# Thirty-Two Years of IEEE VIS: Authors, Fields of Study and Citations

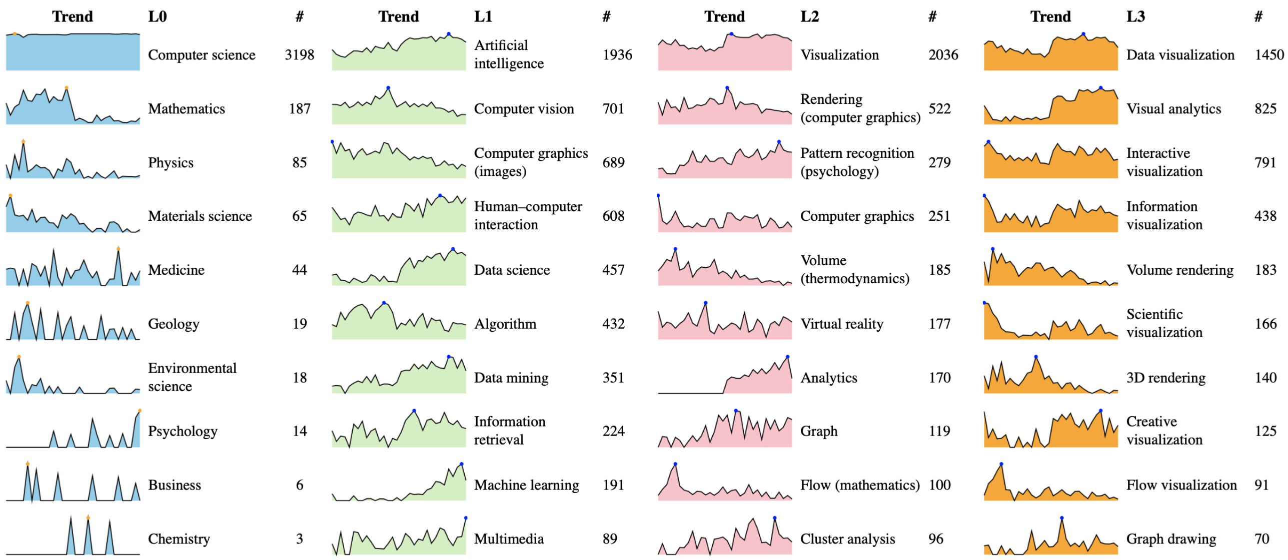


Fig. 1: Fields of study at different levels appearing in 3,233 VIS publications in the past 32 years. The "Trend" indicates the proportion of papers falling into a field of study against the total number of papers in that year. Historical highest proportion for each field of study was highlighted. The data in the column of "#" indicates the total number of VIS publications falling into a field of study. Note that one paper may contain more than one field of study at the same level, and that one field of study may belong to multiple higher level fields. For example, Pattern Recognition belongs to both Computer Science and Psychology.


**Abstract**— The IEEE VIS Conference (VIS) recently rebranded as a unified conference and officially positioned within the discipline of Data Science. Driven by this movement, we set out to investigate where VIS stands within the academic field of studies and what other fields are contributing to VIS. We collect data on VIS authors and publications from various sources to analyze authors' country/region origin, affiliations, collaborations, and the fields of study of VIS publications. Our analysis shows that VIS has been growing steadily in terms of the number of accepted papers, authors, and participating countries; cross-country collaboration and collaboration between educational and non-educational affiliations has been on the rise; the proportion of authors from non-education affiliations has been decreasing. We also found that VIS publications and their cited and citing papers are mostly within the Computer Science domain. The subjects of VIS reflect the trends in science, such that an increasing number of VIS publications concerns AI, HCI, Data Science, Data Mining, and Machine Learning. In contrast, the number of publications on traditional sub-fields such as 3D rendering, flow visualization, and flow rendering has been declining. Interactive visualizations of this paper are available at 32VIS.netlify.app.


## 1 Introduction

VIS is the longest-running and the most influential conference in the field of Visualization and Visual Analytics (hereafter collectively called Visualization). It started in 1990, in response to the NSF report of *Visualization in Scientific Computing* [22, 12]. This marked the beginning of the event as well Visualization as an academic field. The first conference had 52 full papers contributed by 118 unique authors from five countries, namely the US, Germany, Australia, Canada, and France. During the past 32 years, VIS has become an international arena: up until 2021, around 6,200 unique authors from 43 countries scattered in all continents across the globe (except for Antarctica) have contributed over 3,200 full papers. Thirty years of history gives us a vantage point to reflect upon the past and think about the future of visualization research.

The visualization community has already started self-reflection. The present unified field of Visualization is the result of several phases of self-transformations. Three sub-conferences, namely Scientific Visualization, Information Visualization, and Visual Analytics, jointly appeared under the umbrella of VISWeek in 2008 and then IEEE VIS starting from 2013 [5, 14]. The unification did not stop at the name level; it soon was expanded to the research and organizational level. In 2021, after three years' work, VIS introduced an Area Model where six areas were chosen to represent common research topics in the three subfields and various domain-specific areas [12, 1]. This allowed papers to be submitted and reviewed together rather than separately [12]. Visualization is now one unified scientific field at all levels: name, research, and organization. Self-reflection was not only done by the organizing body but also by researchers in the community. Publication metadata [14], subject matter [32], figures and tables [5], author genders [26, 23], publication exploration systems[27, 31], and keywords

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[15] have been the foci of these endeavors. We now have a dataset containing past VIS papers' DOIs [14], and a repository of all figures and tables in past publications [5]. We now know that female participation in VIS has been rising [26, 23], that geospatial analysis is an important subject matter in recent VIS papers [32], and how keywords in VIS publications evolved and interacted [15].

There are still, however, many aspects of VIS that we do not know. The most fundamental question facing VIS as a conference is: where does it stand in the landscape of science overall? As of 2022, VIS officially positioned itself within the field of Data Science [12], and most VIS papers were contributed by Computer Scientists [23]. However, the remaining questions include: What fields is VIS drawing upon (e.g., Which papers do VIS papers cite?), and where can we see its influences (e.g., Which papers cite VIS papers?)? Apart from the position of VIS in science, we also know very little about our authors beyond their genders [26, 23]. In the introduction to VIS 2022 and 2021, the official conference website mentioned that "The conference will convene an international community of researchers and practitioners from universities, government, and industry to exchange recent findings ...". The question is, which countries are our authors from, and what is the proportion distribution of different types of author affiliations? Time adds more complexity here: are there any temporal changes in answers to all the above questions? Addressing these questions has significant implications for VIS as well as for the field of Visualization because we are not able to get a complete picture of who are contributing to VIS, which giants' shoulders does VIS stand on, and which fields VIS is influencing, until we examine authors from different aspects than simply their genders, and citation flows among cited (i.e., papers cited in VIS), VIS, and citing (i.e., papers citing VIS) papers.

To address these questions, we collected, merged, cleaned, filled, and aggregated data on VIS authors and publications from various sources. We analyzed authors' country/region (hereafter collectively called country) origins, affiliations, and collaborations. We also looked into the fields of study of VIS publications and those of their cited and citing papers. Based on these data, we built an interactive system where viewers can explore temporal trends in VIS authors, fields of study, and the flow of citations based on fields of study.

Our data shows that VIS has been growing steadily in terms of the number of accepted papers, authors, and participating countries. We found that even though the number of participating countries has been increasing, VIS authors are concentrated on a few countries: together, authors from the top five countries, namely, the US, Germany, China, Austria, and Canada, account for 82.0% of all authors. The dominance of US authors is decreasing, and the number of contributors from China has been increasing. We found that the popularity of cross-country collaboration has constantly been rising: In VIS 2021, 45.0% of all the publications grew out of cross-country collaborations. These collaborations, however, are concentrated on a few countries. Although the ratio of collaborations between educational and non-educational affiliations ("cross-type collaboration") has been growing (with some fluctuations), the ratio of authors from non-educational affiliations has been declining, both within the US and globally. This indicates that cross-type collaboration is becoming popular but VIS is becoming overwhelmingly dominated by authors from universities.

