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Mapping science through editorial board interlocking: connections and distance between fields of knowledge and institutional affiliations

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Abstract

Research is a global enterprise underpinned by the general belief that findings need to be true to be considered scientific. In the complex system of scientific validation, editorial boards (EBs) play a fundamental role in guiding journals' review process, which has led many stakeholders of sciences to metaphorically picture them as the "gatekeepers of knowledge." In an attempt to address the academic structure that governs sciences through editorial board interlocking (EBI, the cross-presence of EB members in different journals) and social network analysis, the aim of this study is threefold: first, to map the connection between fields of knowledge through EBI; second, to visualize and empirically test the distance between social and general sciences; and third, to uncover the institutional structure (i.e., universities) that governs these connections. Our findings, based on the dataset collected through the Open Editors initiative for the journals indexed in the JCR, revealed a substantial level of collaboration between all fields, as suggested by the connections between EBs. However, there is a statistically significant difference between the weight of the edges and the path lengths connecting the fields of natural sciences to the fields of social sciences (compared to the connections within), indicating the development of different research cultures and invisible colleges in these two research areas. The results also show that a central group of US institutions dominates most journal EBs, indirectly suggesting that US scientific norms and values still prevail in all fields of knowledge. Overall, our study suggests that scientific endeavor is highly networked through EBs.

Keywords Editorial board interlocking · Editorial board · Scientific journal · Social network analysis · Diversity

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Introduction

The axiology of sciences has traditionally suggested that findings, theories, and laws need to be true, parsimonious, and universal to be considered scientific (Davis, 1971; Kuhn, 1962; Tellis, 2017). From the myriad of values associated with "good science," these arguably are the most common, suggesting that science is a global enterprise that needs the collective and cumulative determination of many stakeholders worldwide (Chalmers, 1976; Goyanes, 2020a), to review, correct, nuance, improve, challenge, and complement accumulated wisdom (Echeverría, 1995). One of these stakeholders are the editorial boards (EBs) of scientific journals, a body of governance whose intended commitment is to demarcate the limits of scientific knowledge through peer review, editorial advice, and scientific guidelines and suggestions (Teixeira & Oliveira, 2018; Willett, 2013; Goyanes & Demeter, 2020), leading to their metaphoric role of "gatekeepers of knowledge" (Braun et al., 2007; Araújo et al., 2021; Feeney et al., 2019; Hedding & Breetzke, 2021; Metz & Harzing, 2009; Youk and Park, 2019; Baccini & Barabesi, 2010; Mendonça et al., 2018; Lockstone-Binney et al., 2021; Cardenas, 2021).

As Willett (2013) wisely suggests, EBs play a fundamental role in many areas of scientific progress, such as assisting the journal editor, promoting the journal, serving as referees for peer review, and, ultimately, institutionalizing the norms and values associated with legitimate sciences (Goyanes & de-Marcos, 2020). However, the cross-presence of scholars in different scientific journals, a phenomenon often called editorial board interlocking (EBI; Andrikopoulos & Economou, 2015; Baccini & Barabesi, 2010; Goyanes & de-Marcos, 2020), may limit and even hamper their legitimate objectives, as it is considered a proxy of similarity of editorial policies (Teixeira & Oliveira, 2018). Accordingly, extant research has assumed that strong interlocks may contribute to further the knowledge influx, yet could potentially guillotine scientific progress because of less theoretical, methodological, and topical pluralism (Goyanes et al., 2022; Teixeira & Oliveira, 2018). If scientific approaches, expectations, and visions are homogeneous and shared across journals, science runs the risk of paradigmatic stagnation through the creation of invisible colleges that govern, structure, and monitor the progress of scientific fields (Burgess & Shaw, 2010; Crane, 1977; Zuccala, 2006).

So far, prior research has mainly focused on understanding the EB connections of journals in specific research fields, and limited empirical efforts have been implemented to explore cross-field analyses (i.e., understanding the connections of journals in different scientific fields). For instance, research has examined the connections of EBs in economics (Baccini & Barabesi, 2010), tourism (Lockstone-Binney et al., 2021), management (Burgess & Shaw, 2010), finance (Andrikopoulos & Economou, 2015), knowledge management (Teixeira & Oliveira, 2018), geology (Lu et al., 2019), African studies (Mendonça et al., 2018), statistics (Baccini et al., 2009), communication (Goyanes & de-Marcos, 2020), information systems (Cabanac, 2012), information and library sciences (Baccini & Barabesi, 2011), and sociology (Cardenas, 2021), while to our knowledge, only one study has examined cross-disciplinary EBI, considering six different fields of sciences (Goyanes et al., 2022). The patterns of scientific domination at a global scale through EBI are thus only partially understood.

Due to the lack of cross-disciplinary analysis, the scientific community has a limited understanding of the strength of connections between academic fields. This also affects our understanding of the institutional domination that shapes the norms and values of sciences. Understanding these gaps is important for mapping geographical structures in research evaluation and determining the institutional footprint of the gatekeepers of science (Braun et al., 2007). This study, drawing upon data from the Open Editors initiative (Nishikawa-Pacher et al., 2022), considers 215 scientific fields, over 3000 journals, and over 300,000 EB members. The objectives are to: 1) map the connections between fields of knowledge through EBI, 2) understand the EBI connections and distance within and between social sciences and hard sciences, and 3) visualize and discover the institutional representation at university level of sciences through EBI. Ultimately, this exploratory work contributes to the study of editorial boards in sciences by describing their connections within and between fields and their institutional representation. This study sits on the background of EBs as crucial bodies of governance for scientific production and on their interlockings. Results of the study are relevant to scholars, researchers, academic and scientific managers, and policy makers interested in how EB dynamics can shape and influence cross-disciplinary connections, interdisciplinary exploration, diversity, balance, and transcendence across field boundaries. In academic research, this study contributes to the understanding of scholarly networks, their diversity and representation, scientific governance, biases, and systemic imbalances. Scientific management, journal editors and publishers can learn about the role of interlocking making informed decisions about EB composition; funding agencies and policy makers can shape, prioritize and assess the impact of plans for scientific publishing, diversity, and academic collaboration; and academic institutions can benefit from insights into their scholars' involvement in EBs since it reflects institutional prestige and influence.

Editorial board interlocking

So far, previous literature on journals' EB influence on science has focused on the geographical background (Akça & Şenyurt, 2023; Harzing & Metz, 2013; Hedding & Breetzke, 2021), gender representation of EB members (Mauleón et al., 2013; Metz et al., 2016), and the structure of connections between journals within (Teixeira & Oliveira; Goyanes, 2020b) and between fields (Goyanes et al., 2022), visualized through the empirical analysis of EB interlocks. Research has typically framed findings and normative conclusions in terms of the diversity of EB appointments and the potential deleterious effects they may prompt in shaping sciences. In general, it is expected that EBs mirror or at least resemble the cultural, geographical, and gender diversity of society, so they can better capture and understand native and complex social phenomena to create broader empirical knowledge (Dhanani & Jones, 2017). A lack of diversity thereof is thought to limit and marginalize new ways of thinking, research agendas, and priorities (Goyanes, 2020b) that may inform theory development, research, and practice.

