Collaboration Patterns and Impact of Sharing at CHIIR

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ABSTRACT

We studied the collaboration patterns of CHIIR authors, and found that most papers are collaborative. A core of 33% of the CHIIR researchers are directly connected and frequently co-author, and several disconnected clusters also make frequent CHIIR contributions. We also studied citation impact of the CHIIR papers and show that in relation to research design type, theoretical and empirical papers tend to receive more citations than resource papers. With regards to sharing and re-use, papers that share at least one resource tend to have significantly higher citation impact—in particular when sharing data resources and design resources. Re-using resources does not significantly increase citation impact in itself.

CCS CONCEPTS

• **Human-centered computing**;

KEYWORDS

CHIIR, collaboration, citation impact, data sharing and re-use

1 INTRODUCTION

The success of a research community can be evaluated on many different parameters, such as the academic and societal impact of the research conducted and the degree of collaboration between its members [1]. Academic impact in the form of citations has become

part-and-parcel of research evaluations of research groups of all sizes, while societal impact is an increasingly important factor in attracting research funding [5]. Likewise, research collaboration is an important factor in securing funding, and has also been shown to positively influence both the success of research teams [3] as well as the career progression for individual researchers, especially in interdisciplinary fields [22].

Information Interaction and Retrieval (II&R) is a good example of such an interdisciplinary field that brings together people from different backgrounds and disciplines. The *Conference on Human Information Interaction and Retrieval* (CHIIR) conference series started in 2016 as a merger of the IIiX conferences and HCIR workshops and is one of the premier publication venues for II&R research. However, little is known about collaboration patterns in the CHIIR community nor about its research impact after the first seven years of conferences.

In this paper, we present the results of an initial analysis of the CHIIR community and focus on two factors that are important to the success of research community: impact and collaboration. We conducted an analysis of collaboration within the CHIIR community and the citations that CHIIR papers have received over time. We collected the author metadata and citations of all 355 CHIIR papers published in 2016-2022 and annotated each paper along several dimensions, such as research type, method, and the degree to which CHIIR paper authors share and re-use existing resources. We address the following research questions in this work:

RQ1 How well-connected is the CHIIR community in terms of author collaboration?

RQ2 What is the impact of CHIIR publications in terms of citation counts?

RQ3 How is the impact of CHIIR research influenced by the type of research design and research methods used?

RQ4 How does sharing or re-using existing resources influence the impact of CHIIR papers?

2 RELATED WORK

Collaboration & Impact. Earlier bibliometric analysis in specific fields such as information retrieval provided an insight into collaboration and communication practices, observing an increasing

number of co-authored studies [7]. Other work focused on collaboration characteristics such as internationalization, diversity, geographic distribution etc. [2, 6, 12, 20].

Studies investigating the impact of collaboration often analyze the relationship between collaboration and citations. In the field of Library and Information Science, also rather interdisciplinary, Levitt and Thelwall [16] could observe higher citation rates for collaborative work. Also the analysis of the citation behavior of long-term co-authors does not show a general increase in citations, but that it depends on the domain and types of collaboration [9].

The citation impact of several related conferences have been studied, e.g. CHI [4] and CLEF [21].

Sharing and Re-use. While there is an increase focus on Open Science and in particular Open Data, extended documentation of resources especially for sharing and re-use purposes can be time-consuming [15]. Usually this effort needs to come with some kind of benefit. Next to research-intrinsic motivations related to good scientific practices, personal or institutional motivations for sharing or re-using resources has been analyzed by various studies. An interdisciplinary survey conducted by Kim and Stanton [14] revealed a positive influence of domain-specific normative and publisher pressure as well as career benefits on data sharing and re-use behavior. Dorta-González et al. [8] found that data citation is a strong incentive for data sharing. Also a connection between sharing and re-use could be observed: people that re-used open data before are more likely share their own data later. Using the example of clinical trial publications Piwowar et al. [17] found that trials that made their data available are cited 70% more frequently.

In this work, we follow the argumentation of Gäde et al. [10] that II&R research in particular is supported and furthered by three main resource types: (1) research data, (2) research design, and (3) research infrastructure. Therefore the citation analysis presented here does not focus on research data alone but includes also sharing and re-use of resources in general.

3 METHODOLOGY

3.1 Data Collection

To analyze impact and collaboration patterns in the CHIIR community, we view the CHIIR conference papers as an approximation of the research output of this community. We downloaded all 355 full, short, perspective, and demonstration papers for the complete CHIIR conference series duration of 2016-2022. We integrated the bibliographic metadata and full-text of all papers in a shared Zotero library[1].