In terms of fields of study, we found that VIS publications were mostly about Computer Science, with 3,198 (88%) out of 3,233 papers falling into this top-level discipline, followed by Mathematics (5%) and Physics (2%). Similarly, VIS publications were mainly built upon and had their impacts on Computer Science and Mathematical studies. Since the majority of VIS papers are about Computer Science, we explored subfields within each top level discipline. We found that VIS papers' topics were concentrated on only a few subfields within Computer Science, as can be seen in Fig. 1. In addition, citations in and out of VIS papers mostly flew between the same (sub)fields.

In sum, the contributions of our study are as follows. First, we offer insights into the role VIS is playing in today's scientific landscape and also analyze VIS authors from different perspectives than previous studies [26, 23]. In addition, our dataset complements those of [14] and [26, 23], helping make more complete data for future scientometric analyses of VIS. Future researchers may use our workflow to obtain similar data on other fields as well. Lastly, our interactive visualizations reveal temporal patterns of VIS.

## 2 Background

Earlier works that treated visualization publications as their subjects of concern were inspired by InfoVis 2004 Contest [13, 10], which challenged participants to visualize the history of InfoVis. The contest data consisted of 614 InfoVis publications and their over 8,500 references [16]. Eighteen submissions from six countries participated. Authors and research areas were the foci of some of the contest papers we found [30, 18, 19, 8, 29]. Similar attempts were made to visualize VIS authors [7], citation motivations in InfoVis papers [31], and research topics in TVCG papers [17].

These works illustrated the importance of publication metadata, which paves the way for scientometric analysis. Another attempt of collecting comprehensive paper metadata in the field of Visualization, i.e., Vispubdata.org [14], was completed twelve years later, when VIS was 25 years old. The dataset contained cleaned publication data of VIS papers from 1990 to 2016. Data for 2017-2020 was added later. This work inspired many subsequent scientometric analyses [26, 23, 5] and visualization systems [33, 28]. Specifically, based on [14], scholars collected tables and figures in past VIS publications [5], and analyzed VIS author genders and collaborations [23, 26]. They found that female participation in VIS had been constantly rising but gender gaps remained. For example, female authors were less likely to be the last authors [26], and gender balance at VIS was predicted to be achieved only half a century later [23].

The work by Sarvghad et al. [23] looked very similar to ours as we both examined VIS authors and research areas. A closer examination revealed that we were different. [23] focused on collaborations among different research areas, genders, and institutions, whereas we looked at (1) collaborations based on author country origins and the types of their affiliations, and (2) citation flows among VIS, cited, and citing papers. Also, in [23], a paper's field of study was inferred from the authors' research areas, which might change from time to time, whereas our fields of study data was directly derived from each paper itself. That being said, our study corroborated some major findings in [23] but from different angles.

Apart from authors, keywords were an important element in publications. Co-word analysis was applied to keywords in VIS publications from 1990 to 2015 [15]. Key themes among VIS papers, the relationships among these themes, and how keywords emerged and evolved were examined. It was found that pre-defined keywords provided on the precision conference system had mainstream topics, whereas topics extracted from keywords in original VIS PDFs did not. Similar work was conducted in CHI publications [21].

Some scientometric studies on visualization and related fields, for example, InfoVis [11], CSCW [6], CHI [3] and IndiaHCI [9], instead of focusing on one or two aspects, did a comprehensive overview of their fields of interest.

## 3 Data collection and processing

In this section, we detail how we collected and processed data on VIS papers. All data collection was completed in early March of 2022.

### 3.1 DOI collection

Our study analyzed full papers of VIS published between 1990 and 2021. In the following, we describe how we identified the DOIs of these papers.

We obtained from vispubdata.org [14] the DOIs and titles of 3,394 VIS papers published from 1990 to 2020. Following the practice of [5], we only included conference and journal publications and case study papers but excluded posters, panels, and keynote documents (i.e., those with the paper type of "M" as coded in [14]). We excluded these publications because (1) neither IEEE Xplore [1], a dig-

[1] https://ieeexplore.ieee.org/Xplore/home.jsp

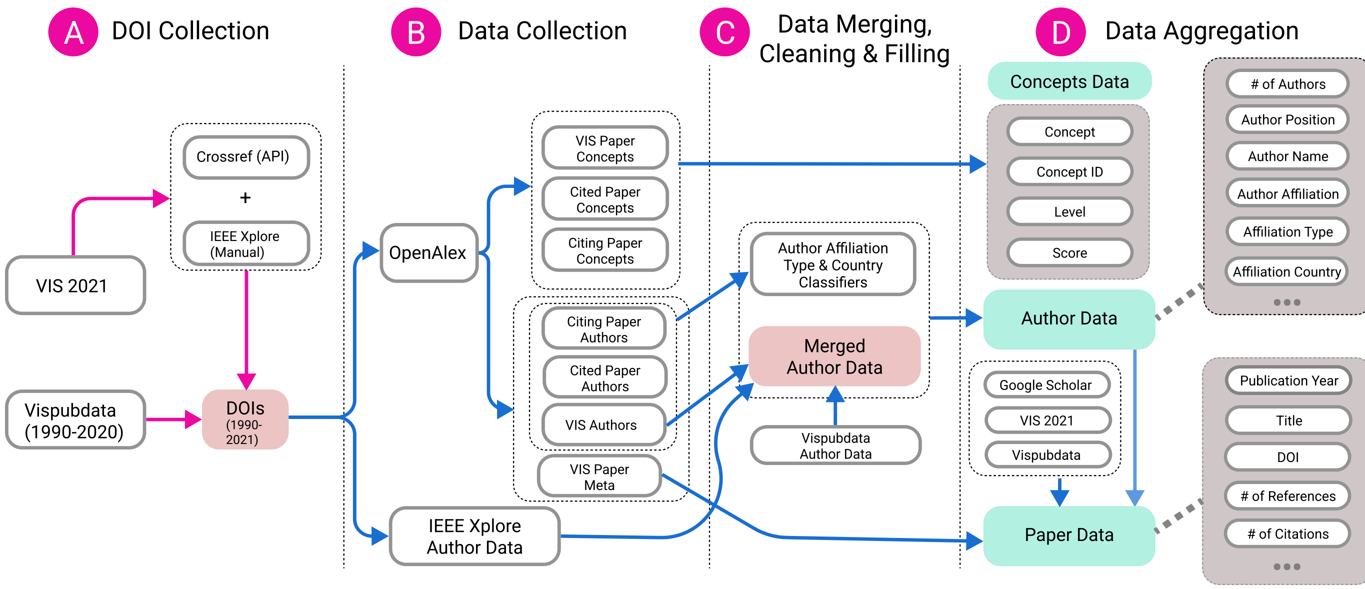


Fig. 2: Data processing pipeline. We started from Vispubdata and VIS 2021 to get the paper DOIs, with which we obtained data on relevant papers from OpenAlex and IEEE Xplore. We then merged and cleaned data and filled in missing data. Some of the paper data, for example, whether a paper is a cross-country or a cross-type collaborative paper, came from author data. The final outputs were three major data files: authors, concepts, and paper meta.

ital library containing papers published by IEEE and its partners nor Vispubdata [14] contained information on them consistently. For example, both sources lacked posters from 2017 and 2019; and (2) they differ qualitatively from full papers. After this exclusion, we had 3,073 papers. We found no duplicates in their titles but found one paper with an invalid DOI (10.0000/00000001). We removed this paper from our further analysis. The final result of this step was 3,072 paper DOIs from Vispubdata [14].

