greenspon, & Rodrik, 2025; Angus, Atalay et al., 2021; Auschra, Bartosch, & Lohmeyer, 2022; Bajwa & König, 2019; Dewidar, Elmestekawy, & Welch, 2022; Huber, Inoua et al., 2022; Mason, Merga et al., 2021; Murphy & Zhu, 2012;

Nielsen & Andersen, 2021; Rad, Martingano, & Ginges, 2018; Roberts, Bareket-Shavit et al., 2020). Such inequalities contribute to the accumulation of resources and influence among a narrow scientific elite, reinforcing intellectual hegemony and privileging dominant discourses while marginalizing underrepresented topics, ideas, and methodologies, with implications for intellectual pluralism and innovation (Azoulay, Fons-Rosen, & Zivin, 2019; Lewis, 2022).

To address this problem, this study examines long-term patterns of authorship concentration and elite dominance across three closely related domains of management and organizational research (MOR): Management (MNGT), Human Resource Management (HRM), and Industrial-Organizational Psychology (IOP). Drawing on 60 years of publication records from 42 top-tier journals, we investigate whether a concentrated group of scholars disproportionately occupies journal space, how this concentration has evolved over time, and whether dominance patterns differ systematically across these fields. Authorship concentration and stratification are driven by interrelated mechanisms, including cumulative advantage, commonly referred to as the Matthew effect (Feichtinger, Grass et al., 2021; Merton, 1968; Traag, Brady et al., 2025), invisible colleges (Bal, van Rossenberg, & Orhan, 2025; Crane, 1972; Price & Beaver, 1966), and unequal access to physical, symbolic, and social capital (Bourdieu, 1986; Zhang, Wapman et al., 2022). Previous research has documented the lack of diversity (mainly based on geographical and gender-related factors) in management and organizational research; however, we identify this lack of diversity as not the primary systemic barrier. Instead, we conceptualize authorship inequality as a form of *disparity* rather than surface-level diversity. In doing so, we provide a comparative, longitudinal account of authorship inequality in MOR that complements previous work on lack of diversity, cumulative advantage, and elite reproduction (Hunt & Blair, 1987; Swanson, Wolfe, & Zardkoohi, 2007; Talukdar, 2015).

The relevance of this inquiry is elevated by the growing scarcity and symbolic value of publication opportunities in top-tier journals. In most parts of the world, academic careers are increasingly dependent on publications in top-tier journals, resulting in heightened competition within academia. This intensified publication pressure has led to a surge in rejection rates for top-tier journals, including those in MOR. For example, the *Journal of Applied Psychology*, which reported a rejection rate of 73% in 1970 (Fleishman, 1971), reached a rejection rate of 94% by 2024 (Eby, 2025). Similarly, the *Journal of Management Studies* (2025) reported a rejection rate of 94% in 2025, alongside an average of 543 days from initial submission to final acceptance. Such figures are often interpreted as indicators of rigor and quality, and editors frequently reinforce this interpretation by signaling that scarce journal space is reserved for authors who truly deserve it (Bal et al., 2025). Even though acceptance rates continue to decline, expectations to publish in these elite outlets still expand, as hiring, promotion, and other professional rewards remain closely tied to such publications (Aguinis, Cummings et al., 2020; Edwards & Roy, 2017; Orhan, 2020). Within this system, however, publication success increasingly depends on access to time, networks, and institutional resources that enable scholars to withstand an exceptionally demanding and prolonged review process, rather than on the consistent evaluation of intellectual quality alone (Zivony, 2019). Under these conditions, publication in elite journals functions as a central form of symbolic capital and legitimacy, conferring prestige, professional recognition, and material rewards while shaping career trajectories and future access to resources (Fogarty & Zimmerman, 2019). As Willmott (2011) critically argues, this dynamic can foster a form of journal list fetishism, in which the place of publication comes to be treated as a proxy for scholarly worth, often at the expense of substantive intellectual contribution and pluralism.

Against the backdrop of rising rejection rates and increasing publication scarcity, concerns have intensified that scholarly publishing systems do not operate as neutral or meritocratic arenas (Sharpe, 2024). Accumulating evidence instead suggests that systemic biases related to author identity, institutional affiliation, geographical location, and academic status continue to shape evaluative outcomes, even under conditions of heightened selectivity (cf. Huber et al., 2022; Kulal, Abhishek et al., 2025). In response to systemic inequalities, diversity, equity, and inclusion (DEI) issues have garnered significant attention within academic communities, including in MOR fields, in the last decade. For example, the American Psychological Association (APA) has recently unveiled a strategic plan[1] for its journals, aimed at addressing "systemic inequities and bias" in publishing, including efforts to "diversify the community of authors, editors, and readers" and to "address systemic and institutional barriers faced by underrepresented scholars." Similarly, other major scholarly societies, including the Academy of Management (AOM), the Society for Industrial and Organizational Psychology (SIOP), and the Association for Psychological Science (APS) have publicly committed to fostering inclusivity in research (Academy of Management, 2024; Association for Psychological Science, n.d.; Gibson, Payne et al., 2018; Society for Industrial and Organizational Psychology, 2016). Despite these efforts, top-tier journals remain disproportionately represented by specific groups of researchers, particularly those affiliated with elite institutions and dominant regions, indicating that formal inclusion efforts have not fundamentally altered the hierarchical structure of academic publishing (Auschra et al., 2022; Nielsen & Börjeson, 2019). While greater demographic or geographical representation may emerge at the margins, such inclusion often remains conditional on reinforcing, rather than challenging, prevailing theories, paradigms, and epistemic assumptions.

In this regard, we identify rising authorship concentration as the core systemic issue. Representational inclusion alone cannot serve as evidence of distributive equity; what matters for inequality is not simply whether new identities become represented, but who occupies and controls scarce publishing space. We therefore conceptualize authorship concentration as a disparity indicator that captures the unequal distribution of publication opportunities and symbolic capital among scholars. In the following section, we elaborate on the conceptual framework and explain why diversity initiatives focused primarily on representation fail to address the structural dynamics of disparity that sustain persistent inequalities in scholarly publishing.

1.1. The Effects of Authorship Concentration

A central mechanism through which inequalities in scholarly publishing emerge and persist is explained by the concept of the Matthew effect. This effect explains how early success increases visibility and subsequent opportunities, leading to cumulative advantages (Krauss, Danús, & Sales-Pardo, 2023; Merton, 1968). Although the Matthew effect provides a mechanism for the accumulation of advantage, it does not specify what *form* inequality takes in scholarly publishing. To clarify this, it is essential to distinguish between different conceptualizations of "diversity" and to explain why not all forms are equally relevant for understanding inequality in scholarly research. Drawing on Harrison and Klein's (2007) framework, diversity can be understood in three distinct ways: *variety, separation*, and *disparity*. *Variety* refers to differences in kind or category, such as backgrounds, geographical locations, or areas of expertise. In other words, it reflects how many different types of units are represented in a group. *Separation* captures differences in position along a continuum, often manifesting as divergent ideas, values, or perspectives. This dimension highlights differences in position or

[1] https://www.apa.org/pubs/authors/equity-diversity-inclusion.

opinion along a single continuum, reflecting opposition, disagreement, or polarization. *Disparity*, by contrast, concerns the unequal distribution of resources within a collective, such that a small subset holds disproportionately more of a valued asset (e.g., prestige, influence, authority, or control over decision-making) than the rest. These forms of diversity are not interchangeable and do not share common causal mechanisms or outcomes. Harrison and Klein further highlight a common conceptual error, which is the tendency to conflate distinct diversity constructs or to mistakenly operationalize one form while theorizing another.

Currently, many DEI initiatives primarily aim to enhance diversity as *variety*, often through representational targets, statistical adjustments, or visibility-based interventions (Hellerstedt, Uman, & Wennberg, 2024; Hoang, Suh, & Sabharwal, 2022). In the context of scholarly publishing, this distinction matters because policy frameworks on DEI frequently operationalize diversity in terms of *variety* (representation) or, to a lesser extent, *separation* (polarization), while they are often publicly justified as solutions to systemic inequalities driven by *disparity* (Halffman & Leydesdorff, 2010). Yet, disparity concerns the unequal distribution of valued resources and social goods, such as prestige, authority, and influence, which in turn produces distributive inequity, hierarchical stratification, and longstanding discrepancies in opportunity structures (Harrison & Klein, 2007). Accordingly, the initiatives centered on representation may coexist with, or inadvertently legitimize, persisting structural inequalities, allowing prestige, authorship concentration, and gatekeeping power to reproduce existing hierarchies rather than transform them (Bal et al., 2025; Orhan, Bal, & van Rossenberg, 2025). Even when scholars from "diverse" backgrounds gain entry, they may face pressures of epistemic mimicry, being expected to reproduce and conform to dominant norms of legitimacy (Bal, Orhan et al., 2026). This dynamic is particularly consequential in the social sciences, where ontologies and epistemologies are context-dependent and where the coexistence of multiple paradigms is both inevitable and necessary for intellectual debate and knowledge production (Edmonds, 2017; Flyvbjerg, 2012). However, increasingly stringent editorial and review processes can narrow epistemic possibilities by rewarding conformity to dominant theoretical frameworks, normative language, and prescriptive style adapted by journals, as well as narratives of the elite core (Heesen & Romeijn, 2019; Lewis, 2022; Morgan-Thomas, 2026).