A growing body of research has focused on understanding the structure of science through EBI (Andrikopoulos & Economou, 2015; Baccini & Barabesi, 2010; Goyanes & de-Marcos, 2020), offering descriptive insights into both the representation and connections of individual members, institutions and geographies in conforming journals' EBs. As in the field of business, where board members can be strategically appointed to different companies, thus providing counseling and expertise across organizations, in sciences an EB member can also occupy a seat on more than one EB—a phenomenon theorized as editorial board interlocking (Baccini & Barabesi, 2010).

Numerous empirical studies have investigated journal connections through editorial interlocks, often focusing within specific fields of study (Baccini & Barabesi, 2010; Mendonça et al., 2018; Lockstone-Binney et al., 2021; Cardenas, 2021). Findings may vary depending on the academic discipline, yet a prevailing consensus in the literature affirms that exploring EB interlocks can illuminate the structure of elite institutions, scholars, geographies, and the interconnected relationships that influence the primary expectations, research benchmarks/standards, academic styles, and priorities in the sciences (Goyanes, 2020b; Teixeira & Oliveira, 2018). Research has proposed that EB interlocks represent positions of influence (Baccini & Barabesi, 2010). Those positioned in top-tier journals may thereby exert influence over the vision and primary paradigms of such journals. This influence can yield both positive and deleterious effects: on one hand, interlocks may establish clear norms and values associated with excellent research. For instance, EB members across different journals can facilitate the exchange of scientific ideas, acting as bridges for sharing ideas and scientific practices, thereby fostering the dissemination of relevant knowledge (Teixeira & Oliveira, 2018).

Simultaneously, EB interlocks may contribute to and facilitate research endogamy (the same scholars publishing in the same top-tier journals), a lack of research diversity (Goyanes, 2020b), and the formation of invisible colleges (Zuccala, 2006). Furthermore, editorial interlocks may raise significant concerns regarding potential conflicts of interest, as board members may introduce biased decision-making when determining whether to accept or reject papers from affiliated institutions or academic peers. Finally, a notable prevalence of specific profiles across different journals can potentially reinforce and solidify existing power structures, ultimately impeding the recognition and potential influence of peripheral voices (Mendonça et al., 2018).

All things considered, if EBs are considered the main bodies of governance for most journals (Baccini & Barabesi, 2010; Mendonça et al., 2018; Lockstone-Binney et al., 2021; Cardenas, 2021), understanding their connections and structure through interlocks may cast light on the invisible power structures that set the agendas, scientific patterns and legitimization process of sciences through peer review. However, despite the importance of EBs as "gatekeepers of knowledge" (Braun et al., 2007; Araújo et al., 2021; Feeney et al., 2019; Goyanes & de-Marcos, 2020; Hedding & Breetzke, 2021), limited research has been conducted on EBI across journals of different fields of knowledge. Thus far, prior literature has mainly focused on interlocks within fields of study (Baccini & Barabesi, 2010; Burgess & Shaw, 2010; Lockstone-Binney et al., 2021; Mendonça et al., 2018), examining in detail their connections through the emergence of invisible colleges. To understand how the gatekeepers of knowledge establish a network of connections in most journals of sciences, we pose the following research question:

RQ1: What are the connections between fields of knowledge through EBI?

Beyond the connection of fields of study through EBI, particularly important is to understand the potential distance (or closeness) between such fields of knowledge (Goyanes et al., 2022). More specifically, this study aims to explore the EBI connections within and between social sciences and hard sciences in order to indirectly understand which fields are bridging the knowledge gaps between the naturally distant disciplines of sciences. Ultimately, answering this question is interesting and relevant because it holistically sheds light on the fields of knowledge that serve as bridges of scientific ideas, and that therefore have a critical impact on the circulation of novel research practices and innovative methodologies that may ultimately be accepted across fields of knowledge and taken as scientific benchmarks. However, to date, prior studies on EBI have mainly focused on understanding connections between fields, thereby neglecting how invisible colleges emerge from the connections established throughout the sciences. More formally, the second research question stands as follows:

RQ2: What are the connections within and between social sciences and hard sciences?

Finally, it has been largely shown by extant research, that the impact of universities on knowledge production varies according to a myriad of factors, such as the quality of the human resources, the funding, or the research tradition of such entities. In addition, as previously mentioned, the impact of scientists' research output may also significantly influence their likelihood of being invited to join the EB of different journals (Braun et al., 2007; Andrikopoulos & Economou, 2015; Baccini & Barabesi, 2010; Goyanes & de-Marcos, 2020). However, despite the importance of understanding the patterns of institutional domination by means of examining the institutional representation and connections of EB interlocks, to our knowledge, no empirical research has explored this phenomenon. Especially, exploring the institutional domination and connections through EBI may enable us to offer a realistic picture of the scientific institutions that arguably have the strongest impact on shaping science as we know it. In a more formal research question:

RQ3: Which institutions are in dominant positions in editorial boards and what are their connections through EBI?

Method

Data sources and coding

We took the data for this study from the 2022 Open Editors dataset.[1] The Open Editors initiative records 594,580 EB members from 7352 journals covering 26 publishers. Open Editors gathered data semiautomatically by scraping the web pages of the main academic publishers. Although it covers only a portion of all publishers, the editors recorded in Open Editors were responsible for and processed approximately a fifth of the total scientific production in 2021 (Nishikawa-Pacher et al., 2022). Open Editors provides the name, affiliation, and role of editors as reported in the web page of the journal, and the name, publisher, and ISSN of the journal. For this study, we coded the name, affiliation, and affiliation country of EB members. Journal information was taken from the Journal Citation Report (JCR). We considered all journals included in the Social Science Citation Index (SSCI) and Science Citation Index Expanded (SCIE), which are also in the Open Editors dataset. SSCI and SCIE are the two main JCR indexes for the social sciences and science & technology respectively. For each journal, we coded the ISSN, name, field, impact factor, and quartile. The field for each journal was taken from the JCR. The JCR 2021 classifies journals in 235 categories listed under the SSCI or SCIE. For journals listed in more than one category, we used the first category listed in the JCR. For each category, we coded the name and the index (SSCI or SCIE). Seven categories were listed under both indexes in the JCR and coded as "Both"; these categories were: "History & philosophy of science," "Nursing," "Psychiatry," "Substance abuse," "Rehabilitation," "Green & sustainable science & technology," and "Public, environmental & occupational health." Thirteen JCR categories had no journals in the Open Editors dataset and were omitted from this study.