170 full papers presented at VIS 2021 were not part of [14]. We collected their titles from the official website of VIS 2021. We found no duplicates in these titles. Using the package of habanero [24], we obtained these papers' DOIs from Crossref [2] based on title queries backed up by manual data collection from IEEE Xplore if automation failed (See *Supplementary material (SM)* for details.). We inspected the DOIs of these 170 VIS 2021 papers and found all of them were valid. Thus far, we had 3,242 (3,072 + 170) papers.

### 3.2 Data collection

After identifying the papers to include in our study, the next step was to collect relevant data on them. Given the motivation behind our study, we need information on VIS papers from these aspects: (1) VIS authors, and (2) fields of studiy of VIS, cited, and citing papers. For authors, we need author names, positions, and affiliations. For cited and citing papers, we want numbers of counts, paper titles, and fields of study. Neither IEEE Xplore nor Vispubdata [14] has complete information on all these variables, so we collected the data from OpenAlex as they offered much richer data on author affiliations and publications' fields of study. Other outlets such as PubMed, Web of Science, Scopus, Crossref, Google Scholar do not offer the metadata we wished to collect. For detailed accounts on how we ended up choosing OpenAlex, refer to *Supplementary material*.

Among all 3,242 papers, we were able to identify 3,233 of them in OpenAlex through a combination of title and DOI queries, whereas 9 papers did not exist. We excluded them from our following analyses. In sum, our collection consisted of 3,233 VIS full papers published from 1990 to 2021, including data on their authors, fields of study, and paper meta. Examples of variables we had are shown in Fig. 2.

| | Free | Author | Cit. | Ref. | Field | Maintained | API |
|---|---|---|---|---|---|---|---|
| WoS | ✗ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Scopus | ✗ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| PubMed | ✓ | ✗ | ✓ | ✗ | ✗ | ✓ | ✓ |
| JSTOR | ✓ | ✗ | ✗ | ✗ | ✗ | ✓ | ✓ |
| Crossref | ✓ | ✗ | ✓ | ✓ | ✗ | ✓ | ✓ |
| Google | ✓ | ✗ | ✓ | ✗ | ✗ | ✓ | ✗ |
| Semantic | ✓ | ✗ | ✓ | ✓ | ✗ | ✓ | ✓ |
| MAG | ✓ | ✓ | ✓ | ✓ | ✓ | ✗ | ✗ |
| OpenAex | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Table 1: Availability of key features on popular scholarly databases

### 3.3 Data merging, cleaning, and filling

For author data, we relied on IEEE Xplore and OpenAlex, coupled with Vispubdata [14] for cross-validation. From IEEE Xplore, we collected author information, including the number of authors, author position, author name, IEEE author ID, and author affiliations. From OpenAlex, we collected the same data (except for IEEE author ID), plus author affiliation type and affiliation's alpha-2 (ISO 3166) country code (e.g., US, CN, DE, etc). We compared the number of authors for each paper in the two datasets and found IEEE Xplore was incorrect in one paper (DOI: 10.1109/TVCG.2008.157): it listed five authors, but there were only four when we checked the PDF. Also, IEEE Xplore did not contain information about the paper of 10.1109/VIS.1999.10000. We fixed these errors and updated IEEE Xplore author data. Among 12,409 authors in the dataset obtained from IEEE Xplore, only 333 (2.7%) contained more than one affiliation. For consistency and simplicity, we only included their first affiliation in our further analyses.

We merged the IEEE Xplore and OpenAlex author data based on exact matching of DOI and fuzzy matching of author names. We then compared the number of authors for each paper in our merged dataset with the DBLP [3] author information collected by [14]. We identified 17 instances where the two datasets disagreed. We checked the original PDFs of these 17 publications and found our merged author data was incorrect in 4 papers and DBLP was incorrect in 13 papers. We updated our merged dataset with correct author data. The final merged author data consisted of 12,413 authors. Note that unless we specify they are "unique authors", authors, as we call them in our paper, might be duplicates. For example, if one author is present in 10 VIS publica-

[2] https://www.crossref.org/

[3] https://dblp.org/

tions, we consider them as 10 authors. This is because we were more interested in author country origins and affiliations than authors per se. Deduplicating authors did not make sense in our study because authors may change their countries and/or affiliations from time to time.

IEEE Xplore missed affiliation information for 165 authors; after the merging procedure, 58 authors still missed this information. We filled in this missing data based on author descriptions and email addresses in the original paper PDFs, author profiles on IEEE Xplore, and open web search. For some papers where we were uncertain of our conclusions, we requested from original authors, via email, information regarding their affiliations at the time of publication. When we were manually collecting affiliation data, we filled in the author affiliation type and country origin following OpenAlex's criteria. During this data filling process, we corrected the errors we noticed in author names, author affiliations, and affiliation country codes.

This merged author data, however, was still incomplete in author affiliation type and affiliation country code, which were necessary in our following analyses. Among 12,413 authors, 2,024 (16.3%) missed affiliation type and 1,893 (15.3%) lacked country information. There were also problems for observations that were complete in these two variables: the available data from OpenAlex on affiliation type and country codes were based on affiliation strings provided by OpenAlex. These strings, however, were slightly different from those on IEEE Xplore. Therefore, even for rows where affiliation type and country data were complete, we were not 100% sure that they were correct information for the actual authors. Fortunately, IEEE Xplore provided affiliation information for 99% of all 12,413 authors; the rest were added in our above mentioned data merging & filling procedure. Since IEEE Xplore is the official data source on VIS authors, we regarded their data as reliable.

To automatically infer affiliation type and country code from affiliation names offered by IEEE Xplore, we utilized classifiers. We assumed that OpenAle's classifications of affiliation type and country codes based on affiliation strings were mostly accurate, and they were: we randomly selected 100 observations where OpenAlex data were complete and we concluded that the mappings were 94% correct for affiliation types and 98% correct for country codes. We built two separate multiclass text classification models ("classifiers") with logistic regression (one for affiliation type and the other for country code) based on author data of 3,233 VIS papers, 39,758 unique cited papers, and 59,570 unique citing papers. After deduplication, we obtained 74,401 feature-label pairs for affiliation type classification and 76,482 for country code classification. We randomly split the data into the training set (80%) and the test set (20%). The affiliation type classifier reached a test set accuracy of 95.4% (precision, recall and F1 scores were almost the same). Its train set accuracy was 98.1%. The country code classifier reached a test set accuracy of 94.1%, which was almost the same for precision, recall, and F1 scores. Its train set accuracy was 97.1%. We applied these two classifiers to our complete author affiliation data obtained from IEEE Xplore. After predictions were complete, we randomly selected 100 rows and checked prediction accuracy. 99 out of 100 predicted country codes were correct; the one error occurred on an American branch of a German company. The prediction for affiliation type was 96% correct. The reason why country code predictions were nearly perfect was that many affiliation names on IEEE Xplore contained country information.

### 3.4 Data aggregation

From Vispubdata [14], we collected for each paper its title, DOI, and publication year. We also obtained conference track information, i.e, InfoVis, SciVis, VAST, and Vis. We assigned "VIS" to all papers presented in 2022 because starting from 2021, VIS no longer distinguished between these tracks.

From OpenAlex, we collected each paper's number of references and citations. Based on title queries backed up by DOI queries, we collected citation counts on Google Scholar, which were used (1) as validation of citation data from OpenAlex and (2) in our citation analyses. We were able to identify all 3,233 papers except for one paper (DOI: 10.1109/VISUAL.1995.480792). From the official website of VIS 2022 [4], we obtained the historical information on award-winning papers. We considered a paper as an award-winning paper if it received Best Paper Award, Honorable Mention Award, or Best Case Study Award. Based on our author data, we decided for each paper, whether it is (1) cross-type collaboration, i.e., collaborations between educational affiliations and non-education affiliations, (2) cross-country collaboration, and (3) involving authors from the United States. These variables were important in our analyses of collaboration patterns in VIS and also the changing role of US authors.