Within MOR specifically, scholars have argued that academic careers tend to be structured by conformity to institutionalized evaluative norms (Kenworthy, Opatska, & Vintoniv, 2026; Macdonald & Kam, 2007). Another related pathway to inclusion is collaboration with elite authors and networks, including practices that may take the form of honorary authorship or prestige-based coauthorship dynamics (Greenland & Fontanarosa, 2012; Kong, Mao et al., 2019). Both pathways deepen cumulative advantage and thereby intensify concentration: Conformity stabilizes citation-based legitimacy around dominant paradigms, while elite collaboration consolidates authorship-based prestige and solidifies gatekeeping authority. Recent studies also confirm that many fields in social sciences are heavily dominated by hyperprolific elite researchers, that top journals are densely concentrated, and that these concentrations are rising (e.g., Abramo & D'Angelo, 2025; Freeman, Xie et al., 2026; Zavadskiy, Muniasamy, & Mithas, 2026). As a negative impact of concentration, Azoulay et al. (2019) argue that elite scientists often regulate entry into scientific fields through dense collaboration networks and agenda-setting practices that shape what counts as relevant, rigorous, and publishable research. When many of the most prolific authors simultaneously hold gatekeeping roles as editors and reviewers, or maintain close professional ties to those who do (Brogaard, Engelberg, & Parsons, 2014; Burgess & Shaw, 2010; Colussi, 2018; Heffernan, 2021), authorship concentration can become self-perpetuating. Accordingly, concentration strengthens existing power positions, enabling dominant groups to accumulate further visibility, credibility, and influence, while epistemic diversity, a core condition for scientific progress, is constrained by selection mechanisms that systematically favor established paradigms (Heesen & Romeijn, 2019). Counternarratives and alternative research programs face barriers to recognition, often gaining legitimacy only after dominant research agendas lose momentum (Azoulay et al., 2019). Thus, researchers from underrepresented backgrounds confront not only cumulative advantage processes such as the Matthew effect, but also deeper systemic inequalities produced by sustained elite dominance (Lewis, 2022). As a result, elite dominance stifles intellectual diversity by narrowing the range of ideas, questions, and methodological approaches deemed legitimate within top-tier journals.

These dynamics have broader consequences. A growing body of research suggests that concentration can hinder creativity and innovation and produce superstar-driven distortions in knowledge development (Azoulay et al., 2019; Azoulay, Graff Zivin, & Wang, 2010; Kelty, Baten et al., 2025). When knowledge production is governed by intangible endowments such as prestige, concentration can become persistent, as recognition clusters in a small set of elite institutions and actors (Freeman et al., 2026). Thus, underrepresentation of voices in research can be best understood not as an isolated inclusion deficit but as an outcome of dominance: a structural mechanism in which a narrow elite repeatedly occupies journal space, converts publication success into prestige, and subsequently leverages that prestige to shape standards of legitimacy, thereby reproducing further publication advantage.

This dominance becomes especially consequential when elites also hold gatekeeping positions. Network evidence on editorial governance shows that evaluative authority is often concentrated in "(in)visible colleges," through which a small set of actors control access to scarce journal space and defines the criteria of publishability (Burgess & Shaw, 2010). Editorial boards thus function not only as quality control bodies but also as infrastructural mechanisms of inequality reproduction, stabilizing disparity through unequal power over what is perceived as legitimate scholarship (Bal et al., 2025). In this sense, inequality is reproduced recursively: Elites occupy boards, boards shape publication outcomes, publication outcomes generate prestige, and prestige further legitimizes elite authority.

A recent study by Vieira, Ferreira et al. (2024) investigates the phenomenon of hyperprolific authorship through the lens of collaboration structure rather than individual productivity alone. The authors show that extremely high publication output is closely associated with durable, high intensity coauthorship ties, with hyperprolific authors disproportionately embedded in dense, persistent collaboration structures. Proximity to such authors also increases the likelihood that similar productivity patterns emerge among their collaborators. Productivity, therefore, appears relationally produced, sustained by stable collaboration infrastructures that facilitate rapid and repeated publication. In turn, these network effects contribute to authorship concentration and heightened disparities.

Overall, the Harrison and Klein (2007) framework prepares the ground for the argument that inequalities in scholarly publishing cannot be adequately addressed through representational indicators alone. If disparity is the core mechanism through which dominance is reproduced, then authorship concentration represents an observable manifestation of that process. Therefore, examining who occupies journal space, how frequently the same scholars recur, and whether such patterns intensify across time provides a direct way to operationalize and examine *disparity* within publishing systems. Accordingly, in the next section, we describe the data, measures, and analytical approaches used to examine long-term authorship concentration and elite dominance across the three subfields investigated.

2. METHODS

2.1. Study Rationale and Motivation

To investigate the phenomenon of authorship inequality, our study employs a quantitative discovery approach (Bamberger & Ang, 2016). Using this approach, we combine bibliometric analyses with abductive reasoning to uncover and interpret patterns of authorship concentration. This enables us to generate empirical insights and formulate plausible explanations of how and why authorship inequalities emerge. Our analysis focuses on three domains: Management (MNGT), Human Resource Management (HRM), and Industrial-Organizational Psychology (IOP). We selected these subfields for several reasons. First, they share disciplinary proximity, common publication norms, and overlapping scholarly interests, while still maintaining distinct academic traditions. They draw on similar theoretical foundations and address comparable concepts such as culture, motivation, performance, leadership, and workplace behavior, but they differ in methodological and epistemological approaches (Bucklin, Alvero et al., 2000). In this regard, scholars can readily publish across these journals, which are often considered substitutable across fields with modest methodological adjustments or theoretical repositioning (Aguinis, Ramani et al., 2017; Guest, 1994; Highhouse, Zickar, & Melick, 2020). Second, they are embedded in similar professional communities and policy conversations, as evidenced by shared associations such as AOM, APA, and SIOP. Third, their parallel emphasis on DEI initiatives further positions these fields as suitable empirical settings for examining the structural and historical roots of inequality that such associations seek to address, as well as for illuminating the kinds of actions that may become possible once these underlying dynamics are more clearly understood.

The timeframe of 1960 to 2019 provides a longitudinal perspective on historical trends, capturing the evolution of publishing norms. The choice of 1960 as a starting point is technical because reliable bibliographic coverage is not consistently available in our data set before this year across the three subfields. The endpoint, 2019, avoids distortions from the global disruption of research and publishing caused by the pandemic. This 60-year span is sufficiently long to capture structural changes in academic competition and the growth of journals within these domains. It also maximizes comparability across disciplines, as by beginning in 1960, we observe a period where journals are mature enough for a historical analysis of trends in authorship concentration.

Finally, in addition to conceptual and empirical motivations, our study is also informed by direct and recurring observations from our own experiences. As the author team, we identify ourselves as organizational psychology researchers, and our study on this topic stems not only from theoretical concerns but also from persistent patterns we observed in our academic environment. Over the past 2 decades, we have repeatedly noticed the same names appearing in top-tier journals at disproportionately high frequencies. These observations led us to a series of critical questions: Were these patterns idiosyncratic or reflective of structural realities? Could our perceptions be shaped by cognitive biases such as availability heuristics, or was there empirical evidence of concentrated authorship? To answer these questions, we carried out systematic, comparative, and data-driven scientometric analyses to assess whether our impressions aligned with actual publication trends. We extended our inquiry beyond IOP to include its closest neighboring fields, enabling us to evaluate whether the observed dynamics were field-specific or indicative of broader structural inequalities in knowledge production and visibility.

2.2. Data Sources: Journal Selection and Data Extraction

We selected journals from the 2021 Academic Journal Guide (AJG) from the Chartered Association of Business Schools. The AJG, previously known as the ABS List, plays a crucial role in assessing the performance of academics operating in a wide range of business and social sciences and is commonly used for bibliometric research in the fields of MOR (Murphy & Zhu, 2012; Serenko & Bontis, 2024; Willmott, 2011). Our inclusion criteria targeted journals rated 4*, 4, and 3 in the fields of "General Management, Ethics, Gender, and Social Responsibility," "Human Resource Management and Employment Studies," "Organisation Studies," and "Psychology-Organizational." We excluded journals outside our research scope, those with inconsistent ratings of 3 or lower in the last three rankings, and those not classified by the Journal Citation Reports (JCR) of Clarivate Analytics. To cross-validate the journal field classifications, we recoded them according to corresponding JCR categories and created the lists for each of the three fields of examination. We were particularly interested in examining concentration within top-tier journals, given their outsized influence on researchers' careers and the global competitiveness surrounding publication in these venues (Aguinis et al., 2020). This approach is consistent with prior studies investigating bibliometric analysis and scholarly impact in MOR (e.g., Certo, Sirmon, & Brymer, 2010; Podsakoff, MacKenzie et al., 2008).

2.2.1. Total study population

Although the three domains are conceptually proximate, they differ in overall journal volume and size. According to the AJG 2021 classifications, MNGT comprises 153 journals (combining two subfields; "General Management, Ethics, Gender, and Social Responsibility" and "Organisation Studies"), compared to 57 in HRM and 66 in IOP. These size differences are meaningful, as concentration depends on publication volumes. Yoshikane, Kageura, and Tsuji (2003) suggest that authorship concentration is mechanically shaped by publication volume, because increasing sample size simultaneously reveals new low productivity authors while amplifying cumulative output among prolific authors, causing inequality measures to rise even in the absence of structural change in the author population.

Our analysis focuses on 42 outlets, comprising 15 MNGT journals, 13 HRM journals, and 14 IOP journals, all rated 3 or higher and therefore classified as top-tier within their respective fields. This design intentionally restricts the analytical denominator to elite journal space, where publication carries the greatest symbolic and career value. In Supplementary Material Figure S1, we further show that the total publication volumes of the three fields, and their growth trajectories over time follow broadly similar patterns, supporting cross-field comparability despite differences in overall journal counts.

Publication data were collected from two primary sources. First, we used the Scopus database for individual and journal-level analyses. We extracted data on researchers who published "articles" and "reviews" in the selected journals between January 1960 and December 2019, excluding editorials, notes, conference papers, letters, and errata. The complete data set is available on the Open Science Framework website[2]. Data were also segmented into three timeframes: 1960–1979, 1980–1999, and 2000–2019.