We initially took all of the editors and EB members in the Open Editors dataset which were part of the boards of the 3038 journals also listed in the JCR, resulting in a subset of

[1] Open Editors: https://openeditors.ooir.org/

385,440 EB members. Nearly a quarter (24.38%) of the journals listed in the JCR were also present in the Open Editors dataset; just over a quarter (26.30%) of the journals in the SSCI and 23.93% of the journals in the SCIE were present in the Open Editors dataset. Journals from the first two quartiles (Q1 and Q2 of the JCR) were better represented than the other two quartiles: 31.85% for the SSCI and 31.05% for the SCIE. Data were collected in July 2022 covering the JCR 2021 and the version of Open Editors updated in February 2022.[2]

Preprocessing and graph construction

Preprocessing of the dataset to construct the graph was divided into three stages: Joining of the data sources (Open Editors and JCR), unification of institution names, and deduplication of EB members. During the initial stage, we first cleaned the data by removing character coding inconsistencies, common abbreviations (e.g., "PhD" or "Prof"), and HTML tags that were also in the Open Editors dataset because of the website scraping method used to collect data. We then performed an inner join between the journals of the Open Editors dataset and the journals of the JCR using ISSN (or eISSN). These produced a list of the 3,038 JCR journals that are also included in the Open Editors database, as well as a list of their 385,440 EB members.

Unification of institutions (stage 2) was necessary, because journals report affiliation information heterogeneously. There may be differences in institutions' names (e.g., "Harvard University," "Harvard Univ.," or "University of Harvard"). Journals can also report the full affiliation of EB members including departments and areas of specialty, or they may not indicate the country. We first tried to determine the affiliation country by searching for a predefined list of countries, states, and capital cities (using the ISO 3166) in the reported affiliation field. We then used the Research Organization Registry (ROR) web API[3] to determine the affiliation institution name and country for all EB members. The ROR provides two ways to query the API. We first used the "Affiliation" smart matching parameter, which returns a potential affiliation for a given string and a binary flag indicating whether the returned organization is correctly matched. This returned a positive match for 279,350 EB members (72.48%). For them, we used the affiliation name and country from the ROR record. For the remaining unmatched EB members, we used the "Query" parameter of the ROR API, which returns a list of the first 20 search results from the registry. We took the first result of the ROR query and compared it fuzzily with the original affiliation string using the Python FuzzyWuzzy library.[4] We utilized the ROR affiliation name and country when there was a coincidence above 0.9 while comparing only the extracted institution name, or above 0.8 when comparing both the affiliation name and country. Common threshold values vary between 0.7 and 0.95 (Grzebala and Cheatham, 2016), with lower values biased towards false positive matches and higher values biased towards false negatives. A value of 0.8 is recommended for comparing names in datasets with high variation or error rates, while higher values can be used for data with a narrower range of variation (Peng et al., 2014). Our choice of threshold values aims to reduce false positives, setting a higher value when comparing only one parameter and a lower value when comparing both the affiliation name and country. This returned a match for 34,391 EB members (8.93%). For the remaining 71,699 EB members (18.59%), we could not determine an affiliation

[2] The CSV files from https://github.com/andreaspacher/openeditors (commit e5c4e82).

[3] Research Organization Registry REST API documentation: https://ror.readme.io/docs/rest-api

[4] FuzzyWuzzy library (0.18). https://pypi.org/project/fuzzywuzzy/

using the ROR registry and we kept the details extracted from the original affiliation field from Open Editors. For 1812 (0.47%) of these records, it was not possible to determine any affiliation information either because it was empty, or it included only numbers and non-alphabetical symbols. These were coded as missing. For the rest, we found that most cases corresponded to EB members in which only partial information was reported, such as location (e.g., "London"), position (e.g., "Professor"), degree (e.g., "Dr Sci"), or different forms of the name for a department, unit, or area of research (e.g., "Molecular biology" or "Nuclear medicine"). The remaining records were mostly companies, small research centers, government- related institutions, and NGOs not included in the ROR registry, and each of these institutions has very few EB members in the dataset. The country could not be determined for 2633 EB members (0.68%). This was the case when only a generic position was indicated (e.g., "Independent Researcher," "Private Practice," "Self-employed"), no affiliation information was provided, or the affiliation did not include a country and it did not match any record in the ROR registry.

The final stage of the preprocessing was the deduplication of EB members. The aim was to find the scholars that are part of the boards in two or more journals (i.e., the interlocks). First, we compared the names of all EB members, which yielded 69,465 matching records. However literal string matching does not work when names are reported in different ways (e.g., "David Simons", "D. Simons", or "Simons, D."); to deduplicate the remaining records—and considering the computational needs of comparing over 230,000 records—we used a text mining algorithm for efficient fuzzy string comparisons with large datasets. We compared EB members using cosine similarity between size 3 ngrams computed for each name. The awesome_cossim_topn function from the sparse_dot_topn library[5] was used to produce all possible matches efficiently. For each EB member, we identified an initial list of the top 50 potential name matches (i.e., EB members with a similar name based on the cosine similarity of the ngrams) with a minimum coincidence threshold of 0.7. For each potential match, we then compared the affiliation name and affiliation country of the EB member using the token_sort_ratio function of the FuzzyWuzzy Python library for fuzzy string matching. This function detected similarities between two strings of multiple words (which can be in different order) by making them lowercase, removing punctuation, tokenizing each word, reordering them alphabetically, and then calculating the Levenshtein distance similarity ratio between both. Each potential match was considered a coincidence when the ratio was, both over 0.8 for affiliation name and over 0.9 for affiliation country. For the 1705 records for which the country could not be determined, we used a threshold ratio of 0.9 for the affiliation name. This process returned 6104 additional matches. Finally, 315 duplicate records representing the same EB member in the same journal were removed. These were probably introduced by the Open Editors scraping method.

The final dataset included 309,772 unique EB members, and 385,125 connections, with 3038 journals listed under 215 JCR categories. An EBI graph was constructed as a bipartite graph of EB members and journals. The connections were represented as a bi-adjacency matrix. We used the NetworkX library[6] to construct and analyze the graph. The final graph contained 312,810 nodes (309,772 scholars and 3,038 journals) and 385,125 edges.