Each paper's fields of study on OpenAlex are represented as concepts. Concepts are hierarchical such that they have different levels; Level 0 (i.e., Computer Science, Mathematics, Psychology, Physics, Chemistry, etc.) is the top-level that does not have ancestors. For VIS cited and citing papers, we collected all their L0, L1, L2, and L3 concepts. Detailed statistics of these concepts are available in Table 2.

Based on Fields of Study data from Microsoft Academic Graph, OpenAlex trained a classifier that assigned concepts of different levels to a paper [5]. Assigned concepts had associated scores in a way that concepts of a higher score were a better representation of a paper. Concepts with a score lower than 3.0 were not assigned. We collected concepts data from OpenAlex for 3,233 VIS papers, 39,758 unique cited papers, and 59,570 unique citing papers.

## 4 Results

In this section, we show our analysis results.

### 4.1 General Trends

Overall, we found three trends: VIS is becoming more popular, impactful, and collaborative.

The rise in popularity can be seen in the increase in the number of publications and unique authors. As presented in Fig.3 b, in the first conference in 1990, there were 52 full papers. This figure grew to 169 in 2021. With an acceptance rate of around 25% in all sub-conferences in the past decade [14], this growth indicates that there have been an increasing number of submissions to VIS. There was also an increase in the number of unique authors as shown in Fig.3 c. In 1990, there were 118 unique authors, whereas this number grew to 673 in 2021, a 470% increase. The growth of VIS popularity was also evident in the increasingly diversified country origins of authors, which we will discuss later.

As evident in Fig.3 d and e, the impact of VIS can be seen in the increase in both the absolute number and proportion of citations attributed to non-VIS publications. In 2021, VIS papers were cited 11,353 times by publications outside of the VIS community, almost doubling the number in 2011 (6,173). The proportion of citations attributed non-VIS papers also showed an upward trend. In the first five years, the proportion of citations attributed to non-VIS papers fluctuated between 70% and 80%; since 1998, this figure had been above 80% and sometimes even above 90%. In 2021, this number was 85%. The proportion of non-VIS papers in cited papers, however, showed a slightly downward trend, indicating that VIS had been increasingly built upon past work in the community itself, especially during the first two decades of VIS history.

The collaborative nature of VIS is evident in three aspects: the increase in (1) the average number of authors, and (2) the proportion of papers resulting from cross-country collaborations and (3) cross-type collaborations.

In the first ten years, VIS publications were contributed by on average two to three authors. In the next decade, i.e., from 2000 to 2010, this number was between three and four. Starting from 2012, the average number of authors per paper had been constantly above four, peaking at 5.3 in 2019. In 2021, this number was around 5. (See *Supplementary material* for details.)

In the first conference in 1990, among 52 full papers, only 2 were by authors from different countries as indicated by Fig.3 h: one was a US-Germany collaboration and the other was between the US and

[4] http://ieeevis.org/year/2022/info/history/best-paper-award

[5] https://github.com/ourresearch/openalex-concept-tagging

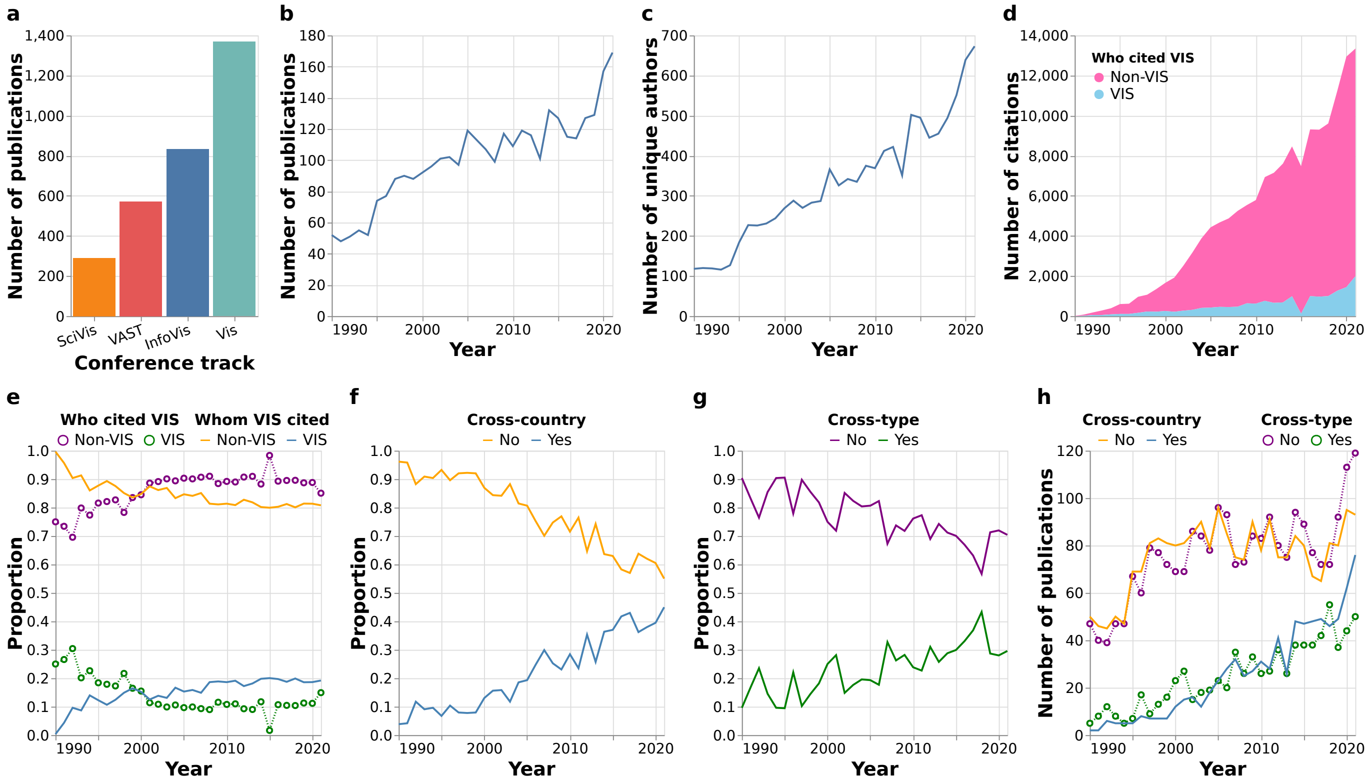


Fig. 3: General trends. **a** Number of publications of each of the five tracks. **b** Number of VIS publications each year. **c** Number of participating unique authors each year. Note that among 12,413 authors, 101 of them did not have OpenAlex author ID so they were not included here. **d** Number of citations from VIS and non-VIS papers. **e** Proportion of VIS and non-VIS papers that were cited in and citing VIS publications. **f** and **g** Proportion of cross-country collaboration, and cross-type collaboration. **h** Number of publications from cross-country collaboration and cross-type collaboration.