We collected the citations of each CHIIR paper from Google Scholar using the SerpApi service[2]. While no citation index is complete, we used Google Scholar, because computer science fields in general—and conferences in particular—are poorly covered in traditional journal-based citation indexes such as Web of Science and Scopus. To collect citation information, we first used SerpApi to query Google Scholar for the title of each of the 355 papers. Seventeen papers produced more than one hit in Google Scholar and these were resolved manually. Out of all 355 papers, 344 had

received at least one citation. Next, we downloaded the snippet information for each of the 4406 citing publications using SerpApi and extracted the relevant paper metadata, including publication year (if available). All citation data was collected in September 2022.

3.2 Data Annotation

In order to provide a more fine-grained analysis of the CHIIR community's research output, we annotated each publication for a number of different aspects: research *type*, research *method*, and whether paper authors *shared* or *re-used* existing research resources, such as data, design elements or infrastructure components. An overview of our annotation scheme can be seen in Figure 1. None of the annotation codes were mutually exclusive. We also annotated each publication for a set of *research foci*, but do not use this data in the analysis presented in this paper. We annotated the collection of 355 papers in reverse-chronological order with each paper annotated by a single annotator. Within each year, no order was enforced in the annotation process and no steps were undertaken to structure the allocation of papers to annotators.
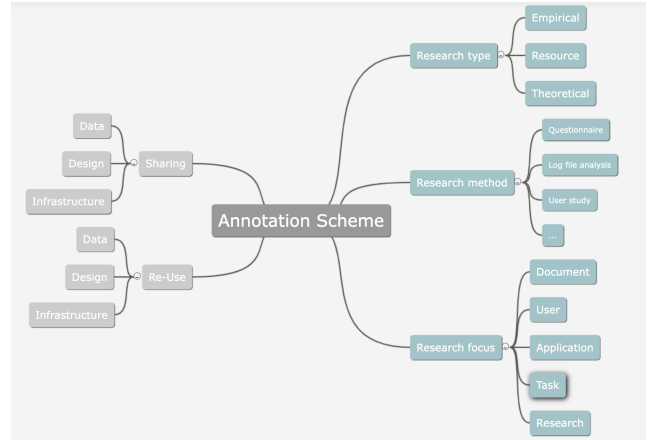

Figure 1: High-level overview of our annotation scheme with five top-level categories. None of the codes were mutually exclusive.

Research type. To categorize research type, we took Kelly's definitions of empirical research types—exploratory, descriptive and explanatory—as our point of departure [13], and added categories for *theoretical* work (such as in perspective papers), *predictive* work (i.e., training a machine learning classifier for a particular purpose), and *resource papers*, which present a new dataset, service or infrastructure (such as in demo and resource papers). During the annotation process, the authors discussed their categorization research approaches and found significant interpretative differences in what constitutes which type of empirical study as Kelly's tripartite distinction did not create mutually exclusive categories. In our final analysis, we therefore only distinguish between *empirical*, *theoretical* and *resource* papers.

Research method. We used an iterative, open coding approach to arrive at our research method categorization, bootstrapped with a

set of common research methods. We concentrated mostly on data collection methods (e.g., questionnaires, interaction tracking via log files), but also annotated methods for data analysis (e.g., factor analysis). At the end of the annotation process, we consolidated the list of research methods into a final set of categories.

Sharing & re-use. For sharing and re-use, we distinguished between the three types of research resources defined by [10]: data, design, and infrastructure. We defined *re-use* as any use after the initial publication and *sharing* as providing access to any resource type to allow future re-use. Any example of sharing or re-use is annotated as such (distinguished by resource type), but sharing/re-using multiple resources of the same type is only annotated once.

3.3 Data Cleaning & Analysis

After extracting all the codes for all 355 papers from our shared Zotero library including all paper metadata, we performed basic data cleaning of the dataset. After the consolidation phase of our coding scheme, we also performed this consolidation on the codes in our annotated dataset. We formulated whitelists of accepted codes for research method, type, focus and sharing/re-use and filtered our dataset using these lists. All analyses in the rest of the paper were performed on this filtered dataset[3]. We performed all analyses using a combination of Python and R.

For the collaboration analysis, we normalized author names so name variants were mapped to a single one, which reduced the number of distinct authors from 754 to 742. We performed co-author analysis using VOSviewer [23].