[5] sparse_dot_topn library by the ING Wholesale Banking Advanced Analytics team: https://github.com/ing-bank/sparse_dot_topn

[6] NetworkX. Network Analysis in Python. https://networkx.org/

Social network analysis

This study focuses primarily on descriptive and exploratory analysis to outline the composition of EBs and the connections they form between them, between fields and between institutions. The bipartite graph of EB members and journals was analyzed using social network analysis (SNA). For each individual node (journal or EB member), we computed the following metrics: degree, closeness centrality, and betweenness centrality. Degree is the number of connections for each node. Closeness centrality is a measure of the inverse distance of a node to all others. A node with a high closeness centrality is close to others, having better and faster access to them or to the information they spread through the network. We used normalized harmonic closeness centrality, because it is adequate for unconnected networks. Betweenness centrality is a measure of the number of the shortest paths that go through a node. A high value for betweenness suggests that the given node plays a significant role as a bridge in the network, connecting parts that are otherwise disconnected or remote. Such nodes also have better access to the information that goes through the overall network.

We used the following metrics to measure the structural properties of the overall network: density, number of strongly connected components, average path length, average clustering coefficient, and also the average of the individual network metrics previously described (degree, closeness, and betweenness). Density is the ratio between the number of edges and all possible edges. A strongly connected component is a part of the network in which each node is reachable from each other node. The number of connected components is then a measure of the level of connectedness or fragmentation of the network. Average path length is the average of the length of the shortest path between all pairs of nodes. The average clustering coefficient is a measure of the strength of local connections. In social networks, participants usually create local groups characterized by a relatively high density of ties compared to ties connecting with the rest of the network. Social networks also tend to show low density while still allowing short average paths between all actors.

Given the size of the bipartite graph (> 310,000 nodes), it was computationally challenging to obtain the individual and network metrics that required computation of the distance between each pair of nodes. For this reason, we used the network of interlockings to compute the following network metrics: closeness centrality, betweenness centrality, diameter, and average path length. The network of interlockings includes all of the EB members (57,600) that interlock two or more journals (degree > = 2) and all of the journals.

To analyze the relations between fields, we built a weighted projection with nodes representing fields, which are connected by the number of EB members (weight) that interlock journals in both fields. Similarly, to analyze institutions and their connections, we also built a projection of institutions weighted by the number of journals in which connecting institutions share at least one EB member. We used n-slices to find and visualize the subgroups of activity in the field and institutional networks. We also computed all of the network metrics previously mentioned for these two projections, and fed linear regression models to test whether the number of scholars in EBs of institutions explains network metrics. This study uses four networks: the overall bipartite network containing all nodes, the network of interlockings containing all journals and only EB members with degree larger than one, the projection of fields weighted by the number of shared EB members, and the projection of institutions weighted by the number of journals in which they share at least one EB member.

Finally, we used the Louvain method to extract the community structure of the large network (Blondel et al., 2008). It optimizes modularity for each node, which is a measure of the relative density of edges inside communities with respect to edges outside communities. The Louvain heuristic method returns the grouping of the nodes of a given network as a modularity class for each node. Given the size of the network it was unfeasible to determine the areas of activity by visual inspection and interpretation. The Louvain method outperforms other well-known community extraction methods in terms of computational time. We inspected the journals of each modularity class that contained more than 3% of all the nodes as identified by the algorithm and manually gave each a name representative of its main area of activity as interpreted by us.

We used the Gephi open platform to produce the visualizations of all of the networks (Bastian et al., 2009) and the ForceAtlas2 layout (Jacomy et al., 2014), which is the default layout algorithm in Gephi and provides a good balance of performance and personalization for typical networks.

Results

Structural properties of the EBI social network

The bipartite overall network of EB members and journals contains 312,810 nodes and 385,125 edges, which thus presents a density of 0.041%. The average degree is 1.24 (SD = 0.58) for EB members and 126.8 (SD = 703) for journals. Journals show a wide variation in degree, with 31 journals reporting only one EB member, while five journals had more than 10,000 EB members; 57,600 EB members interlock two or more journals. This shows a wide variety in the way EBs configure across disciplines, with journals opting for a minimal number of seats while others include many. The average closeness centrality is 0.242 (SD = 0.039) for interlocking EB members and 0.196 (SD = 0.062) for journals. Considering the size of the network, all interlocked EB members and journals are relative close to the center having expedite access to key actors. The average betweenness centrality presents an average that is less than 0.001 for interlocking EB members and 0.005 (SD = 0.038) for journals. Visualization of the overall bipartite network is difficult because of its size. The network of interlockings also presents a significant challenge, with over 60,000 nodes and 132,000 edges. Community detection made it possible, however, to outline the main areas of academic activity (Fig. 1). Upon interpretation of the modularity classes returned by the Louvain method, we found a central area of activity that includes journals on life, healthcare, and psychology. Social sciences form a separate class on the right of the figure. Three other small classes are close to the main area of activity: physics and chemistry, bioengineering, and earth & environmental sciences. Engineering journals and scholars spread through the bottom part of the graph, filling in the gaps between the other classes.

The overall bipartite network has 289 connected components, which represent the number of areas with independent activity unconnected to the rest of network through EBI. The main connected component includes 303,101 scholars (97.81% of the overall graph) and 2740 journals (90.19%), which form 378,337 connections (98.15%) with a density of 0.046%. There is only one component with three journals, and eight components with two journals. The remaining 280 components include only one journal that are not connected to any other journals through EBI. Most journals then tend to be connected creating a central

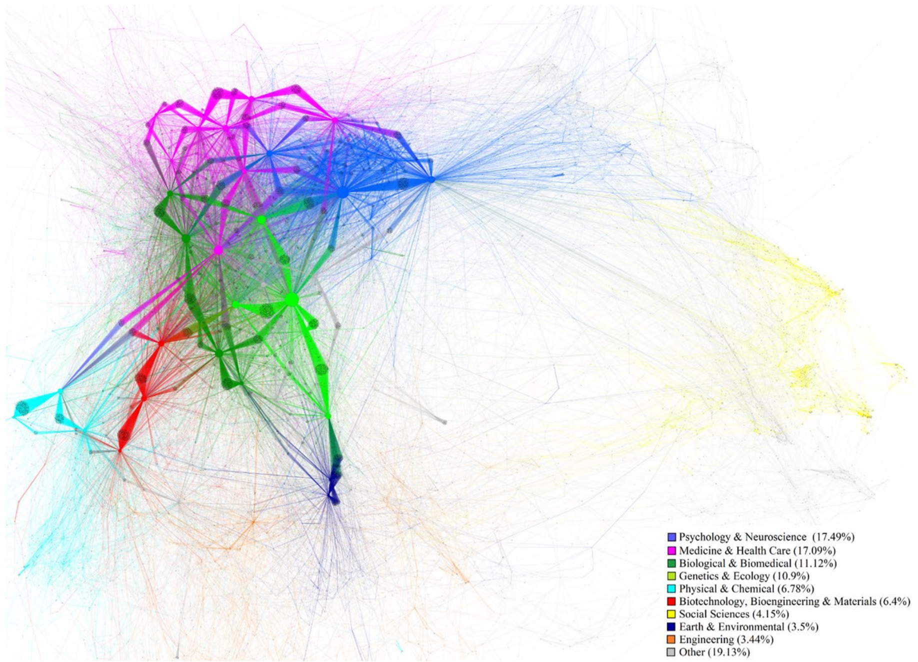

Fig. 1 Central part of the network of interlockings colored by main areas of scientific activity using the Louvain community detection algorithm. Percentages in the legend represent the size of each community in the overall network of interlockings