2.2.2. Authorship disambiguation and data processing

The data were retrieved from two bibliographic databases, Scopus and Web of Science (WoS). Scopus was prioritized for analyses of individual-level productivity because of its reliable Author ID system, which substantially improves author name disambiguation (Kawashima & Tomizawa, 2015). Prior research has further demonstrated the suitability of Scopus Author IDs for bibliometric analyses (e.g., Aman, 2018; Baas, Schotten et al., 2020). Baas and colleagues also reported that Scopus author profiles have an average precision of 98.1% and an average

[2] https://osf.io/rpbvt/?view_only=017c7afd486d49ce856d455579236517.

recall of 94.4% in assigning publications to the correct author, suggesting high accuracy in author disambiguation. To further mitigate disambiguation issues at the journal and field levels, we implemented additional verification procedures by checking consistency in author names, institutional affiliations, and publication histories. For the most productive authors within each journal and field, potential ambiguities were manually examined. Given the sensitivity of productivity-based analyses, we manually validated the top publishing authors for each journal to minimize the risk of underreporting, overreporting, or misattributing publication records.

To cross-validate our findings, particularly those related to field-level inequalities and historical trends, we also retrieved data from WoS. WoS was used primarily for longitudinal, field-level analyses because it offers more stable document and journal classification over time (Wang & Waltman, 2016). For both databases, only peer-reviewed publication types, specifically articles and reviews, were included.

2.3. Measurement of Authorship Inequality

2.3.1. Top author productivity, authorship share, journal and field dominance

Using the Scopus data set (over 60,000 records), we extracted all authors who published at least five papers in the sample of 42 journals, yielding a final sample of 4,825 highly productive researchers. Based on this sample, we analyzed dominance patterns at three levels: author-level productivity, journal-level concentration, and cross-field comparisons. This multilevel approach enables us to assess the extent of authorship concentration and elite dominance across the domains examined. Similarly, when we constructed the lists of the top 10 most productive authors of each journal and field, we cross-checked our lists by comparing journal-level searches. Inaccurate document labeling, type, and authors were excluded from our analyses.

2.3.2. Gini coefficient calculations

The Gini coefficient, which ranges from 0 to 1, is used to interpret disparities in resource allocation and explains the concentration of distribution. A Gini coefficient of 0 indicates perfect equality in distribution, 0.5 reflects very high inequality, and 1 represents perfect inequality. It is a common and preferred method for assessing *disparity* (Harrison & Klein, 2007), and is also frequently utilized in scientometrics research (see Lietz et al., 2024; Nielsen & Andersen, 2021; You, Lee et al., 2024). Additionally, Adams, Rogers et al. (2020), based on Leydesdorff, Wagner, and Bornmann's (2019) findings, favored using the Gini coefficient over other measures to assess imbalances in distributions. In our study, we manually calculated Gini coefficients. Values were sorted in ascending order, and the coefficient was computed using the rank-based formulation,

$$G = \frac{2\sum ix_i}{n\sum x_i} - \frac{n+1}{n},$$

which is computationally efficient for large samples.

Both Scopus and WoS data sets were used to calculate the extent of concentration in each field. Relying on these two databases allowed us to cross-validate the results and minimize potential distortions arising from database-specific coverage, indexing practices, and classification differences. The Scopus data set was prioritized for calculating author-level disparities (i.e., Lorenz curves) due to its more reliable author identification system (Baas et al., 2020), while historical trend analyses were conducted at the field level to ensure greater stability in longitudinal comparisons (Adams et al., 2020). For field-level inequalities, WoS produced more conservative estimates, which we report to avoid overstating historical disparities.

3. RESULTS AND FINDINGS

3.1. Study Scope

Table 1 provides an overview of the journal sample and the underlying publication corpus used in the study. The table lists all journals included in the analysis, together with their acronyms and AJG (2021) quality ratings. For each journal, we report the number of articles and reviews indexed in Scopus, as well as their combined total ("Total docs"). In addition, the table indicates the first year from which Scopus coverage was available and provides the average annual output per journal during the observed coverage period. The journal set spans three domains: HRM (n = 13 journals), MNGT (n = 15 journals), and IOP (n = 14 journals). Across the 42 journals, the full data set contains 60,034 documents, including 55,732 articles and 4,302 reviews. Field-specific totals show that output volume differs substantially across domains. The HRM field contributes 15,414 documents (14,245 articles; 1,169 reviews), the MNGT field contributes 20,223 documents (18,039 articles; 2,184 reviews), and the IOP field contributes 24,397 documents (23,448 articles; 949 reviews). These figures indicate that IOP contains the largest volume of publications in the data set, while HRM represents the smallest overall field in terms of indexed document counts (Supplementary Material Figure S1 summarizes long-run publication trends).

3.2. Author-Level Analyses

Before turning to field-specific rankings and distributional evidence, we first visualize the publication portfolios of the most productive scholars in the data set. Supplementary Material Figure S2 plots researchers who published more than 50 papers in the 42 top-tier journals and shows both their total publication volume (in parentheses) and the distribution of their output across HRM, MNGT, and IOP outlets. The most productive author in the sample published 156 papers, followed by four other researchers who have authored more than 100 papers in our top-tier journal sample. The top 10 most prolific authors published an average of 111.1 papers.

In the data set of the select group of 4,825 authors who published more than five papers, only 77 individuals (1.60%) published more than 50 papers. The results provide evidence that exceptional publication output is disproportionately concentrated in IOP outlets. Among the 77 researchers, 58 (75.32%) published more than half of their articles in IOP journals, suggesting that the most prolific authors are highly specialized, publishing predominantly within IOP and exhibiting strong domain concentration. Conversely, only six researchers (7.79%) had no IOP publications, indicating that almost all extremely productive scholars in the data set are embedded, at least partially, within IOP publishing networks. This pattern becomes even more visible at the very top of the distribution. Researchers with more than 70 publications (n = 28) collectively produced 2,501 articles, of which 2,067 (82.65%) appeared in IOP outlets. These findings suggest that IOP constitutes the primary field in which extreme publishing productivity is accumulated and reproduced, reinforcing the view that elite productivity is not evenly distributed across closely related domains but concentrated within a particular field ecosystem (Supplementary Material Figure S2).

3.2.1. Top contributors of each field

Building on this visual overview, Table 2 presents the top 10 most productive researchers in each field (IOP, MNGT, HRM) and reports their publication counts within the journals included in the sample (total career output in the field is provided in parentheses). The table highlights substantial differences in productivity intensity across fields. IOP exhibits notably

Table 1. List of journals analyzed

Title	Acronym	AJG rating (2021)	Count of articles	Count of reviews	Total docs	Scopus data from	Average output per year
Human Resource Management Journal	*HRMJ*	4*	713	35	748	1990*	24.93
British Journal of Industrial Relations	*BJIR*	4	1,239	98	1,337	1963‡	23.46
Human Resource Management	*HRM*	4	1,643	82	1,725	1961*	29.24
Industrial Relations: A Journal of Economy and Society	*IR*	4	1,588	10	1,598	1961*	27.08
Work, Employment and Society	*WES*	4	1,182	236	1,418	1987*	42.97
Economic and Industrial Democracy	*EID*	3	967	315	1,282	1980*	32.05
European Journal of Industrial Relations	*EJIR*	3	422	67	489	1995*	19.56
Human Resource Management Review	*HRMR*	3	722	11	733	1991*	25.28
Industrial and Labor Relations Review	*ILRR*	3	664	144	808	1978‡	19.24
Industrial Law Journal	*ILJ*	3	1,009	28	1,037	1972*	21.60
International Journal of Human Resource Management	*IJHRM*	3	2,872	66	2,938	1990*	97.93
New Technology, Work and Employment	*NTWE*	3	495	11	506	1986*	14.88
Work and Occupations	*W&O*	3	729	66	795	1974*	17.28
HRM total (*n* = 13)			**14,245**	**1,169**	**15,414**		
Academy of Management Journal	*AMJ*	4*	1,505	217	1,722	1975‡	38.27
Academy of Management Review	*AMR*	4*	635	322	957	1978‡	22.79
Administrative Science Quarterly	*ASQ*	4*	496	49	545	1975‡	12.11
Journal of Management	*JoM*	4*	1,789	141	1,930	1975*	42.89
Organization Science	*OrgSci*	4*	1,422	80	1,502	1996*	62.58
Human Relations	*HumRel*	4	3,331	142	3,473	1960*	57.88
Journal of Management Studies	*JMS*	4	1,963	160	2,123	1964*	37.91
Organization Studies	*OrgStud*	4	1,774	192	1,966	1980*	49.15
Academy of Management Perspectives	*AMP*	3	228	97	325	2006*	23.21
British Journal of Management	*BJM*	3	1,032	48	1,080	1990*	36.00
California Management Review	*CMR*	3	1,475	235	1,710	1970*	34.20
European Management Review	*EMR*	3	234	14	248	2009*	22.55
International Journal of Management Reviews	*IJMR*	3	323	79	402	1999‡	19.14
Journal of Management Inquiry	*JMI*	3	924	232	1,156	1992*	41.29
Organization	*Org*	3	908	176	1,084	1994*	41.69

Table 1. (continued)

Title	Acronym	AJG rating (2021)	Count of articles	Count of reviews	Total docs	Scopus data from	Average output per year
MNGT total (*n* = 15)			**18,039**	**2,184**	**20,223**		
Journal of Applied Psychology	*JAP*	4*	5,728	111	5,839	1960*	97.32
Personnel Psychology	*PPsych*	4*	1,854	58	1,912	1960*	31.87
Journal of Occupational and Organizational Psychology	*JOOP*	4	1,363	62	1,425	1975*	31.67
Journal of Occupational Health Psychology	*JOHP*	4	774	39	813	1996*	33.88
Journal of Organizational Behavior	*JOB*	4	1,764	135	1,899	1981‡	48.69
Journal of Vocational Behavior	*JVB*	4	2,971	80	3,051	1971*	62.27
Leadership Quarterly	*LQ*	4	1,123	67	1,190	1990*	39.67
Organizational Behavior and Human Decision Processes	*OBHDP*	4	1,888	29	1,917	1985*	54.77
Applied Psychology: An International Review	*AP:IR*	3	1,599	104	1,703	1961*	28.86
European Journal of Work and Organizational Psychology	*EJWOP*	3	631	10	641	2005*	42.73
Group and Organization Management	*GOM*	3	1,184	45	1,229	1976*	27.93
Human Performance	*HumPerf*	3	524	60	584	1988*	18.25
Journal of Managerial Psychology	*JMP*	3	1,241	115	1,356	1986*	39.88
Work and Stress	*W&S*	3	804	34	838	1987*	25.39
IOP total (*n* = 14)			**23,448**	**949**	**24,397**		
Total (*n* = 42)			**55,732**	**4,302**	**60,034**		

Note. *Full coverage; ‡Partial coverage with some missing years.

higher publication volumes among top producers, with the most prolific author publishing 135 papers in IOP journals and the top 10 producing an average of 93.2 publications (*SD* = 17.95). By comparison, MNGT shows lower top-producer output, with the leading author publishing 70 papers and a top 10 mean of 51.3 (*SD* = 7.78). HRM displays the lowest concentration at the top, with the top-ranked author publishing 54 papers and a mean of 41.2 publications among the top 10 (*SD* = 6.80). Overall, the table indicates that extreme productivity is most pronounced in IOP, consistent with stronger authorship concentration at the upper tail of the distribution.