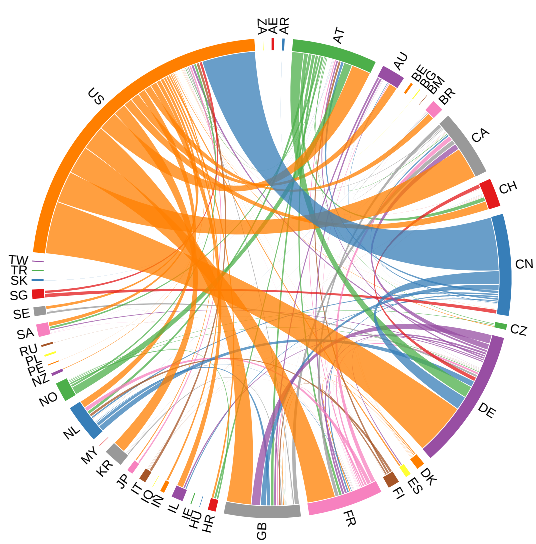


Fig. 4: VIS author collaboration network. The top ten most collaborative countries/regions are: US, Germany (DE), China (CN), Austria (AT), UK (GB), France (FR), Canada (CA), Netherlands (NL), Switzerland (CH), and Australia (AU). 69.2% of all collaborations throughout the history of VIS occurred among these countries.

Canada. As demonstrated in Fig.3 f, in the first half of VIS history (1990-2005), the yearly proportion of cross-country collaboration papers was always below 20%. After 2006, this figure remained above 20%; since 2014, above 30%. The most recent year, i.e., 2021, saw a historical high: 45% of all papers were cross-country collaborations. These collaborations, however, were highly concentrated, as can be seen in Fig. 4. After deduplicating the collaboration pairs in each paper such that if a paper had five authors (four from the US and one from China), we assigned only one pair, namely "US-CN" to it, we had 1,221 collaboration pairs with 2,442 nodes (i.e., collaborating countries). The top 10 most active countries in cross-country collaboration, namely, the US, Germany, China, Austria, the UK, France, Canada, Netherlands, Switzerland, and Australia, appeared in 1196 (98.0%) pairs among all 1,221 pairs. Together, collaborations among these most collaborative countries were responsible for 69.2% of all collaborations throughout the history of VIS.

Similar growth was observed in cross-type collaborations. As shown in Fig.3 g, the proportion of cross-type collaboration fluctuated between around 10% and 30% in the first half of VIS (1990-2006). In the years following 2007, this proportion was always above 20%, peaking at 43.3% in 2018. Since then, the proportion had dropped a little bit. In 2021, 30.0% of all publications were cross-type collaborations.

### 4.2 Country origin and types of author affiliations

In 1990, 118 unique authors from only five countries (Fig.5 a) participated in VIS; 108 (91.5%) of them were from the US (Fig.5 b), with the remaining ten authors' country origins scattered in Germany (4), Australia (3), France (2), and Canada (1). Beginning from the third conference in 1995, the number of participating countries had always been at least ten, and since 2003, at least fifteen. Since 2008, this number fluctuated around twenty, peaking in VIS 2021 where there were 27 participating countries.

Although authors from diverse places participated, the majority of them came from only a few countries. The top five sources of authors, namely the US, Germany, China, Austria, and Canada were responsible for 82.0% of all 12,413 authors. If we consider the top ten, which

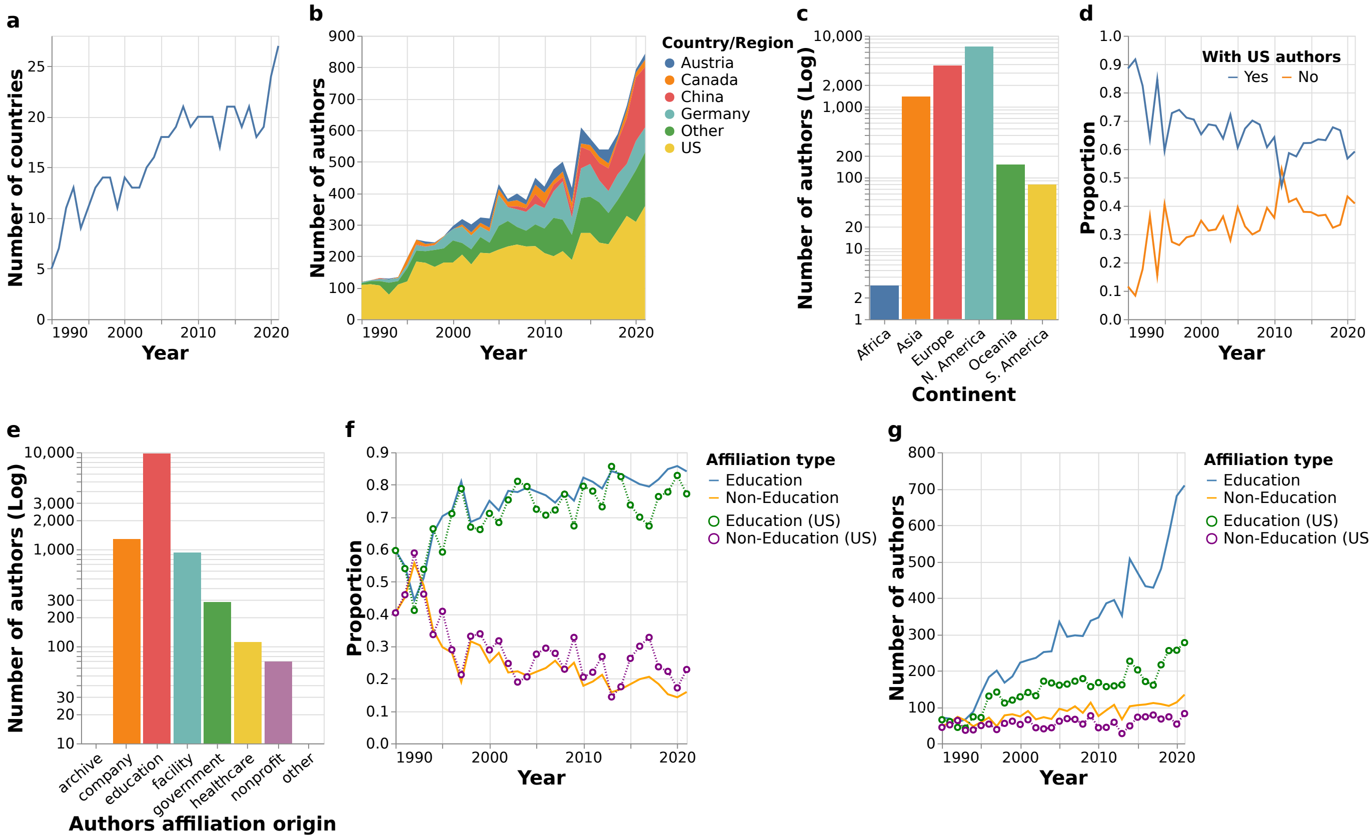


Fig. 5: Authors. **a** Number of participating countries by year. **b** Temporal changes in the number of authors from top five countries. **c** Distribution of authors by continent. **d** Temporal changes in the proportion of papers involving US authors. **e** Distribution of authors by affiliation type. **f** and **g** Proportion and absolute numbers of authors from education and non-education affiliations. Both the global data and US data were plotted.

would add the UK, Netherlands, France, Switzerland, and Australia, this figure increased to 92.7%. In terms of continents, almost all authors (98%) came from North America (56.6%), Europe (30.4%) and Asia (11.1%) as depicted by Fig.5 c. Throughout the past 32 years, only 3 authors came from Africa, 80 (0.6%) from South America, and 153 (1.2%) from Oceania.

There were some redistributions in authors' country origins among the above top sources. As can be seen in Fig.5 b, the dominance of the US has been declining, and the number of authors from China has been increasing. In terms of the accumulative number of author, China (8.1%) is the third-largest source, only after the US (53.1%) and Germany (13.2%). If we looked at the number of authors in yearly terms, China overtook Germany in 2017 as the second-largest author source and has remained in that place since then. Considering the 258 authors from Hong Kong SAR separately did not change the overall statistics: Mainland China is still the third-largest author source in terms of the accumulative count and has been the second-largest in terms of yearly counts since 2019.