area of interlocking while a number of journals (9.81%) are like islands whose EB activity is not affected by interlocking. Areas of interlocking activity with a high number of journals are unusual or do not occur with more than three journals. The average clustering coefficient of the bipartite network is 0.75, which means that the social network of EB members and journals establishes numerous local connections despite the relatively low density. The average path length is 7.84. The representativity of the main connected component and the existence of short paths relative to the network size, along with the clustering coefficient, suggests that scientific endeavor is well connected through EBI.

Connections between fields

Most connections (252,276 representing the 65.5%) are within fields. 51,214 (16.53%) scholars interlock the EBs of journals of two or more fields, creating 114,726 inter-field connections (35.5%). This suggests that journals enroll a certain number of scholars from different fields in their EBs. These may be scholars who have interdisciplinary profiles conducting research in different fields or in the topics that connect different areas. Only one field (nanoscience & nanotechnology) is not interlocked with other fields. The visualization of the projection of all fields is provided as Supplementary Material (SM1) in high resolution. It includes 215 nodes and 3622 edges with a density of 15.74%. Table 1 shows the network metrics of three of the networks analyzed in this study. Average degree is 33.85, average closeness centrality is 0.56, while average clustering coefficient is 0.75. We also observe short path lengths since average path length is 1.97, which represents

Table 1 Structural properties of the three networks analyzed

Property	Overall bipartite network	Projection of fields	Projection of institutions (20-slice)
#nodes	312,810	215	1,293
#edges	385,125	3,622	252,229
Density	0.04%	15.74%	30.02%
#Connected components	289	2	1
Avg. path length	7.84	1.97	1.72
Diameter	22	4	3
Avg. degree	EB members: 1.24 Journals: 126.8	33.85	390
Avg. closeness centrality	EB members: 0.242 Journals: 0.196	0.56	0.64
Avg. betweenness centrality	EB members: < 0.001 Journals:.005	0.005	0.001
Avg. clustering coefficient	0.75	0.62	0.85

For the overall bipartite network: (1) average degree, average closeness centrality, and average betweenness centrality present different values for each partition (EB members and journals); and (2) average path length, diameter, closeness centrality, and betweenness centrality, are computed for the subnetwork of interlockings (EB members and journals with degree > = 2)

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approximately half the diameter of the projection of fields. As for the metrics of individual nodes in this projection, the results (Table 2) show that the two top fields are the same for all metrics, while the top 10 is also very similar. Multidisciplinary fields are in the top positions, particularly for betweenness centrality. Although we could not discern any tendency or pattern, top ranked fields tended to show at least one of the following features: they have a substantial number of journals, or they have journals with many EB members.

Most of the fields establish more connections through EBI with other fields of the same index. There are 2821 (77.89%) inter-field connections within the same index, while 801 (22.11%) are between indexes. We can also observe in the projection that nodes representing fields of the social sciences included in the SSCI cluster together and separately from the fields of the sciences included in the SCIE. Only two fields break this tendency: The Psychology field of the SCIE establishes more connections to fields in the SSCI than to fields in the SCIE. Similarly, the field "Psychology, multidisciplinary" is closer to the SCIE fields than to the SSCI fields; however, given its nature and that the SCIE has more fields, it is in a central rather than a one-sided position. The results suggest, then, that there is a separation between the sciences and the social sciences, such that multidisciplinary connections are more frequent and stronger (as represented by the number of shared EBs) within each (SSCI and SCIE) than between them.

To examine the separation within and between indexes, we analyzed the distribution of weighted links for the projection of fields. The five fields listed under both JCR indexes were omitted. Results (Table 3) show a statistical difference between the weights of edges connecting the fields from the same index and the weights connecting fields from different indexes. Weights connecting fields within SCIE are higher than those connecting SSCI fields. The distribution of weights also suggests that fields are closer to other fields of the same index than to fields of the opposite index as measured by the number of EB members

Table 2 Top 10 fields for each network metric of the projection of fields

#	Degree		Closeness centrality		Betweenness centrality	
1	Multidisciplinary sciences	155	Multidisciplinary sciences	0.864	Multidisciplinary sciences	0.102
2	Psychology, multidisciplinary	121	Psychology, multidisciplinary	0.784	Psychology, multidisciplinary	0.053
3	Neurosciences	109	Neurosciences	0.756	Materials science, multidisciplinary	0.038
4	Biochemistry and molecular biology	106	Biochemistry and molecular biology	0.748	Physics, multidisciplinary	0.033
5	Physiology	102	Physiology	0.739	Biochemistry and molecular biology	0.030
6	Environmental sciences	98	Environmental sciences	0.730	Neurosciences	0.028
7	Public, environmental and occupational health	97	Public, environmental and occupational health	0.728	Environmental sciences	0.027
8	Materials science, multidisciplinary	97	Materials science, multidisciplinary	0.726	Physiology	0.026
9	Genetics and heredity	95	Genetics and heredity	0.723	Public, environmental and occupational health	0.024
10	Pharmacology and pharmacy	94	Pharmacology and pharmacy	0.721	Economics	0.020

Degree represents the number of connections from a field to all other fields (range 0–155)

Closeness centrality and betweenness centrality are normalized (range 0–1)

Table 3 Distribution of weighted links within and between indexes (SCIE and SSCI) for the projection of fields

Group	*n*	Mean	SD	Median	Significance
From SSCI to SSCI	539	8.06	68.20	1	$H = 111.22$ $p < 0.001$
From SCIE to SCIE	2431	26.20	111.27	3	
Between SCIE & SSCI	390	8.55	23.68	2	

Categories included in both JCR indexes are not included

SSCI Social Sciences Citation Index, *SCIE* Science Citation Index Expanded

Significance was computed using a Kruskal–Wallis test

Table 4 Average path length of fields within and between indexes for the projection of fields

From	To	*n*	Mean	SD	Median	Significance
From SCIE	To same (SCIE)	158	1.90	0.26	1.93	$W = 20{,}163$ $p < 0.001$
	To other (SSCI)	158	2.10	0.30	2.07	
From SSCI	To same (SSCI)	49	1.70	0.29	1.73	$W = 1406$ $p < 0.001$
	To other (SCIE)	49	2.11	0.24	2.06	