Table 3 shows the frequency distribution of researchers by publication volume in each field (HRM, MNGT, IOP), based on the number of articles published in the journal sample. Across all domains, the distribution is highly right-skewed, with the vast majority of researchers appearing only a few times in the data set. In HRM, 14,323 researchers published 1–4 articles

Table 2. Top-10 most productive researchers in each field and publication counts

	IOP		MNGT		HRM	
Rank	Top publisher in the field	Publication count in IOP journals	Top publisher in the field	Publication count in MNGT journals	Top publisher in the field	Publication count in HRM journals
1	Researcher1 (156)	135	Researcher29 (70)	70	Researcher53 (57)	54
2	Researcher3 (130)	108	Researcher36 (63)	57	Researcher30 (68)	47
3	Researcher4 (112)	103	Researcher56 (56)	54	Researcher50 (57)	46
4	Researcher8 (94)	92	Researcher67 (52)	52	Researcher51 (57)	46
5	Researcher7 (95)	89	Researcher85 (49)	49	Researcher104 (46)	41
6	Researcher2 (138)	85	Researcher70 (52)	48	Researcher158 (39)	38
7	Researcher9 (90)	83	Researcher86 (49)	48	Researcher64 (53)	37
8	Researcher10 (87)	83	Researcher61 (54)	47	Researcher188 (37)	35
9	Researcher12 (84)	80	Researcher109 (45)	45	Researcher210 (35)	35
10	Researcher16 (79)	74	Researcher76 (51)	43	Researcher244 (33)	33
Mean (*SD*)	93.2 (*17.95*)		51.3 (*7.78*)		41.2 (*6.80*)	

Note. The total number of publications in all three fields is stated in parentheses.

and 1,034 published 5–20 articles, whereas only 54 authored 21–40 articles and just five reached 41–60 publications, with no researchers exceeding 60 articles. A similar pattern is observed in MNGT, where 16,927 researchers fall within the 1–4 range and 1,793 within 5–20, with only 98 publishing 21–40 articles and 11 exceeding 40. IOP exhibits a notably heavier upper tail: While most authors still fall within 1–4 (22,115) and 5–20 (2,235), substantially more researchers reach high-volume categories (243 with 21–40; 34 with 41–60; 14 with 61–80), and a small number exceed 80 articles (including one author above 120). Overall, the table indicates that IOP contains the largest pool of highly prolific researchers, consistent with stronger authorship concentration at the extreme upper end of the productivity distribution.

Data also suggest that IOP attracts a broader researcher base in this top-tier journal sample. Across publication-volume categories, IOP consistently contains more unique authors than HRM and MNGT, indicating a larger pool of researchers publishing in IOP outlets. This is particularly visible in the 1–4 and 5–20 publication ranges, but extends into the upper tail of the distribution, where IOP includes substantially more highly productive researchers than the other two domains.

Table 3. Frequency distributions of researchers' publication count

	Article count							
	1–4	5–20	21–40	41–60	61–80	81–100	101–120	over 120
HRM	14,323	1,034	54	5	0	0	0	0
MNGT	16,927	1,793	98	10	1	0	0	0
IOP	22,115	2,235	243	34	14	5	2	1

3.3. Journal-Level Analyses

The average publication counts of the top 10 most productive authors in each journal are shown in Table 4. *JAP* takes the lead, with the top 10 contributors publishing an average of 38.6 papers, followed by *JVB* (M = 29.5) and *LQ* (M = 24.2). In comparison, the highest journal-level averages are lower in the other domains. Among MNGT journals, *OrgStud* shows the highest top 10 mean (M = 16.4), whereas in HRM, *IJHRM* ranks first (M = 20.6). Overall, IOP journals display consistently higher values, resulting in a higher mean across outlets (M = 17.54, SD = 8.38) than HRM (M = 10.53, SD = 4.23) and MNGT (M = 9.62, SD = 4.02).

We conducted an additional test to evaluate whether the productivity of the most productive researchers differs by field. Given the skewed distribution of publication counts and the nonnormality of journal-level averages, we employed a Kruskal-Wallis nonparametric ANOVA, which is the most appropriate method for comparing groups with nonnormality and unequal variances (Vargha & Delaney, 1998). *Post hoc* comparisons indicate that the average publication count of top 10 authors is significantly higher in IOP journals than in both HRM (H = 2.81, p = .015) and MNGT (H = 3.22, p = .004). These patterns are visually presented in Figure 1, which shows violin plots of journal-level averages and shows that IOP exhibits not only a higher central tendency but also a wider upper tail, driven by journals in which a small subset of elite scholars accumulates unusually high publication volumes. The extreme productivity observed in IOP is not only an author-level phenomenon but is also

Table 4. Average publication count of the top 10 most productive researchers in journals

	IOP		HRM		MNGT	
	Journal	Avg	Journal	Avg	Journal	Avg
	JAP	**38.6**	***IJHRM***	**20.6**	***OrgStud***	**16.4**
	JVB	**29.5**	***ILJ***	**17.6**	***AMJ***	**15.4**
	LQ	**24.2**	***BJIR***	**11.4**	***JoM***	**13.9**
	PPsych	19.7	*IR*	11.3	*HumRel*	13.4
	OBHDP	19.2	*HRM*	11	*JMS*	12.1
	W&S	16.8	*HRMJ*	9.6	*CMR*	11
	JOB	15.7	*WES*	9.4	*OrgSci*	9.6
	GOM	15.3	*EID*	9.3	*Org*	9.2
	JOHP	13.7	*HRMR*	9.3	*ASQ*	8
	JOOP	11.7	*W&O*	8	*JMI*	7.8
	EJWOP	11.7	*ILRR*	7	*BJM*	7.6
	JMP	11.5	*EJIR*	6.5	*AMR*	6.8
	AP:IR	9.7	*NTWE*	5.9	*AMP*	6.2
	HumPerf	8.3			*IJMR*	4
					EMR	2.9
Mean (*SD*)	17.54 (*8.38*)		10.53 (*4.23*)		9.62 (*4.02*)	

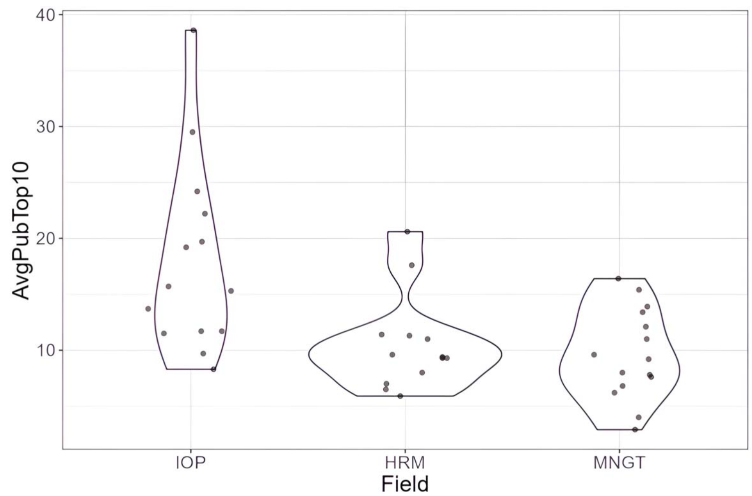

Figure 1. Violin plot—Comparisons of average publication count of the top 10 most productive researchers.

reflected in journal-level allocation patterns, suggesting that leading IOP outlets devote disproportionately more publication space to a small scientific elite relative to HRM and MNGT.