When comparing papers by citations it is important to take the age of the papers into account: older papers have had more time to accumulate citations than more recent papers. We therefore considered citations counts within citation windows of one, two and three years after publication. Because the publication date of citing papers is often reduced to the publication year—and because CHIIR papers are typically published in March around the time of the conference—we operationalize this as follows. All citing papers published in the same year as a cited CHIIR paper were counted towards the one-year citation window. Thus, for a CHIIR paper published in 2017, the one-, two- and three-year citations windows are based on citing papers published in 2017, 2017-2018 and 2017-2019 respectively. This means that the CHIIR 2021 and 2022 papers have had a smaller time window than earlier CHIIR papers and their three-year counts are missing. Therefore, in the analysis below these papers are excluded. In order to utilize more of the citation data we also calculated the normalized citation count for each paper by dividing them by the number of years since publication. For each paper, we added the six months between CHIIR 2022 and the Google Scholar crawling to the paper's age.

4 RESULTS

4.1 Collaboration

The 355 CHIIR papers were authored by 742 distinct authors, with a mean of 3.4 authors per paper ($Md = 3$, $SD = 1.6$). The distribution of number of authors per paper is shown in Figure 2, split both by research design type (a) and by year (b). Instead of visualizing the frequencies using a histogram, we estimate the underlying probability density function using kernel-density estimation to better visualize the entire distribution. With only 17 single-author papers (5%), we get a first indication that II&R research is a collaborative endeavour. Theoretical papers tend to have fewer authors than other research designs, and make up the majority of single-authored papers. All resource papers have multiple authors and also have higher probability of having five or more authors. Over the years, the number of authors per paper has varied somewhat, with the peak of the distribution shifting towards a higher number of authors in more recent years.

The mean (median) number of co-authors that an author collaborated with is 6.8 (5), with a maximum of 53 and variance of 6.1. This distribution is fairly stable although a break over years suggests that there seems to be a trend towards higher numbers of co-authors (see the right plot in Figure 2).

This suggests that the CHIIR co-author network might be dense. A connected component analysis shows a giant component of 244 authors (33% of all authors—shown in Figure 4) and in total a dozen components of at least 10 authors. The authors in Figure 4 each belong to their own local network, but also occasionally co-author with people outside their immediate circle—and thus help to build a giant component of directly connected CHIIR researchers. If all CHIIR authors are included in the analysis, several groups of co-authors are revealed as large, separate components as well as many smaller ones without co-author links to other components (Figure 5).

Overall, the co-author analysis shows that there is a strong core of CHIIR researchers that collaborate broadly (and probably across institutional and national boundaries) as well as several groups of authors that frequently contribute to CHIIR, but are more local in their collaboration. In future work, we plan to consider other indicators of connectedness, such as the citation network within the CHIIR community, both between authors and author clusters.

4.2 Impact

When we look at academic impact in terms of normalized citation counts, during the first seven years of CHIIR, its publications have received an average of 3.05 citations per year ($Md = 2$, $SD = 4.45$). Figure 6 shows the normalized citation counts for all CHIIR papers. While an average between two to five citations per year may not seem high, it is close to the impact of CHI publications during the same period [18].

4.2.1 Research Type. In order to visualize the potential influence of research type on a paper's academic impact, we generate kernel-density estimations for the number of received citations after one, two and three years per research design type, as shown in Figure 7. Figure 7 shows that while the curves for empirical papers and resource papers are fairly similar, theoretical papers tend to get more citations in the first year. After two and three years, the differences become more pronounced, with resource papers having fewer citations on average than empirical and theoretical papers. Among the latter two design types, there are a small number of papers that accumulate more and more citations. No such papers exist among