Categories included in both JCR indexes are not included. Significance was computed using Mann–Whitney tests

SCIE Science Citation Index Expanded, *SSCI* Social Sciences Citation Index

shared. To further analyze the distance within and between each index, we also computed the average path length from each field to all fields in the SSCI and to all fields in the SCIE (Table 4). The results show that the differences are statistically significant between indexes. The social sciences are closer to other fields of the social sciences than to the fields in the sciences by 0.33, which its substantial, because it represents 16.76% of the average path length. The distance also increases by 0.2 (10.16% of average path length) for fields in the sciences when connecting to fields in the social sciences through EBI. We also checked for statistical differences between network metrics for the fields of both indexes. There are no differences in degree ($H = 0.64$, $p = 0.42$), closeness ($H = 1.70$, $p = 0.19$), and betweenness ($H = 0.65$, $p = 0.42$), which suggests that all fields have a similar number of connections, central position in the network, and number of paths that go through them. The difference in the clustering coefficient is statistically significant ($\mathrm{Mdn}_{\mathrm{SCIE}} = 0.62$, $\mathrm{Mdn}_{\mathrm{SSCI}} = 0.53$, $H = 11.37$, $p < 0.01$), which suggests that fields in the sciences tend to form closer connections with their neighboring fields than fields in the social sciences do with their neighbors.

Figure 2 presents a 20-slice of the projection of fields to facilitate visualization and identification of the main subgroups of activity between fields as linked through EBI. We can observe a group at the top right of the figure, which includes the fields of health and life sciences. These fields also connect to the fields related to physics and chemistry, which form a second group in the right side of the figure. Engineering-related fields are at the bottom and present less connections through EBI. The social sciences group on the left with business, management, and economics fields forming a connected subgroup, while psychology and education-related fields form another subgroup. The grouping observed here also resembles the one presented using the community detection method (Fig. 1). In the 20-slice of the projection of fields, we can further observe the separation of sciences and social sciences in the core of the EBI network. "Psychology, multidisciplinary" is the only field that presents a number of connections with other fields listed under both the SSCI and

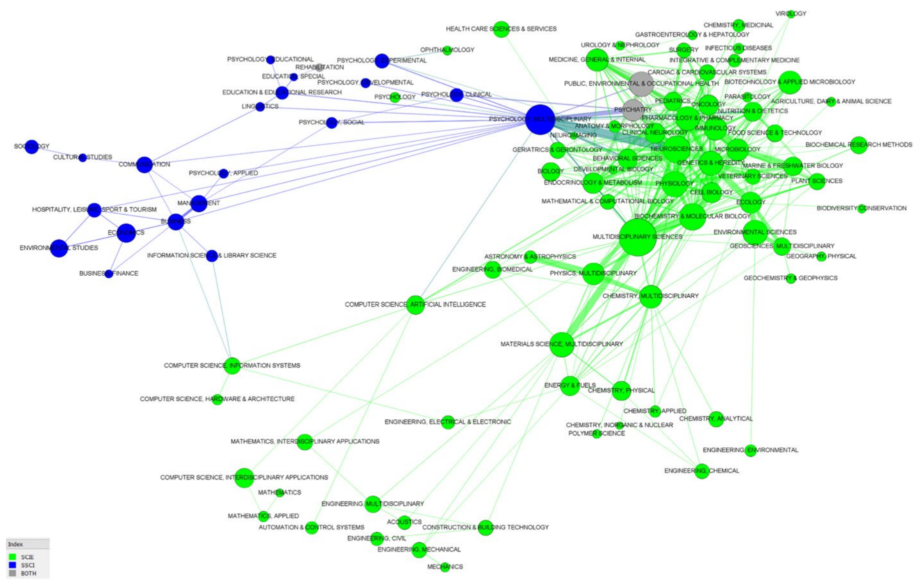

Fig. 2 Projection of JCR categories and their interlockings (25-slice). Node size is proportional to degree. Line thickness is proportional to the number of shared EB members between the connecting categories

SCIE. Connections between fields in the different indexes become the exception when we focus on the part of the network in which connections are larger (fields interlocking 20 or more EB members).

The analysis of EBI then reveals that most of the connections (RQ1) occur within fields, while only around one sixth of scholars interlock the EBs of journals from two or more fields. Journals then include scholars from different fields in their EBs, possibly due to interdisciplinary research interests. Fields form the following main clusters of interdisciplinary activity: Health and Life Sciences, Physics and Chemistry, Engineering, and Social Sciences. Regarding the connections between social sciences and hard sciences (RQ2), most occur within the same index, but some (22.11%) span between indexes. There is a clear separation as evidenced by: (a) Social science fields clustering separately from the other three clusters representing the hard sciences, (b) shorter path lengths to fields within the same index, and (c) higher weight of links between fields of the same index.

Institutional representation

The exact number of institutions is difficult to determine because of the limitations of the affiliations reported by journals, as indicated in the Methods section. To analyze the institutions, we first included all of the records found on the ROR registry. We then created a filter to add all affiliations that include common names (e.g., university, hospital, institute, academy) in different languages and variations (e.g., centre, center). Finally, we manually checked all affiliations with 10 or more EB members in the dataset. This filtered out the cases in which the affiliation only reports a position, location, and/or name of department, resulting in a subset of 24,800 different institutions with around 18.6 million connections. The final graph represents the projection of institutions

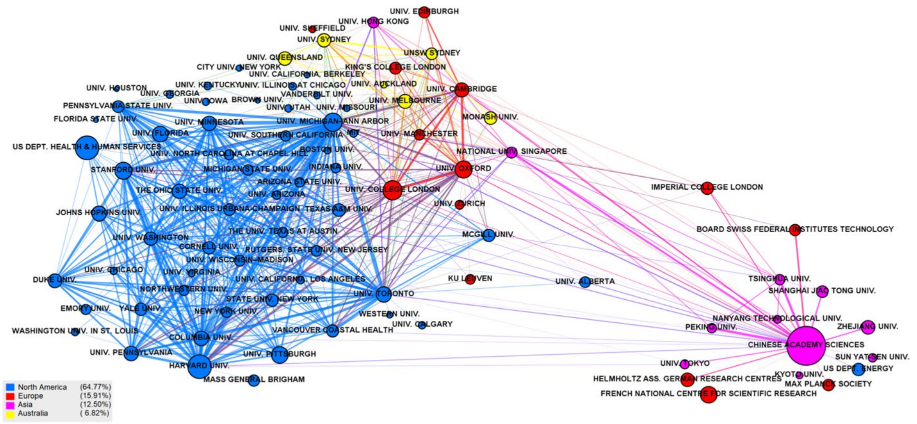

Fig. 3 Projection of institutions and their interlockings (100-slice). Node size is proportional to the number of scholars in the dataset. Line thickness is proportional to number of journals in which connecting institutions share at least one EB member

weighted by the number of journals in which each pair of institutions share EB members. This graph is challenging in computational and visualization terms, so we opted for the 20-slice (1293 nodes, 252,229 edges) of the projection of institutions to compute the network metrics and for the 100-slice of the projection of institutions (88 nodes, 658 edges) for the visualization presented in Fig. 3. These slices represent the main subgroup of institutional connections through EBI.