Looking at the US involvement in VIS from another angle, however, revealed that the US dominance still existed. As shown in Fig.5 d, in the first five conferences, i.e., between 1990 and 1994, the proportion of papers involving at least one US author had always been above 80%, except for in 1993 when the proportion plunged to 63.6%. From 1995 to 2010, this number fluctuated between 60% and 70% and then dropped to a historical low at 47.1% in 2011. The number then went back again and has been between 50% and 70% ever since. In 2021, 59.2% of all accepted papers involved at least one US author. In terms of the accumulative count in the past 32 years, 65.4% of all 3,233 VIS publications had US involvement.

Another important dimension of author affiliations is their types. There are eight affiliation types as defined by OpenAlex, which were based on the terminology set by the Research Organization Registry [6] (ROR). Fig. 5 e shows the proportional distribution of the affiliation types of 12,413 VIS authors. Our data revealed that 78.3% of the authors are affiliated with a university (i.e., marked as "education"), with the remaining 21.7% of them scattered among companies (10.3%), facilities (7.5%), government (2.3%), healthcare (9%), NGOs (6%), archive organizations (1%) and other types (1%). Because of the dominance of educational affiliations and also because of possible overlaps in the classification of non-educational affiliations, for example, some laboratories could be either considered as government or facility, we decided to collapse all non-educational affiliations into one type ("non-education") in all of our following analyses.

The dominance of universities did not start from the very beginning of VIS. In fact, as can be seen in Fig. 5 f, which shows the proportion of educational versus non-educational affiliations, authors affiliated with a non-educational research institution were a salient part of the conferences. For the first three years, these authors were increasing in proportion to a point where there were more authors from non-education affiliations than those from education affiliations in the year 1992. However, since then, authors from non-educational affiliations had steadily declined in proportion. For almost every year starting from 1995, authors affiliated with non-educational entities accounted for only 20%-30% of all participating authors. Since 2010, this number fluctuated at around 20%. In 2021, 84.1% of all authors came from universities; only 15.9% of them were from non-educational affiliations.

This decline in the proportion of non-educational affiliations was due to the fact that both within the US and globally (Fig. 5 g), the number of authors from non-educational affiliations remained stable at around 100 whereas the number of authors affiliated with universities grew steadily. In fact, as is evident in Fig. 5 g, the majority (65.8%)

[6] https://ror.org/

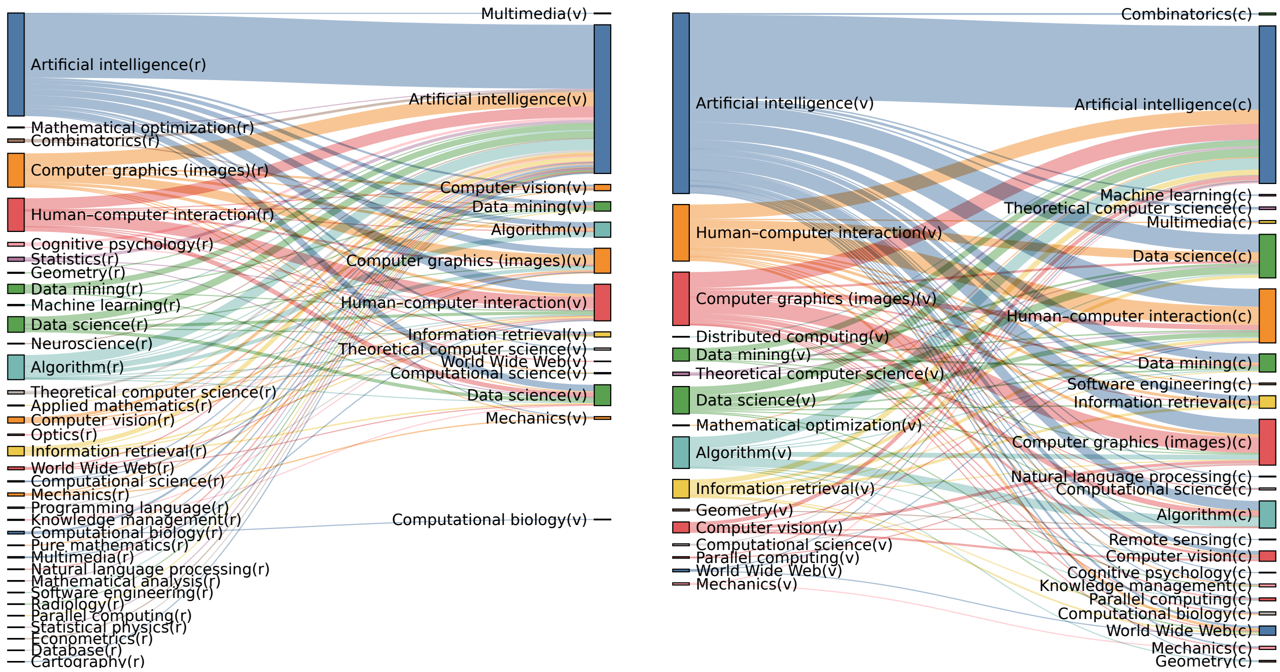


Fig. 6: Citation flows based on L1 fields of study. **Left**: Top 100 citation flows, or "pairs", from cited papers, i.e., papers cited in VIS, to VIS papers; **Right**: Top 100 citation flows from VIS papers to citing papers, i.e., papers citing VIS. The letter after each concept indicates the source: r means reference, v means VIS, and c means citing papers.

of authors affiliated with non-educational entities came from the US, whereas there has been an influx of non-US authors who grew at a faster rate as a group than US authors and who mostly (84.2%) came from universities.

### 4.3 Fields of study

Our fields of study analyses were based on OpenAlex's concepts data on VIS papers and their cited and citing papers. OpenAlex assigned concepts of different levels to each paper based on the paper title, document type (e.g., journal, book, conference, patent, thesis, etc.), the journal title. Within each level, the number of concepts assigned to a paper can be zero or above one. It is possible, therefore, that one VIS paper was assigned not a single Level0 (L0) concept whereas another one had two L0 concepts.

We first analyzed L0 concepts of VIS, cited, and citing papers. L0 is the top level, and concepts of this level, for example, Computer Science, Mathematics, and Philosophy do not have ancestors.

Among 3,233 VIS papers, only two missed L0 concepts, and 393 (12.2%) of them had more than one L0 concept. There were 39,758 unique cited papers accumulated over the past 32 years, among which 39,543 (99.5%) of them had at least one L0 concept, and 9,914 (24.9%) of them had more than one L0 concept. The two figures for 59,569 citing papers were 59,304 (99.6%) and 11,538 (19.4%), respectively. In sum, almost all papers we studied were assigned at least one L0 concept with some of them having more than one. Recognizing that some papers were interdisciplinary, we decided to include all assigned L0 concepts of each paper. Detailed statistics are reported in Table 2.

| Source | Description | L0 | L1 | L2 | L3 |
|---|---|---|---|---|---|
| VIS papers (3,233) | unique concepts | 17 | 110 | 1,218 | 508 |
| | at least one | 99.9% | 90.5% | 96.6% | 72.6% |
| | more than one | 12.2% | 66.7% | 78.9% | 48.9% |
| Papers cited in VIS (39,758) | unique concepts | 19 | 272 | 6,015 | 4,532 |
| | at least one | 99.5% | 88.0% | 92.2% | 59.5% |
| | more than one | 24.9% | 59.8% | 73.2% | 33.3% |
| Papers citing VIS (56,569) | unique concepts | 19 | 270 | 6,105 | 4,530 |
| | at least one | 99.6% | 86.8% | 93.5% | 59.3% |
| | more than one | 19.4% | 59.4% | 76.0% | 33.4% |

Table 2: Availability and counts of L0-L3 concepts for VIS, cited, and citing papers. For each source, the number in the parenthesis indicates its total number. For example, there were 3,233 VIS papers. The first row indicates the total number of unique concepts present at that level in that source. The second and third line indicates the percentage of papers having at least one concept in that level, and that of those having more than one. For example, 17 L0 concepts were present in VIS papers. Among 3,233 VIS publications, 99.9% of them had at least one L0 concept, and 12.2% of them had more than one L0 concept.