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[3]We make our dataset and source code for the analysis scripts available at https://github.com/marijnkoolen/CHIIR-2023-Sharing-Citing/.
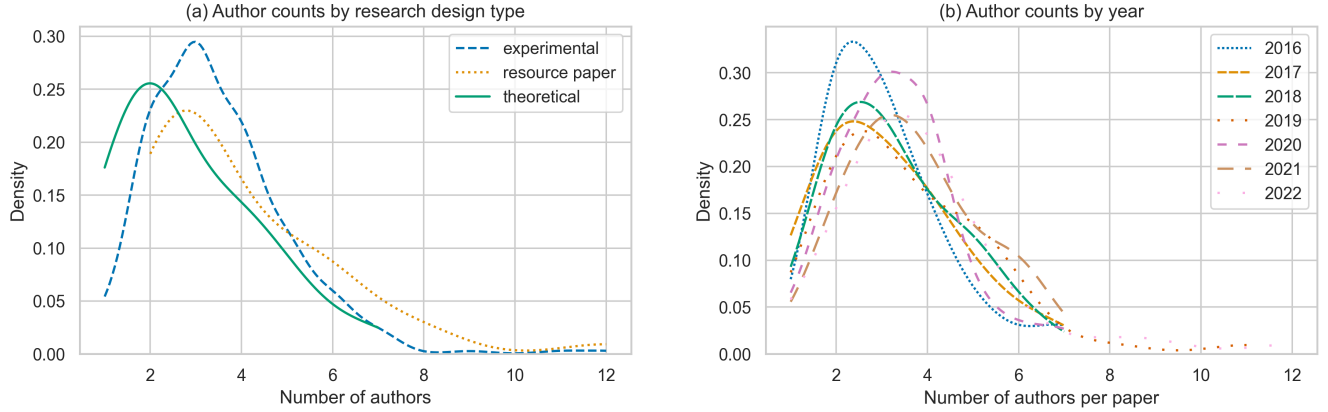
Figure 2: Number of authors per paper for all 355 CHIIR papers by research design type (a) and by year (b).
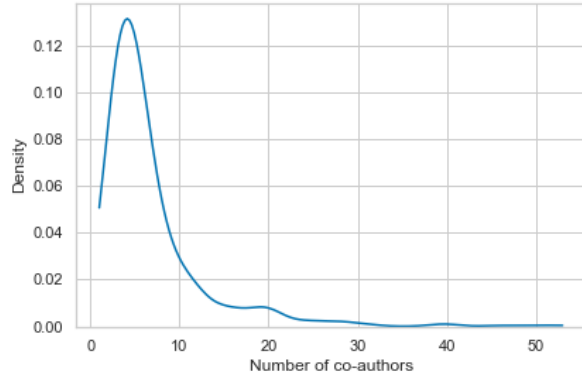

Figure 3: Distribution of the number of co-authors per author.

the resource papers. Thus, in terms of citations, resource papers seem to have lower impact than empirical and theoretical papers.

4.2.2 Research Method. Figure 8 shows the kernel-density estimation plots for the number of citations per research method. Coding has resulted in 27 different data research methods, many of which are uncommon in CHIIR papers. The 10 most frequently annotated methods, shown in Figure 8, are all used in at least 20 papers. After one year, evaluation papers have more probability mass at higher numbers of citations than other methods. With longer time windows, crowdsourcing papers are more likely to get citations. Content analysis and eye-tracking studies have high probability mass at the low end of citation counts.

4.2.3 Sharing & Re-use. Gäde et al. [10] argued for the importance of sharing and re-using existing II&R resources from the perspective of increased reproducibility. In this section, we analyze whether sharing and re-use also has other benefits, such as in terms of impact. To study how sharing and re-use affects citation impact, we annotated all 355 CHIIR papers with six special tags related to resource sharing and re-use: three for sharing data, design or

infrastructure resources and three for re-using one of these three resource types. If a paper shared more than one resource of the same type, it was only annotated once, but a paper sharing both data and design resources was annotated as such.

Table 1 provides an overview of sharing and re-use activity for all seven years of CHIIR proceedings. It shows that re-use is more common at 99 papers than sharing at 38 papers and that the majority of these come from empirical papers. Furthermore, infrastructure re-use clearly lags behind data and design re-use, likely due to the complexities of re-using infrastructure components for new, custom experimental setups [11].

When examining the impact of sharing, we found that papers that share at least one resource received 4.92 (normalized) citations on average ($SD = 6.15$), whereas papers that do not share, received 2.83 citations ($SD = 4.16$). As citation counts are not normally distributed, but instead follow a Poisson distribution according to Stewart [19], we conducted a Mann-Whitney U test, which revealed that sharing at least one resource results in a statistically significant increase in the number of received citations ($U(N_{share} = 38, N_{no\ share} = 317) = 4842, z = 1.98, p = 0.048$)). In contrast, re-using

Table 1: Overview of sharing and re-use activity split by research type for all CHIIR papers from 2016-2022 ($N = 355$). The 'Union' column represents the union of the three resources, so it shows how often at least one of the three resource types is shared or re-used.