3.4. Cross-Field Comparisons and Elite Dominance

Moreover, we extend our analysis beyond field-level inequality indicators by examining whether the same elite scholars repeatedly dominate multiple journals within each domain. Figures 2–4 visualize cross-journal authorship concentration by reporting the top 10 most

	HRMJ		BJIR		HRM		IR		WES		EID		EJIR	
1	Researcher320	13	Researcher1296	13	Researcher570	19	Researcher779	17	Researcher520	11	Researcher22	17	Researcher188	10
2	Researcher673	11	Researcher244	13	Researcher1401	13	Researcher244	13	Researcher461	11	Researcher128	16	Researcher534	8
3	Researcher434	10	Researcher667	13	Researcher47	12	Researcher902	12	Researcher443	10	Researcher1283	10	Researcher311	8
4	Researcher284	10	Researcher289	12	Researcher104	12	Researcher210	11	Researcher272	10	Researcher3130	8	Researcher1102	7
5	Researcher500	10	Researcher833	12	Researcher6	10	Researcher1243	11	Researcher51	9	Researcher765	8	Researcher3260	6
6	Researcher864	9	Researcher335	11	Researcher112	10	Researcher585	10	Researcher1514	9	Researcher3343	7	Researcher662	6
7	Researcher175	9	Researcher262	10	Researcher2189	9	Researcher1873	10	Researcher141	9	Researcher2817	7	Researcher1852	5
8	Researcher282	9	Researcher1953	10	Researcher2682	9	Researcher630	10	Researcher2672	9	Researcher3630	7	Researcher1875	5
9	Researcher1026	8	Researcher501	10	Researcher668	8	Researcher322	10	Researcher1281	8	Researcher3866	7	Researcher3835	5
10	Researcher281	7	Researcher188	10	Researcher146	8	Researcher1242	9	Researcher335	8	Researcher632	7	Researcher1747	5

	HRMR		ILRR		ILJ		IJHRM		NTWE		W&O	
1	Researcher62	18	Researcher585	11	Researcher158	36	Researcher630	32	Researcher443	9	Researcher309	12
2	Researcher6	12	Researcher665	9	Researcher740	18	Researcher50	27	Researcher196	6	Researcher590	11
3	Researcher84	11	Researcher210	8	Researcher850	17	Researcher147	23	Researcher1093	6	Researcher1216	11
4	Researcher351	9	Researcher750	7	Researcher972	17	Researcher104	21	Researcher50	6	Researcher529	9
5	Researcher179	8	Researcher244	7	Researcher967	17	Researcher145	20	Researcher2043	6	Researcher3234	7
6	Researcher74	8	Researcher692	6	Researcher947	17	Researcher369	19	Researcher623	6	Researcher3376	6
7	Researcher634	8	Researcher962	6	Researcher1445	14	Researcher730	19	Researcher632	5	Researcher1194	6
8	Researcher768	7	Researcher578	6	Researcher1344	14	Researcher538	16	Researcher5532	5	Researcher4761	6
9	Researcher674	7	Researcher232	6	Researcher1485	13	Researcher588	15	Researcher6615	5	Researcher3817	6
10	Researcher210	6	Researcher276	6	Researcher1332	13	Researcher468	14	Researcher631	5	Researcher4756	6
11	Researcher147	6										

3 journals

Researcher210
Researcher244

2 journals

Researcher6
Researcher30
Researcher50
Researcher51
Researcher104
Researcher147
Researcher188

Researcher281
Researcher322
Researcher335
Researcher443
Researcher668
Researcher585
Researcher632

Figure 2. The most productive of HRM journals.

	AMJ		AMR		ASO		JOM		OrgSci		HumRel		JM S	
1	Researcher154	24	Researcher137	8	Researcher183	19	Researcher36	19	Researcher1245	12	Researcher94	17	Researcher61	20
2	Researcher59	19	Researcher319	8	Researcher1752	9	Researcher2	18	Researcher1141	11	Researcher86	16	Researcher114	14
3	Researcher183	16	Researcher125	8	Researcher125	8	Researcher49	17	Researcher997	10	Researcher5	15	Researcher545	14
4	Researcher82	16	Researcher178	7	Researcher424	7	Researcher41	15	Researcher1362	9	Researcher679	15	Researcher109	11
5	Researcher36	15	Researcher37	7	Researcher262	7	Researcher186	14	Researcher240	9	Researcher70	14	Researcher1204	11
6	Researcher240	14	Researcher1466	6	Researcher1791	7	Researcher261	14	Researcher875	9	Researcher29	13	Researcher56	11
7	Researcher726	13	Researcher1187	6	Researcher1047	6	Researcher2387	11	Researcher919	9	Researcher1	11	Researcher297	11
8	Researcher23	13	Researcher445	6	Researcher3221	6	Researcher243	11	Researcher214	9	Researcher1942	11	Researcher214	11
9	Researcher162	13	Researcher3610	6	Researcher240	6	Researcher315	10	Researcher459	9	Researcher80	11	Researcher70	10
10	Researcher287	11	Researcher48.	6	Researcher859	5	Researcher77	10	Researcher1040	9	Researcher31	11	Researcher695	9

	OrgStud		AM P		BJM		CMR		EMR*		IJMR		JM I	
1	Researcher20	26	Researcher2347	10	Researcher706	9	Researcher670	17	Researcher2936	5	Researcher30	6	Researcher29	12
2	Researcher476	17	Researcher61	8	Researcher1046	8	Researcher1531	13	Researcher1507	4	Researcher2382	6	Researcher56	11
3	Researcher340	17	Researcher2569	7	Researcher886	8	Researcher1567	13	Researcher1567	3	Researcher6042	4	Researcher454	10
4	Researcher86	17	Researcher4164	6	Researcher333	8	Researcher1430	13	Researcher1328	3	Researcher2468	4	Researcher499	9
5	Researcher85	16	Researcher948	6	Researcher1149	8	Researcher67	11	Researcher1596	3	Researcher3177	4	Researcher771	9
6	Researcher196	16	Researcher537	6	Researcher568	8	Researcher2143	9	Researcher214	3	Researcher324	4	Researcher1081	9
7	Researcher340	14	Researcher1587	6	Researcher61	7	Researcher168	9			Researcher377	3	Researcher273	8
8	Researcher418	14	Researcher1017	5	Researcher115	7	Researcher1749	9			Researcher6810	3	Researcher378	8
9	Researcher378	14	Researcher109	4	Researcher1092	7	Researcher149	8			Researcher64	3	Researcher1109	8
10	Researcher56	13	Researcher683	4	Researcher215	7	Researcher2689	8			Researcher1092	3	Researcher330	8

*Only more than 3 publications were taken into account

	Org	
1	Researcher577	12
2	Researcher566	11
3	Researcher454	10
4	Researcher499	9
5	Researcher771	9
6	Researcher1081	9
7	Researcher273	8
8	Researcher378	8
9	Researcher1109	8
10	Researcher330	8

3 journals	2 journals	
Researcher29	Researcher36	Researcher183
Researcher56	Researcher70	Researcher287
Researcher61	Researcher86	Researcher377
Researcher214	Researcher109	Researcher378
Researcher240	Researcher125	Researcher1092

Figure 3. The most productive of MNGT journals.

productive authors in each journal, separately for HRM (Figure 2), MNGT (Figure 3), and IOP (Figure 4). Each journal panel lists the 10 most prolific contributors within that outlet, together with their publication counts. The heatmap shading highlights differences in intensity, enabling the identification of journals in which publication space is disproportionately

	JAP		PPsych		JOOP		JOHP		JOB		JYB		LQ	
1	Researcher8	55	Researcher26	27	Researcher6	18	Researcher1	23	Researcher117	23	Researcher143	40	Researcher16	54
2	Researcher3	33	Researcher8	26	Researcher10	13	Researcher98	18	Researcher27	21	Researcher201	36	Researcher34	40
3	Researcher12	47	Researcher12	25	Researcher124	13	Researcher216	14	Researcher19	20	Researcher18	35	Researcher24	25
4	Researcher9	36	Researcher9	21	Researcher89	11	Researcher375	13	Researcher5	20	Researcher58	32	Researcher102	20
5	Researcher13	35	Researcher96	18	Researcher307	11	Researcher10	13	Researcher57	14	Researcher1	28	Researcher38	19
6	Researcher55	34	Researcher11	18	Researcher816	11	Researcher21	13	Researcher87	13	Researcher384	28	Researcher239	19
7	Researcher14	34	Researcher48	16	Researcher13	11	Researcher197	12	Researcher66	12	Researcher212	27	Researcher212	17
8	Researcher31	33	Researcher5	16	Researcher672	11	Researcher7	10	Researcher10	12	Researcher93	24	Researcher208	17
9	Researcher83	31	Researcher20	15	Researcher988	10	Researcher19	10	Researcher1	11	Researcher111	24	Researcher825	16
10	Researcher23	28	Researcher830	15	Researcher4	10	Researcher4	10	Researcher6	11	Researcher521	24	Researcher568	15

	OBHDP		APIR		EJWOP		GOM		HumPerf		JMP		W&S	
1	Researcher151	26	Researcher1160	15	Researcher1	21	Researcher221	34	Researcher9	10	Researcher5	19	Researcher249	24
2	Researcher122	24	Researcher11	12	Researcher21	16	Researcher497	24	Researcher489	10	Researcher394	17	Researcher7	22
3	Researcher291	20	Researcher4	11	Researcher22	15	Researcher637	21	Researcher6	9	Researcher1	14	Researcher245	20
4	Researcher199	20	Researcher62	10	Researcher10	12	Researcher700	15	Researcher161	9	Researcher94	13	Researcher119	19
5	Researcher794	19	Researcher7	9	Researcher7	9	Researcher258	11	Researcher4	8	Researcher1835	11	Researcher45	17
6	Researcher449	19	Researcher5	9	Researcher833	9	Researcher2111	10	Researcher310	8	Researcher331	9	Researcher22	16
7	Researcher723	17	Researcher2560	9	Researcher90	9	Researcher13	10	Researcher232	8	Researcher2472	8	Researcher4	15
8	Researcher117	16	Researcher3931	8	Researcher219	9	Researcher2	10	Researcher507	7	Researcher1481	8	Researcher6	13
9	Researcher114	16	Researcher2131	7	Researcher250	9	Researcher1391	9	Researcher482	7	Researcher1573	8	Researcher485	12
10	Researcher550	15	Researcher2510	7	Researcher45	8	Researcher1285	9	Researcher531	7	Researcher360	8	Researcher219	10

6 journals	5 Journals	4 Journals	3 journals	2 journals	
Researcher1	Researcher7	Researcher7	Researcher5	Researcher11	Researcher22
Researcher4	Researcher10	Researcher10	Researcher8	Researcher12	Researcher45
			Researcher9	Researcher13	Researcher55
				Researcher19	Researcher219
				Researcher21	

Figure 4. The most productive of IOP journals.

occupied by a narrow set of elite scholars. Importantly, the figures also allow assessment of elite recurrence across outlets, that is, whether the same scholars repeatedly appear among the most productive authors across multiple journals within a field.