The affiliations that present more EB members are the Chinese Academy of Sciences (2113), Harvard University (1291), the United States Department of Health and Human Services (also 1291) and the University College London (1048). The largest connections, however, are between the North American universities of Michigan–Ann Arbor, Harvard, Toronto, Minnesota, Washington–Seattle, Stanford, and Columbia, which share members in the EBs of over 170 journals. The largest connections between non-American institutions are found between the University College London and the University of Oxford (ranked 14th, sharing EBs in 157 journals) and the Chinese Academy of Sciences and Peking University (ranked 19th, sharing EBs in 155 journals). In terms of network metrics (Table 5), the Chinese Academy of Sciences is in the first position of all metrics and maintains a prominent role in terms of number of connections, position, and number of communication paths that go through its EBIs. The top 10 institutions for degree and closeness centrality are the same, meaning that the number of connections plays a significant role in the distance to other institutions through EBI. The North American universities of Michigan–Ann Arbor, Minnesota, and Toronto follow. The universities of Sydney, Oxford, and Queensland are the other three non-American institutions present in the top 10 positions for degree and closeness centrality. Results for betweenness centrality show a shift in the trend of dominance of North American institutions, because they are not present in the top three. It is also worth noting that only three institutions in the top 10 are from the United States. The results then suggest that British, Australian, and Chinese institutions tend to establish more bridges with institutions of other geographies than North American institutions, which are mostly connected to other North American institutions.

Although only four of the top 10 institutions in terms of number of scholars are also in the top 10 for any of the network metrics, linear regression models show that the number of

Table 5 Top 10 Institutions for each network metric of the projection of institutions (20-slice)

#	Degree		Closeness centrality		Betweenness centrality	
1	Chinese Academy Sciences	168	Chinese Academy Sciences	0.881	Chinese academy sciences	0.166
2	Univ. Michigan–Ann Arbor	161	Univ. Michigan–Ann Arbor	0.848	Univ. Oxford	0.091
3	Univ. Minnesota	141	Univ. Minnesota	0.847	Univ. Queensland	0.076
4	Univ. Toronto	137	Univ. Toronto	0.837	Univ. Michigan–Ann Arbor	0.050
5	Univ. Sydney	134	Univ. Sydney	0.835	Univ. Toronto	0.047
6	Univ. Oxford	133	Univ. Oxford	0.835	Tsinghua Univ	0.042
7	Univ. Queensland	130	Univ. Queensland	0.830	US Dept. Health & Human Services	0.041
8	The Ohio State Univ	128	The Ohio State Univ	0.830	Univ. Alberta	0.038
9	Univ. Alberta	128	Univ. Alberta	0.829	Univ. Minnesota	0.035
10	Vancouver Coastal Health	125	Vancouver Coastal Health	0.828	Univ. Cambridge	0.025

Degree represents the number of connections from an institution to all other institutions (range 1–168)

Closeness centrality and betweenness centrality are normalized (range 0–1) seats in EBs of an institution explains the degree ($R^2=0.51$, $F=1398.8$, $p<0.001$), closeness centrality ($R^2=0.50$, $F=1311.5$, $p<0.001$), and betweenness centrality ($R^2=0.64$, $F=2289.4$, $p<0.001$). This suggests that the overall number of scholars in boards is a good predictor of the relevance of an institution.

Figure 3 presents the 100-slice of the projection of institutions, which shows the main subgroups of EBI activity among them. We can observe a main group with most North American institutions, which closely connect to British and Australian institutions. On the right, we can observe a separate group with a few Asian and European institutions, showing fewer connections to the main central group. This arrangement probably explains the betweenness rank of British (Oxford and Cambridge) and Asian (Tsinghua and Chinese Academy of Sciences) institutions. Because they are the key agents connecting the main group with their local institutions, they are in a substantial number of shortest paths in the network. The University of Queensland seems to play a similar role as a bridge connecting US and British institutions to Australian ones. Other geographies are underrepresented and do not appear in the slice or top positions of the network metrics. The University of Sao Paolo is the first of other geographies, ranked 13th for degree and closeness centrality and 50th for betweenness centrality.

Institutions from North America dominate in establishing the strongest connections forming a tight cluster of EBI activity (RQ3). Notably, British, Australian, and Chinese institutions tend to bridge across geographies more than North American institutions, which primarily connect within their own region. With the only exception of the Chinese Academy of Sciences, most prominent positions are occupied by institutions from English-speaking countries. All other geographies are significantly underrepresented.

Discussion

This study represents an effort to visualize connections in sciences through EBI (Andrikopoulos & Economou, 2015; Baccini & Barabesi, 2010; Burgess & Shaw, 2010; Goyanes & de-Marcos, 2020; Mendonça et al., 2018) and social network analysis. More specifically, drawing upon data from the Open Editors initiative (Nishikawa-Pacher et al., 2022), we provide several inter-related empirical contributions to further our understanding of the scientific, geographical, and institutional connections across different fields of research. Beyond the main empirical findings outlined below, this study embodies the empirical endeavor of holistically comprehending through the analysis of social networks the reach and intensity of connections within and between most fields of sciences through EBI.

First, our research clearly illustrates the connections between fields of knowledge through EBI (RQ1). Extant research has largely focused on mapping and visualizing within-field EBI (see Baccini & Barabesi, 2010; Lockstone-Binney et al., 2021; Cardenas, 2021), so the network structure that governs both within and between fields of knowledge has remained unclear (Goyanes et al., 2022). This study contributes to this line of research by examining 215 different scientific fields and showing the main patterns of scientific domination across fields of sciences. Our results first show a substantial level of collaboration between all fields, as observed in the density of the graph. In general, the findings portray relatively high inter-disciplinary interactions between fields of knowledge through the cross-presence of EB members in different journals. More technically, the size of the main connected component and the existence of short paths relative to the network size, along with a high clustering coefficient, suggests that scientific endeavor is highly networked through EBI.