The L0 concept of Computer Science appeared in 3,198 (87.6%) of all 3,233 VIS publications, followed by Mathematics (187; 5.1%), Physics (85; 2.3%), Materials Science (65; 1.8%) and Medicine (44, 1.2%). Similar patterns were found in cited and citing papers. Among 39,758 unique cited papers, the L0 concept of Computer Science appeared in 32,706 (64.9%) of them, followed by Mathematics (5479; 10.9%), Psychology (3,041; 6.0%), Physics (1,958; 3.9%), and Medicine (1,464; 2.9%). Among 59,569 unique citing papers, 53,853 (75.2%) of them had the Computer Science component, followed by Mathematics (5,144; 7.2%), Medicine (2033; 2.8%), Psychology (1,669; 2.3%), Physics (1,456; 2.0%) and Biology (1,374, 1.9%). What these statistics reveal is that **VIS papers were mostly about, built upon, and had their impacts on, Computer Science and Mathematical studies**. Psychology was also an important source of inspiration, and Medicine a field where VIS publications had influences (For details on L0 concepts in VIS, cited, and citing papers, refer to *Supplementary material*). Because the majority of L0 concepts in VIS, cited and citing papers were all Computer Science, we focused on L1-L3 concepts in our analysis of (1) the popularity trends of concepts in VIS publications and (2) the citation flows based on concepts.

As clear in Fig. 1, at each level, VIS publications over the years were concentrated on only a few concepts. 110 L1 concepts were present in VIS papers but only 9 of them appeared more than 100 times throughout 32 years. There were significantly more L2 (1,218) and L3 (508) concepts present in VIS publications, but again, only 9 (for L2) and 8 (for L3) of them had a frequency of over 100, respectively. Not surprisingly, except for two concepts in L2, namely Flow (mathematics), and Volume (thermodynamics), **all of these high-frequency concepts were subfields within the discipline of Computer Science**. We also noticed that **the overall trends in science were reflected in the**

**ups and downs of popular concepts in VIS publications** such that we saw an increase in the number of studies involving Artificial Intelligence (AI), Human Computer Interaction (HCI), Data Science, Data Mining, Machine Learning (ML) and Analytics whereas the popularity of traditional subfields such as Computer Graphics, Volume Rendering, Flow Visualization, and 3D Rendering, had been declining.

We were also interested in upon which (sub)fields VIS was built and where VIS influences flew. Within each level, we chose the concept with the highest score to represent each paper if there were multiple concepts assigned; Otherwise, citation flows would be over-represented by interdisciplinary papers. **We found that at each level, citations mostly flew between the same subfields.** For example, in L1, VIS papers mostly cited, and were mostly cited by, studies falling into the subfields of AI, HCI, Computer Graphics, Algorithm, Data Science, Data Mining, and Information Retrieval, as can be seen in Fig. 6. Similar patterns were found in L2 and L3 concepts. The most frequently appearing concept at each level, namely AI (L1), Visualization (L2) and Data Visualization (L3) cited, and was cited by, papers involving various subfields within each specific level. More details on, and temporal patterns in, citation flows are available in interactive visualizations of this paper at 32VIS.netlify.app.

Visualization as a field is interdisciplinary [15, 23]. We explored the co-occurrence of concepts within each level for VIS publications. We found that at each level, co-occurrences of concepts were mostly between the most frequently appearing concepts. This finding, that **VIS is interdisciplinary, but only confined to a few fields, both within (L1-L3) and outside of (L0) Computer Science**, corroborates and adds to the result in [23]. More details on concept co-occurrences of VIS papers can be found in *Supplementary material*.

### 4.4 Citation analysis

Like in other bibliometric studies [25, 2, 4], citations of IEEE VIS papers were heavily skewed to the right such that the top 20% papers

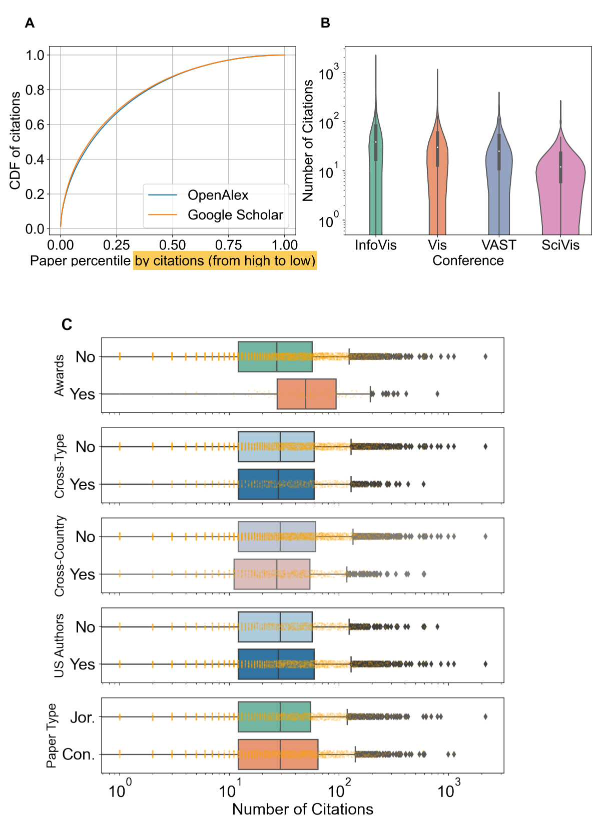


Fig. 7: Citations. **a** shows citations were highly skewed. **b** and **c** are citation comparisons between different groups.

received 60% of all citations. This pattern was the same if we used citation data from Google Scholar, which ishighly correlated with that from OpenAlex (with a Pearson's $r$ of 0.98).

We were interested in what paper characteristics were associated with more citations. We first compared group-wise citation counts, for example, between cross-type and non cross-type collaboration papers, using non-parametrical tests (We used one-way ANOVA for four different conference tracks). Our results showed that only award-winning and conference tracks were significant predictors. *Supplementary material covers more details.*

We then regressed the number of citations from OpenAlex on publication year, conference track, paper type, number of authors, cross-type collaboration, cross-country collaboration, involving US authors or, and award-winning. Following the practice of [3], we excluded VIS 2021 papers in our analysis because it was too early for them to receive citations. We made sure the multicollinearity of the model was not an issue. Linearity and homoscedasticity had some slight issues, which could be solved by performing log10 transformation on citation counts. Doing so, however, would make the interpretations of our results less intuitive, so we decided to use the raw citation counts as the outcome variable.

Regression analyses showed that publication year, conference track, paper type and awards are significant predictors of citation counts such that recent publications (b $= -2.63$, $t = -7.17$, $p < .001$), and papers presented in SciVis (b $= -41.21$, $t = -7.35$, $p < .001$), VAST (b $= -13.97$, $t = -2.86$, $p < .01$), and Vis (b $= -35.94$, $t = -8.44$, $p < .001$), had significantly lower citation counts. Published in the journal rather than conference (b $= 21.07$, $t = 4.36$, $p < .001$) and being an award-winning paper (b $= -28.47$, $t = 4.28$, $p < .001$) brought significantly more citations. Number of authors, cross-type collaboration, cross-country collaboration, and involving US authors did not significantly influence the number of citations a paper received. Regressing number of citations on Google Scholar data, or performing log10 transformation on OpenAlex citation counts did not change the overall results. (For detailed analyses and regression results, see *Supplementary Material*).