Figure 2 (HRM journals) suggests a comparatively dispersed authorship structure. Although each HRM journal is characterized by a small set of highly prolific contributors, overlap in the identities of top 10 authors across HRM outlets is limited. Only a small subset of authors appears in the top 10 lists of more than one journal, and instances of recurrence across three journals are rare. This indicates that HRM displays within-journal concentration, yet elite dominance appears to be less consolidated across the field as a whole.

Figure 3 (MNGT journals) displays a similar pattern. Despite the presence of highly productive scholars within individual journals, the overlap of top 10 contributors across MNGT outlets remains modest. Even among the most central journals in management and organization research (e.g., AMJ, ASQ, JoM, OrgSci, OrgStud), the top 10 lists are not dominated by the same small subset of scholars across multiple journals. Overall, MNGT thus shows limited evidence of systematic multijournal recurrence, suggesting that elite productivity is comparatively less field-wide and more distributed across journal-specific communities.

In contrast, Figure 4 (IOP journals) reveals a qualitatively different pattern characterized by strong cross-journal recurrence and multioutlet dominance. The same ultraprolific scholars repeatedly appear across the top 10 lists of multiple IOP journals, often with high publication counts, indicating a unified elite structure operating at the field level rather than at the level of individual journals. Most noticeably, the figure indicates that two researchers (Researcher1 and Researcher4) appear as top 10 contributors in six journals each, a form of multijournal saturation that is not observed in HRM or MNGT.

Flagship IOP outlets (notably *JAP*, *JVB*, and *LQ*) display evidently higher top author publication counts than other journals, indicating that elite dominance is not only field-wide but also disproportionately concentrated in the most prestigious and competitive journals. For example, the leading contributors in *JAP* and *LQ* reach exceptionally high counts relative to typical top 10 values in HRM and MNGT journals, producing a visibly steeper productivity hierarchy within these outlets. Importantly, the figure also shows that a small number of individuals recur across multiple IOP journals, thereby combining within-journal dominance with cross-journal recurrence.

Collectively, these figures provide direct evidence that authorship concentration differs across closely related domains. While HRM and MNGT exhibit concentration within journals, the identities of top contributors vary more across outlets, suggesting weaker field-level consolidation. By contrast, IOP displays a more frequent recurrence of the same elite scholars across multiple journals, consistent with a more closed and self-reinforcing field structure in which publishing success is disproportionately concentrated within a small scientific elite.

3.5. Historical Trends of Inequalities

To assess whether authorship concentration has changed over time, we examined historical trends in inequality across the three fields by calculating Gini coefficients separately for three periods (1960–1979, 1980–1999, 2000–2019), as well as for the full observation window. Figure 5 summarizes these results and demonstrates a clear temporal increase in authorship inequality across all domains.

In MNGT, inequality rises sharply from relatively low levels in the early period (G = .146) to substantially higher levels in later decades (G = .372 in 1980–1999 and G = .428 in 2000–

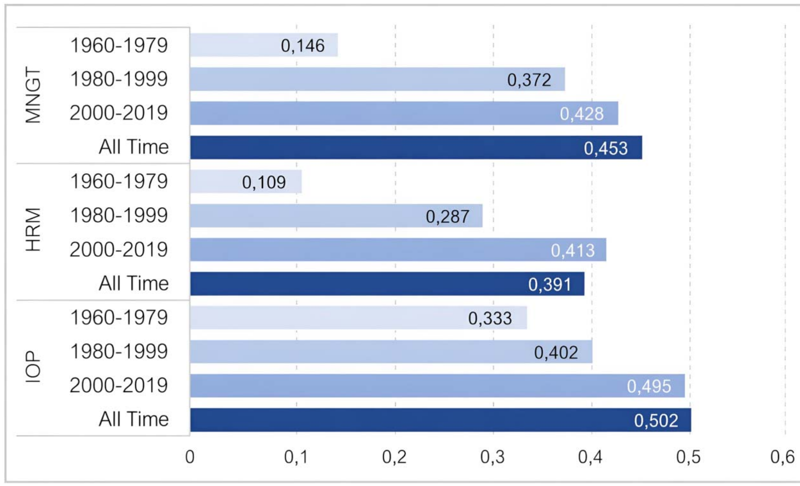

Figure 5. Historical evolution of authorship inequality (Gini coefficients).

2019), yielding an overall coefficient of $G = .453$. HRM shows a comparable growth trajectory, increasing from $G = .109$ (1960–1979) to $G = .287$ (1980–1999) and $G = .413$ (2000–2019), with an all-time value of $G = .391$. IOP exhibits consistently higher inequality throughout the entire historical window. Already in the early period, IOP shows substantial concentration ($G = .333$), which increases further to $G = .402$ (1980–1999) and reaches the highest value in the final period ($G = .495$), with an all-time coefficient of $G = .502$.

Overall, the historical trends show that authorship inequality has been intensifying over time. The results also reveal clear cross-field differences: IOP remains the most unequal domain in every period, while HRM shows lower overall inequality but a pronounced increase in the last period. Taken together, these patterns suggest that elite dominance has become increasingly pronounced across closely related domains, with IOP displaying the strongest and most persistent concentration dynamics.

To better illustrate the growing dominance of the most productive researchers, we computed the share of total publications in each domain authored by the top 1%, 5%, 10%, and 20% of researchers. Table 5 and Figure 6 examine how publication output has become increasingly concentrated among the most productive researchers over time. Across all three fields, the findings show a clear historical shift: A growing share of total publications is captured by increasingly smaller fractions of researchers, indicating intensifying elite dominance.

Table 5 shows that publication output has become increasingly concentrated among the most productive researchers across all domains. In IOP, the top 1% authored 12.6% of all publications in 2000–2019, up from 9.8% (1980–1999) and 7.4% (1960–1979). HRM exhibits an even steeper increase at the very top of the distribution, with the top 1% accounting for 11.2% of publications in 2000–2019, compared to 6.9% in 1980–1999 and 3.4% in 1960–1979. MNGT displays a more gradual but consistent increase, rising from 3.9% (1960–1979) to 7.6% (1980–1999) and 8.8% (2000–2019). Rising inequality is also evident across broader elite segments. In the most recent period, the top 10% of researchers produced 45.5% of all IOP publications, compared to 39.3% in HRM and 38.3% in MNGT. These trends indicate that an increasing share of publication output is captured by a shrinking share of researchers over time. Figure 6 visualizes these historical shifts and shows that top publication shares have

Table 5. Historical trends of publications shares

	IOP			HRM			MNGT		
	2000–2019	1980–1999	1960–1979	2000–2019	1980–1999	1960–1979	2000–2019	1980–1999	1960–1979
Top 1%	12.6%	9.8%	7.4%	11.2%	6.9%	3.4%	8.8%	7.6%	3.9%
Top 5%	32.7%	27.4%	22.8%	27.8%	20.4%	11.0%	25.8%	23.0%	13.5%
Top 10%	45.5%	39.2%	33.7%	39.3%	30.8%	20.2%	38.3%	35.1%	21.9%
Top 20%	60.2%	52.9%	47.3%	53.3%	44.1%	29.4%	54.2%	50.0%	33.0%
Total records	36,071	13,336	3,734	23,085	5,234	327	27,092	8,932	643
# of researchers	14,782	7,048	2,269	11,730	3,470	288	12,722	4,888	539
Avg paper per researcher	2.44	1.89	1.65	1.97	1.51	1.14	2.13	1.83	1.19
SD	4.10	2.46	1.64	2.86	1.34	0.44	2.57	1.93	0.58

risen steadily since the 1960s, with IOP exhibiting the highest concentration across all top segments.

Table 5 also compares the total number of studies published, the number of researchers, and the average output per researcher in each time window across fields. Between 2000 and 2019, the number of researchers publishing in IOP reached 14,782, contributing 36,071 publications. The mean number of publications per researcher was $M = 2.44$ ($SD = 4.10$). During the same period, HRM journals published 23,085 papers authored by 11,730 researchers ($M = 1.97$, $SD = 2.86$), whereas MNGT journals published 27,092 papers from 12,722 researchers ($M = 2.13$, $SD = 2.57$).

To determine whether average productivity differs across fields, we conducted an ANOVA. Results indicate significant differences in mean publications per researcher across domains, with IOP exhibiting a statistically higher average output than HRM and MNGT ($F(2, 25832.11) = 60.88$, $p < .001$). Importantly, despite the larger publication volume and researcher base in IOP, the preceding concentration indicators show that publication output is increasingly captured by a small segment of highly prolific authors.

Overall, the historical patterns reported in Table 5 and Figure 6 indicate that authorship inequalities have intensified across all three fields. Among them, IOP presents the most noticeable profile, combining historically higher concentration levels with sustained growth in elite dominance and publication expansion that remains unevenly distributed.

Figure 6. Shares of total publications by most productive over time.

3.6. Network Analyses

Lastly, we conducted a series of comparative network analyses to better understand the productivity differentials and the temporal development of authorship structures. Coauthorship network maps were generated in VOSviewer (v. 1.6.18). We employed full counting to preserve the relational structure of collaboration networks and to capture how collaborative practices themselves contribute to cumulative advantage. Because our focus is on network closure and elite consolidation rather than individual productivity *per se*, full counting allows repeated group publishing to be reflected directly in node size and link strength. This approach is consistent with our theoretical interest in relational disparity, namely, how publishing advantage is collectively reproduced through stable collaboration circles. Although Perianes-Rodriguez, Waltman, and van Eck (2016) generally advocate fractional counting for most bibliometric applications, they note that full counting offers simpler interpretability and stable link weights, and that differences between methods are often limited in small or weakly collaborative data sets. Accordingly, we intentionally retained full counting to foreground cumulative collaborative advantage, consistent with our emphasis on relational concentration rather than normalized individual contribution. Documents with more than 25 authors per document were removed from the analyses.

The VOSviewer mapping technique positions nodes such that strongly connected authors are placed closer together. Node size represents publication frequency, edge weights correspond to total link strength, and colors reflect average publication year (overlay visualization). Identical layout parameters were applied across HRM, MNGT, and IOP to enable structural comparison.