However, and as expected, not all field connections through EBs have the same intensity of interactions, which suggests different levels of scientific cooperation. Considering our findings, we theorize that these networks of interactions unfold in three main domains: (a) within a field of knowledge, (b) between neighborhood fields of knowledge, and (c) between distant fields of knowledge (i.e., from social sciences to general sciences or vice versa). Despite the interesting nuances in this classification, which are explained in the next paragraph, our finding clearly suggests four main clusters for grouping the different fields of knowledge examined in this study: (a) health & life sciences, (b) physics & chemistry, (c) engineering, and (d) social sciences. Accordingly, beyond the individual fields of knowledge included in different classification platforms such as JCR or Scopus, these four macro-clusters represent the main domains for visualizing the connections stablished in the sciences thorough the exploration of EBI.

Following-up with the connection between the social sciences and general sciences (RQ2), the findings reported in this study claim that the weight of edges connecting fields within the index is larger than that between different indexes (SSCI to SCIE), providing further empirical evidence suggesting that both macro fields of study have little in common in their types of reasoning and ways of establishing evidence (Knorr-Cetina, 1999). This finding evidences a lingering divide between the natural and social sciences, despite systematic efforts to enhance their integration through more collaborative scientific efforts (Heberlein, 1988; Strang, 2009) and calls for novel scientific policies to further their cooperation. Normatively, we assume that complex social problems demand ground-breaking interdisciplinary collaborations. Their absence or limited occurrence might only solve or addresses a particular scientific angle, while missing the big picture or the far-reaching social implications. Inter-disciplinary scientific production/progress is key, but the formation of EBs that understand the need and expectations of research beyond the boundaries of a particular field of knowledge needs to be undertaken to build universal knowledge across epistemic borders.

Adding more evidence to this line of inquiry, our findings also suggest that fields included in the two different indexes (SCIE and SSCI) also cluster together well, suggesting a cohesive space in which scientific information, expectations, norms, and values are evenly shared among EB members (Braun et al., 2007; Goyanes et al., 2022; Teixeira & Oliveira, 2018). This cohesion between indexes may fuel clear normative assessments of what may be considered scientific, thus demarcating "good" science from "bad," while at the same time it may generate impediments, through invisible colleges, to the introduction of novel theories or ways of reasoning that challenge the dominant scientific paradigm (Braun et al., 2007; Burgess & Shaw, 2010; Sedita et al., 2020; Zuccala, 2006). In addition, our findings show a statistically significantly larger clustering coefficient in SCIE fields, suggesting that such fields are more connected to the fields in their neighborhood. In general, ties between journals listed in the SCIE are tighter than for journals listed in the SSCI through EBI, and appear to be consolidating a more structured and connected intellectual terrain.

In summary, while our findings do emphasize cohesion within indexes, the challenge lies in fostering interdisciplinary understanding and collaboration across epistemic borders. Cohesion between fields of study is usual as they rely on shared values of scientific progress, methodological techniques, and problem-solving skills. However, our findings also emphasize the need to foster more scientific communication and collaboration between fields of study to potentially avoid the epistemic, cultural, and language barriers that may prevent a more global, interdisciplinary knowledge production. In this regard, policy and funding may play a crucial role in promoting interdisciplinary research aiming at incentivizing scientific collaborations, but ultimately, journals and editors in chief need to value these contributions to incentivize research networks that can also transpire into and vertebrate future journals' editorial boards. Historically, there was a strong divide between natural and social sciences that is still lingering, yet the multidisciplinary creation of structural networks in the main bodies of governance of scientific journals may potentially alleviate this traditional, yet understandable divide, resulting in a broader and interconnected scientific terrain.

Finally, at the institutional level (RQ3), our findings provide important insights for better understanding the geographical structures that govern the sciences and thus clarifying the institutional footprint of scientific knowledge. First, our findings offer little discussion of what the dominant geographic culture in scholarship is, namely, that it is centered on the United States and Canada (i.e., North America). Other Anglo-Saxon countries such as United Kingdom or Australia are also well represented among EBs of major journals, yet limited diversity is observed: representatives for most parts of the world are rudimentary, particularly from the global South. These findings are fully aligned with prior scholarship focusing on EB representation in different fields (Dada et al., 2022; Palser et al., 2022) and underline the calls for a greater and genuine internationalization of EBs and sciences beyond the usual facade of journals' webpages when describing their aim and scope.

The geographical and institutional dominance of US universities is not surprising, considering their substantial investments in science (UNESCO, 2021). Arguably, both the US government and the research-intensive universities it funds are one of the most important stakeholders in advancing scientific knowledge and, consequently, it seems natural that many of their scholars are cross-listed in many top-tier journals (Goyanes & de-Marcos, 2020). In this case, European and Australian universities seem to provide support for the norms and values associated with sciences in the United States, being relatively well connected to this space of scientific domination. However, our findings also suggest the creation of a parallel territory dominated by China and its most influential institution, the Chinese Academy of Sciences, which is gaining prominence and forming a network structure with other European and Chinese satellites. All in all, our findings represent a step forward in understanding the governance of science, suggesting that US scientific norms, values, and expectations are still rather central, while Chinese scientific efforts are increasingly challenging this lingering *status quo*.

The results of this study are limited to the Open Editors dataset, which provides broad coverage of EBs but does not include the entire universe of publishers. Important publishers such as Springer and Wiley are missing from Open Editors and are therefore not covered. We also found that a small number of journals accumulate a huge number of members (five journals have more than 10,000 EB members). As such publications may act as whales, the question arises as to what extent they shape the network structure and scientific connections via EBI. This study also relied heavily on computerized methods to collect and consolidate data, which may have introduced bias. However, such methods are the only feasible approach to capture the large number of EBs, disciplines, institutions and their connections. Although the use of personal identifiers such as ORCID should be preferred, this study has also shown that fuzzy string name matching is an alternative approach to consolidate the names of scholars, while centralized datasets such as ROR can be used to consolidate institutions. Finally, we focused on the JCR and its categorization as a representative taxonomy for the organization of science, but future studies could also consider other taxonomies of scientific fields and journals. This study also omitted journals not included in the JCR from the Open Editors dataset. We focused on the Web of Science JCR because it is recognized in the scientific community as the most important bibliometric tool for measuring the impact of journals. It is widely used by researchers and institutions to assess the quality and prestige of journals in their respective fields.

As further future work, we suggest the following: (1) Extending the sample to all scholarly publishers, or at least to the most important ones that are missing in this study. Since there are no databases covering these publishers, we suggest using semi-automated methods to crawl and scrape the publishers' websites. (2) In addition to comparing JCR and non-JCR journals, analyze the effects of journal rank on the connections and the structure of the network of interlockings. Since most studies focus on Q1/Q2 JCR journals, it remains an open question what the patterns and roles of Q3/Q4 journals are. (3) As mentioned above, our approach and databases such as Open Editors can be used to examine the impact of whale journals that have an unusually high number of editors on their boards.

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