## 5 Discussion

We began our study with two major questions: (1) Where does VIS stand in science, and (2) where did VIS authors come from. To answer these questions, we collected VIS paper metadata, and also data on VIS authors and citations from vispubdata.org, IEEE Xplore, and OpenAlex, among other sources.

We found that the popularity and impact of VIS have been increasing. The number of accepted publications and that of unique participating authors have been increasing year by year. Given the relatively stable acceptance rate of 25% at VIS during the past decade, these increases indicate there has been a growing number of people involved in visualization research. We also found that a growing number of non-VIS studies have been citing VIS papers. We did not know the overall growth rate for all non-VIS papers (whether citing VIS or not), but this trend nonetheless implied that research outside of the VIS community was influenced by VIS.

In VIS, collaborations have been on the rise [23]. Sarvghad et al. [23] explored inter-institution and inter-discipline collaborations in VIS and found the numbers were growing in the past 30 years. We corroborated this finding from other aspects. Our data showed that collaborations between authors from different countries, and between authors from different affiliation types, i.e., education or non-education, experienced rapid growth. Cross-country collaboration grew from 4% in 1990 to 45% in 2021, and cross-type collaboration increased from 10% in 1990 to 30% in 2021. Our regression analyses showed, however, neither cross-country collaboration nor cross-type collaboration yielded more citations.

Even though cross-country collaboration has been increasingly popular, we found that these collaborations were concentrated on a few countries. The top ten most collaborative countries (US, Germany, China, Austria, UK, France, Canada, Netherlands, Switzerland, and Australia) were present in 98% of all collaboration pairs, and collaborations among these most active countries were responsible for nearly 70% of all cross-country collaborations throughout the history of VIS. This is not surprising. After all, these countries were also the top ten largest author sources from where 92.7% of all VIS authors came.

VIS authors were concentrated on a few countries and continents, but there were some changes in author shares. Authors from the US dominated VIS in the first decade, then authors from Germany became a significant part of VIS in the second decade of VIS. In the third decade, the number of authors from China increased drastically. In terms of total author counts, the US (53.1%) was still the largest author source, followed by Germany (13.2%) and China (8.1%). If we consider year by year statistics, China replaced Germany as the second largest author source in 2017 and has been in that position ever since. Although US authors has been declining steadily in terms of proportion over the years, they still had disproportionate influences on VIS. In the past decade, we saw an upward trend in the percentage of papers involving at least one author from the US. In 2021, although US authors accounted for 42.6% of all authors, they were present in 59.1% of all VIS 2021 publications.

Our results about non-educational affiliations are interesting. We found that the proportion of collaboration between authors from universities and those from non-educational affiliations showed an upward trend: in 1990 only 10% of all publications were cross-type collaborations whereas this number grew to 30%. Given this trend, it is surprising that the proportion of authors from non-educational affiliations, both globally and within the US, has been declining steadily over the years. In the year of 1992, 55.7% of VIS authors were affiliated with non-educational entities whereas this number plunged to 15.9% in 2021. We concluded that this was because of the stable number of authors from non-educational entities at around 100 each year amidst a steadily growing number of authors from universities both globally and within the US. The fact that cross-type collaboration was rising whereas the proportion of authors from non-educational affiliations was declining indicates that the small number of these authors were present in many VIS papers each year.

Using different data and from different perspectives, we corroborated the finding in [23] that (1) most VIS papers fell into the discipline of Computer Science, and that (2) interdisciplinary collaboration within VIS was confined to only a few disciplines. Our data showed that the L0 concept of Computer Science was present in the majority (87.6%) of 3,233 VIS papers. Almost all of the high-frequency concepts in L1, L2, and L3 were subfields of Computer Science. We found that co-occurrences of concepts within each level of fields of study were only between a few fields. Our temporal analyses also showed that VIS went through transformations in terms of popular topics. We found that trending topics such as AI, HCI, Machine Learning, Data Science, and Data Mining were becoming popular in VIS research whereas traditional fields such as Flow Visualization, 3D rendering, and Volume rendering were declining in popularity.

Regarding the role of VIS in science, we found that VIS mostly cited, and were cited by, studies in Computer Science and Mathematics. Our time-series analyses revealed that this pattern was stable throughout the past 32 years. This indicates that VIS is mostly **about**, **built upon**, and **has its impacts on**, Computer Science research. We also found that within each level of concepts, citations mostly flew between the same (sub)fields, which implies that VIS publications did not have diversified inspirations and impacts. Our regression analyses showed that citations counts were significantly lower for papers published in recent years, and papers presented at SciVis, VAST, and Vis. Journal papers and award-winning papers had significantly more citations. This contradicted the finding in [3] that award-winning CHI papers did not get more citations than a randomly selected paper, implying that awards at VIS were able to identify high-impact works.

Our study is not devoid of limitations. First, OpenAlex's mapping from affiliation name to affiliation type (94%) and country codes (98%) were not 100% accurate, slightly weakening the power of our classification models. However, the accuracy for affiliation type mapping was calculated based on eight affiliation types whereas we collapsed all non-educational affiliations into one type in our analyses. If we applied this binary classification, the accuracy of OpenAlex mapping for affiliation type would be 2% higher. The accuracy of our classifiers was also not 100%, although they were pretty close (94% - 95%). Since many country information was part of affiliation names on IEEE Xplore, the country code classifier would have a better performance than its test set accuracy (94.1%). As for affiliation types, 5% errors should not be greate enough to alter our overall results, although we acknowledged that the proportion of cross-type collaboration might be sensitive to these errors. Another concern might be the quality of OpenAlex Concepts data. OpenAlex's V1 Concept classification, which was based on data from Microsoft Academic Graph, only utilized paper title, document type, and journal title. Based on the data we had, we believe concept classification for VIS papers was reliable. For example, we came to the same conclusion as that in [23]—the majority of VIS publications concerned Computer Science—even though we were using different data. Another confirmation came from our observations on the trends of Visual Analytics as a field of study. In 2006, Visual Analytics, Science, and Technology (VAST) was established and joined VIS [14]. The sudden surge of Analytics (L2), and Visual Analytics (L3) in popularity in around 2006 corresponded to this event. Third, the rise of ML, AI, and HCI is reflective of what is happening in the real world.

Our study has the potential to inspire future work in several directions. First, OpenAlex only launched itself in early 2022 and has not been widely used in scientific studies. We found that their data was usable and can be integrated with other data sources. Other researchers may be motivated by our project and consider OpenAlex data, and our workflow, in their studies. Second, analyses like ours are powerful to identify the academic bases (i.e., which fields are they built upon) and impacts (i.e., which fields are they influencing) of a scholarly field. Our approaches can be easily applied to analyses of many other fields, such as HCI and CSCW. Another question we are especially interested in is the relationship and overlap between two (sub)fields, for example, Visualization, and HCI. Comparisons between information visualization and data visualization have been explored with Web of Science data [20]. Similar approaches could apply to the comparison between CHI and VIS. Last but not least, our present study did not include conference papers in PacificVis and EuroVis and journal papers in *Journal of Visualization* and *Information Visualization*. Future work can include those publications to draw a more complete picture of the field of Visualization.

## 6 Conclusion

We studied the authors and fields of study of 3,233 VIS publications in the past 32 years. We also inspected the citation flows from cited papers to VIS, and from VIS to citing papers. We found that VIS has been becoming increasingly popular and collaborative. The number of publications, of unique authors, and of participating countries has been steadily growing. Both cross-country and cross-type collaborations are increasing. The dominance of the US is decreasing, and authors from China are now a major part of VIS. In terms of author affiliation types, VIS is increasingly dominated by authors from universities, although the small (and stable) number of authors from non-educational affiliations have been highly active in collaborating with researchers at universities. We found that VIS is mostly about, built upon, and impacting Computer Science, and that citations in out out of VIS papers flew mostly between the same fields.

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