Figure 7 presents coauthorship networks across three periods (1960–1979, 1980–1999, and 2000–2019) for HRM, MNGT, and IOP, illustrating the temporal development of collaborative structures. For this analysis, the minimum number of documents per author is selected as five, and all authors matching the criteria are included in the mapping.

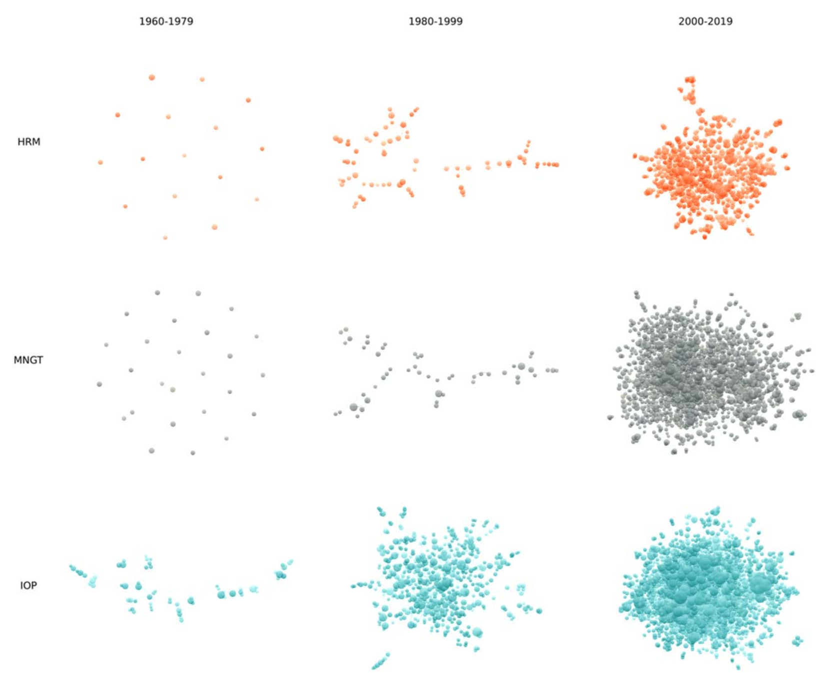

Figure 7. Network analyses.

3.6.1. Temporal evolution of coauthorship networks

During the earliest period (1960–1979), all three fields exhibit highly fragmented networks with minimal collaboration. HRM consists of 16 authors distributed across 16 clusters, with no links, indicating a complete absence of coauthorship ties. MNGT includes 26 authors across 24 clusters, connected by only two links (TLS = 8). IOP shows a higher connectivity, with 64 authors forming 13 clusters and 74 links (TLS = 151), although the overall structure remains relatively sparse and decentralized.

In the second period (1980–1999), collaboration becomes more visible, though unevenly across fields. HRM grows to 71 authors across 12 clusters, with 87 links (TLS = 145), forming elongated, chainlike structures rather than dense cores. MNGT comprises 51 authors in 11 clusters, connected by 66 links (TLS = 118), again characterized by linear and weakly integrated components. IOP expands substantially to 445 authors across 31 clusters, with 849 links (TLS = 1,815), revealing a visibly denser, more centralized structure.

In the most recent period, all fields experience dramatic growth, but with markedly different network topologies. HRM increases to 610 authors across 35 clusters, connected by 1,297 links (TLS = 2,595), forming a moderately dense network with multiple subclusters. MNGT expands to 1,249 authors across 43 clusters, with 3,263 links (TLS = 5,541), exhibiting broader connectivity but a comparatively diffuse core. IOP reaches 1,573 authors across 37 clusters, with 6,530 links and a substantially higher TLS of 12,408, producing a large, densely interconnected core. Notably, IOP displays both the highest number of links and the strongest cumulative link strength, indicating repeated coauthorship among central actors and the consolidation of stable collaboration circles. Additional network analyses are presented in the Supplementary Material. Namely, the mapping of the most productive 50 authors of each field is shown in Figure S4, and the coauthorship networks throughout the 6 decades (1960–2019) are presented in Figure S5 with a minimum of 10 publications.

While all three fields transition from largely individualistic publishing in the early period toward greater collaboration after 2000, IOP uniquely evolves into a densely interconnected network characterized by strong relational closure and cumulative tie strength. HRM and MNGT show increased participation and connectivity but retain comparatively fragmented or diffuse structures.

4. DISCUSSION

In this study, we examined authorship inequality and the extent of elite dominance in management and organizational research, focusing on the three categorically distinct but closely related fields over the 6 decades from 1960. Based on comparative longitudinal analyses of authorship trends in 42 top-tier journals of IOP, MNGT, and HRM, we gather evidence that (1) authorship inequality has been rising in the last 6 decades across all MOR fields. Among these fields, IOP exhibits the most extreme concentration, as supported by findings across different levels of analysis. Results show that elite researchers keep increasing their output across all fields, leading to rising concentrations. Moreover, we find that (2) IOP journals allocate significantly more space to the most productive authors than the journals in the other two fields. Additionally, we show evidence that (3) the superelite scholars of IOP not only publish more articles on average than their counterparts in neighboring fields, but they also dominate journals to a greater extent, as we observe a higher recurrence of the same authors on the top 10 most productive list in IOP journals than those in the other two fields and (4) the most productive IOP scholars are more conservative in their publication venue choices. In addition, while all fields moved toward collaboration, (5) IOP uniquely evolved into a densely interconnected core where success is tied to the collaboration with a small, stable circle of elite, highly productive scholars. These findings have significant implications for theory, practice, and policy design.

4.1. Summary of Findings

Our analysis demonstrates that authorship in management and organizational research is characterized by rising inequalities and increasing concentration. At the individual level, a small group of researchers has accumulated disproportionate influence over time. Among the 4,825 highly productive researchers who published at least five papers in our sample, only 77 individuals (1.60%) published more than 50 papers. Strikingly, the most productive author accumulated 156 publications, and the top 10 most prolific authors averaged 111.1 papers, which are predominantly published in IOP outlets. Similarly, the most productive IOP researchers' publication records greatly deviate from those in MNGT and HRM; while there are 56 researchers with more than 40 papers in IOP, there are only 16 in MNGT and 5 in HRM (cf. Table 3). Moreover, 22 researchers have more than 60 publications in IOP, whereas only one researcher reaches this level in MNGT.

We observed systematic differences in concentration patterns across the three fields. IOP exhibits markedly higher authorship concentration than MNGT and HRM, with its most productive scholars publishing significantly more than their counterparts in the other domains. The top 10 IOP authors averaged 93.2 publications, compared to 51.3 in MNGT and 41.2 in HRM. Moreover, journal-level analyses confirmed that IOP outlets allocate disproportionately more publication space to a narrow scientific elite, with the top 10 contributors to the *Journal of Applied Psychology* averaging 38.6 papers, which is more than double the average in leading MNGT and HRM journals. IOP, in particular, shows more skewed disparities, with greater recurrence of elite authors, higher network interconnectedness among top contributors, and a larger proportional allocation of publication space to the most productive scholars than HRM or MNGT journals.

Our longitudinal Gini coefficient analyses reveal that authorship inequality has intensified over time across all three fields. Between 1960 and 2019, Gini coefficients increased substantially, indicating that publication opportunities have become increasingly concentrated among fewer scholars. This trend accelerated particularly after 2000, coinciding with the intensification of publication pressures and rising rejection rates in top-tier journals. These patterns are further reinforced by our analysis of elite recurrence, which shows that IOP exhibits significantly higher overlap in top 10 author lists across journals, suggesting a more entrenched and interconnected scientific elite.

Another finding concerns the relationship between field size and authorship concentration. Evidence suggests that fields with larger journal ecosystems and greater publication capacity would mechanically exhibit higher authorship concentration among elite producers, insofar as increases in publication volume could intensify cumulative advantage dynamics and concentrate output among already productive authors (Chu & Evans, 2021; Yoshikane et al., 2003). Alternatively, it could intuitively be argued that smaller fields are easier to dominate due to more limited journal space. However, our findings do not support either expectation. MNGT represents the largest field in our sample, both in terms of total journal count (153 journals overall, including 15 top-tier outlets) and total publication volume (20,223 documents), yet it exhibits only a moderate level of authorship concentration across all indicators examined. HRM, the smallest field in terms of total number of rated journals (57 overall, 13 top-tier), displays the lowest concentration. In contrast, IOP lies at an intermediate position in journal count (66 journals overall, 14 top-tier) and publication volume (24,397 documents), smaller than MNGT but larger than HRM, yet shows the *highest* levels of authorship inequality across all measures. These patterns illustrate that authorship concentration is beyond the mechanical consequences associated with journal space or field size. Instead, our findings point to structural differences in how authorship opportunities are allocated and reproduced across fields. In particular, IOP appears to have evolved into a hegemonic, uniquely condensed and relationally closed publishing ecosystem, characterized by dense collaboration networks and highly concentrated authorship structures that differ fundamentally from those observed in HRM and MNGT.

Finally, our network analyses reveal fundamental differences in collaborative structures across fields. IOP is characterized by a large, densely interconnected coauthorship network with high cumulative link strength, indicating repeated collaboration among central actors and the consolidation of stable collaboration circles. The dense coauthorship cores observed in IOP show that cumulative advantage operates relationally, through stable collaboration circles that collectively reproduce elite status. In this sense, authorship concentration reflects not isolated individual achievement but a field-level configuration in which productivity, collaboration, and recognition become mutually reinforcing. In contrast, MNGT and HRM show more fragmented structures with lower network density, suggesting that publishing success in IOP is more strongly associated with embeddedness within tightly knit collaborative networks.

Although not directly presented in this study, we observed that the most productive scholars share a common set of demographic characteristics, such as age (mostly senior), gender (almost always male), race (almost always White, Western), and affiliation (predominantly connected to Western institutions), which dominate journal space disproportionately. These findings complement the previous findings of Bajwa and König (2019), Lin and Li (2023), and Nielsen and Börjeson (2019). These common characteristics and the disproportionate concentration observed in IOP point to distinctive subfield dynamics rather than differences attributable solely to disciplinary approaches. IOP appears to operate through a more centralized, self-reinforcing publication structure, in which scholarly visibility and productivity are tightly coupled to a relatively closed, elite core, and disparities have consistently been more pronounced than in neighboring fields. More broadly, our findings support the view that once a field becomes historically concentrated, accumulated advantages tend to become self-perpetuating, reinforcing existing patterns of dominance over time. At the same time, compared to MNGT and HRM, IOP also combines extreme upper-tail productivity, frequent recurrence of the same authors across journals, and a high degree of hyper-specialization, in which scholars repeatedly publish within narrowly defined thematic and methodological specializations. This narrow focus may itself reinforce elite concentration by rewarding established scholars whose reputational capital aligns with dominant research paradigms. Within this configuration, hyper-productivity is an accepted and normalized practice, sustained by field-level institutional norms, collaborative infrastructures, and evaluative expectations. Early collaboration with well-connected senior scholars may facilitate access to limited valuable resources, accelerate publication trajectories, and consolidate network positions, while simultaneously expanding the productive capacity of established senior researchers. These patterns may also signal strong dual evaluative mechanisms, in which editorial favoritism toward well-known, recurrent authors coexists with heightened scrutiny applied to unfamiliar scholars or institutions. Favoritism may emerge through repeated interactions and reputational signaling, while bias against unknown scholars increases conformity demands regarding theoretical and methodological sophistication, thereby stabilizing elite dominance and elite reproduction (Bal et al., 2025, 2026). Ultimately, IOP has evolved toward a stratified publishing ecosystem in which persistent disparity structures systematically shape publication opportunities and the accumulation of scholarly prestige.

4.2. Theoretical Implications

Our findings have important theoretical implications for how we conceptualize inequality in academic publishing. Our study moves beyond conventional diversity frameworks that focus primarily on *variety* (e.g., gender, geography, affiliation) to examine authorship inequality as a form of structural *disparity*. Following Harrison and Klein's (2007) conceptualization, we distinguish between diversity as *variety* and *disparity* as differential access to valued resources. While efforts to increase demographic diversity remain important, our findings suggest that the fundamental problem in management and organizational research publishing is beyond underrepresentation of particular groups, as the systematic concentration of publishing opportunities is held and exploited by a narrow elite. This distinction is crucial because it shifts analytical focus from individual attributes to systemic mechanisms that produce and reproduce inequality.

Variation in research productivity is an inherent and expected characteristic of scholarly work. Theoretical and empirical evidence suggests that individual performance follows a highly skewed power-law distribution (O'Boyle & Aguinis, 2012; Ruiz-Castillo & Costas, 2014), indicating that a small proportion of researchers account for the majority of research output. Recent observations also confirm a trend of accelerating publication rates and accumulating citations at disproportionate rates, thereby strengthening the hierarchy of the scientific elite (Larivière & Costas, 2016; Nielsen & Andersen, 2021). Consistent with these findings, our analyses show that authorship concentration increases systematically over time, with a small subset of scholars progressively occupying a disproportionate share of available publication space. The patterns also confirm that once a field experiences high disparities, the concentration becomes perpetual over time.

When publication space is under the control of the scientific elite, accumulated reputational advantages could override scientific quality. Li, Aste et al. (2019) show that junior researchers who coauthor with highly productive, prominent scientists gain sustained competitive advantages compared to peers with similar early profiles but without elite collaborators. Early coauthorship with top scientists also increases the likelihood of repeated collaboration with highly cited scholars and substantially raises the probability of eventually attaining elite status oneself. Publishing in top journals at early career stages provides a visible head start in subsequent career advancement in academia (Hou, Wu, & Xie, 2022; Traag, 2021). Brogaard, Engelberg et al. (2024) highlight that articles coauthored with well-known, established researchers receive significantly more citations, regardless of the quality of the articles. These rising authorship inequalities in MOR also reinforce the growing impact of the Matthew effect. Consequently, access to publication has become increasingly contingent not only on research quality but on the accumulated advantages that enable scholars to withstand exceptionally demanding review processes (Zivony, 2019).

4.3. Practical and Policy Implications

The emphasis on quantity by elite researchers raises concerns about the sustainability of the academic publication system. Bal (2021) asserts that highly productive researchers in organizational research publish an average of more than 25 papers per year, equivalent to one paper every 2 weeks. As Harley (2019, p. 293) points out, the glorification of the "heroic workaholic publishing machine" as a role model sets unrealistic expectations for academic careers and provides flawed examples for early-career researchers. Yet, it is becoming highly challenging for early-career researchers to find a place without access to valued resources, as publication space is dominated and controlled by the scientific elite.

Editorial teams have a substantial role in handling submissions more fairly and responsibly. Not only did elite scholars' paper production grow over time, but proportionally, the space allocated to them has also grown significantly. Scholarly societies and editorial boards should also adopt processes and policies to ensure fair representation and address systemic biases and signaling effects in authorship prestige and other metrics. Finally, universities and research institutions should consider the impacts and limitations of authorship concentrations.

4.4. Limitations

Like any large-scale bibliometric study, our analysis has limitations that should be acknowledged. First, we focus on 42 top-tier journals, selected based on widely used quality rankings, which means that our findings speak primarily to the elite segment of the publication system in management and organizational research. Authorship concentration in lower-ranked or regional journals may follow different patterns, and including these outlets could yield a more comprehensive picture of inequality across the full journal hierarchy. In addition, database coverage gaps, particularly missing years for journals like the *British Journal of Industrial Relations* and the *Academy of Management Journal*, may understate elite productivity, though this is unlikely to alter our conclusions about cross-field patterns (see Supplementary Material for missing years in coverage). Second, although we took steps to mitigate author disambiguation issues by relying on databases with robust author identifiers and by manually checking the most productive authors, misattributions or omissions cannot be entirely ruled out. Such errors are unlikely to change the overall pattern of inequality we observe, but they may affect specific counts or rankings at the extreme upper tail. Third, our reliance on full counting rather than fractional authorship may overstate individual dominance in highly collaborative fields, though this approach intentionally foregrounds relational concentration central to our theoretical argument. Moreover, our study is not designed to assess causal mechanisms directly. Although our findings are consistent with theories of cumulative advantage, invisible colleges, and elite gatekeeping, we cannot determine from publication data alone whether specific practices, such as editorial favoritism, network-based review assignments, or institutional biases, drive the observed patterns. Future work could help unpack how informal norms, value judgments, and interpersonal dynamics interact with formal procedures to shape publication outcomes. Finally, we focus on authorship concentration as a structural manifestation of *disparity*, but do not systematically examine how this intersects with *variety* and *separation*. Prior studies in related fields suggest that systemic biases along these dimensions, especially in *variety*, remain pervasive and interact with cumulative advantage processes, yet no studies have examined epistemic separation in relation to research concentration.

4.5. Concluding Remarks

In closing, our findings reveal that publication opportunities in top-tier journals are increasingly concentrated among a narrow scientific elite, with particularly more visible concentration in IOP. With this paper, we underline the structural problems that have been growing over decades. While scholarly societies and journals have made public commitments to DEI, our findings suggest that current approaches may be ineffective if they focus primarily on variety without addressing the structural mechanisms that perpetuate authorship concentration. Meaningful progress will require coordinated interventions that directly challenge cumulative advantage, disrupt network closure, and create genuine opportunities for scholars outside established elites to contribute to top-tier journals.

Importantly, rising authorship concentration should also be understood in relation to the broader competitive dynamics of contemporary academic publishing. Intensifying publication pressure, declining acceptance rates, and prolonged review processes incentivize strategies that maximize output. Hyperprolific publishing can thus be interpreted as a rational adaptation to a highly competitive environment, one that disproportionately benefits scholars with access to stable collaboration infrastructures, shared data sets, and established publication pipelines. These conditions appear particularly salient in IOP, where dense coauthorship networks, recurring collaborations, and incremental research programs facilitate sustained high-volume production. In this sense, hyperprolification is a dual mechanism, stemming from individual publication behavior and editorial selectivity, and is influenced by field-level dynamics and networks.

The implications of these dynamics are cumulative and self-reinforcing. The rise in inequality over the 6-decade period we examined is especially consequential given that it coincides with intensifying publication pressure, heightened competition, and rising selectivity in top journals. If current trends continue, the concentration of publishing opportunities may become even more extreme, further limiting intellectual diversity, stifling meritocratic ideals, and endangering the sustainability of academic careers. Given dysfunctional publication systems, biased editorial processes, perverse incentive schemes, and growing inequalities, the ability to make scientific contributions that count will increasingly become unattainable for many (Aguinis et al., 2020; Bal et al., 2025; Orhan et al., 2025). If the top-tier journal space is fetishized as the sole indicator of scholarly contribution, academic rewards will increasingly privilege conformity and network connectivity over intellectual contribution, reinforcing systemic inequality and narrowing the scope of legitimate knowledge production (Willmott, 2011). Addressing these challenges will require a clear theoretical understanding of systemic biases, alongside corresponding policy interventions and a fundamental reconsideration of how scholarly work is organized and evaluated.

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AUTHOR CONTRIBUTIONS

Mehmet A. Orhan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing—original draft, Writing—review & editing. Yvonne G. T. van Rossenberg: Conceptualization, Methodology, Project administration, Writing—original draft. P. Matthijs Bal: Conceptualization, Project administration, Writing—original draft, Writing—review & editing.

COMPETING INTERESTS

The authors have no competing interests.

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DATA AVAILABILITY

Our main bibliometric data sets are proprietary to Elsevier Scopus and Clarivate Analytics and, therefore, cannot be fully disclosed. However, we have made available data sets and analyses, which can be downloaded from https://osf.io/8z7ka/?view_only=a6c53c6cbbfe47a3a783904244d2685d.

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