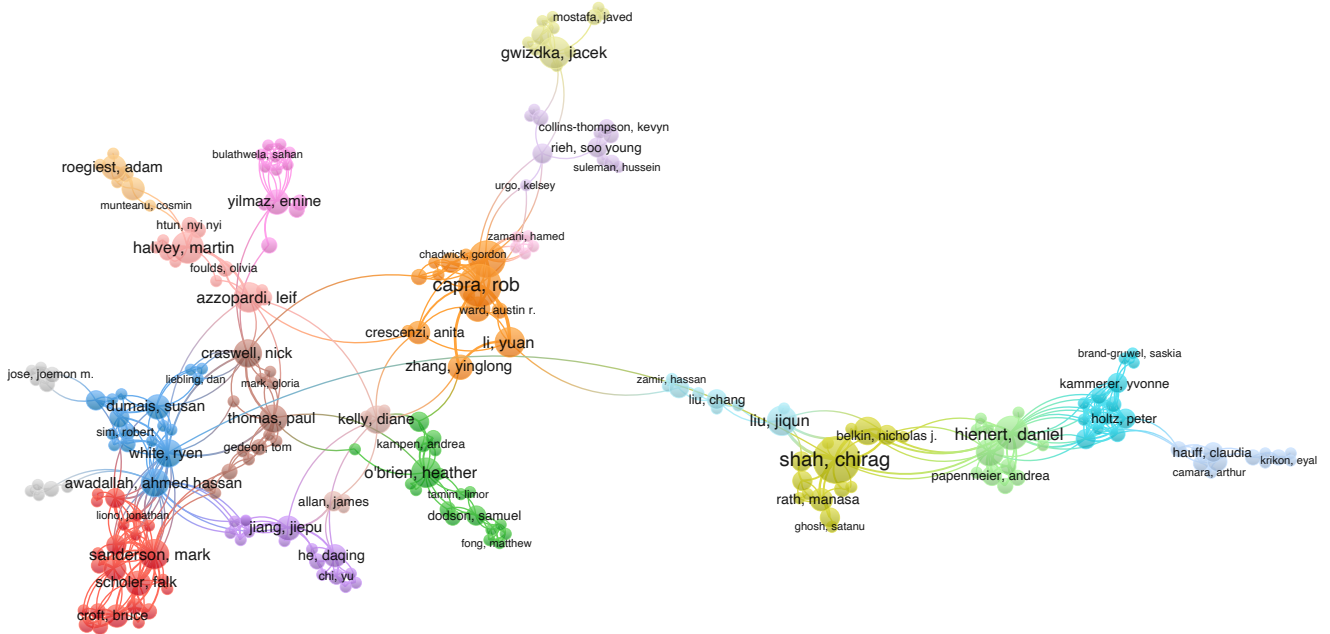|	Data	Design	Infrastructure	Union
Sharing	15	17	13	38
Empirical	13	17	7	31
Resource	3	1	6	8
Theoretical	0	0	1	1
Re-use	51	63	25	99
Empirical	50	59	21	93
Resource	2	3	4	6
Theoretical	0	1	0	1

Figure 4: Co-author network map of the largest component with 244 authors (33% of all authors).

existing resources ($M = 3.36$, $SD = 4.53$) compared to not re-using any existing resources ($M = 2.93$, $SD = 4.42$) does not result in a statistically significant difference in the number of received citations ($U(N_{reuse} = 99, N_{no\ reuse} = 256) = 12064$, $z = 0.70$, p = 0.48).

In order to determine the impact of sharing different resource types with the scientific community—as well as how the research type influences this—we performed a regression analysis with normalized citation count as our response variable. A quasi-Poisson regression was conducted to predict the normalized citation count of CHIIR publications based on whether they shared one of three different resource types (data, design, and infrastructure), whether they re-used at least one resource type, and the type of research design of the publication in question. We chose a quasi-Poisson regression, because citation counts are known to follow a Poisson distribution [19] and because normalized citation counts are not integer values. We did not include the separate resource re-use variables into the regression model, because they are even more likely to be correlated with each other and because our Mann-Whitney U test showed no impact of resource re-use on citation counts.

Table 2 shows the results of our regression analysis. It confirms this as re-using at least one resource does not significantly increase the citation count. Sharing infrastructure resources also does not significantly impact citation counts, something predicted by [11]. Both sharing data resources ($p = 0.014$) and design resources ($p = 0.049$) significantly and positively affect the number of citations: sharing at least one data resource increases the citation count by 1.96 extra citations and sharing design elements 1.70 citations. This suggests that sharing data has the greatest impact of the three, probably because it is easier for other researchers to re-use data than to adopt research design elements or infrastructure. Perhaps surprisingly, empirical papers ($p = 0.014$) are slightly more likely to

incur more citations than resource papers ($p = 0.019$). Theoretical papers were dropped from the model due to their (understandable) lack of sharing resources.

Table 2: Regression values for resource sharing, re-use and research design type according to a quasi-Poisson regression. Variables marked with * are significant at an α of 0.05.

Variable	β	e^β	SE	*p*-value
Shared infrastructure	0.349	1.408	0.341	0.307
Shared data	0.678*	1.961	0.275	0.014
Shared design	0.530*	1.695	0.269	0.049
Re-used at least one resource	-0.012	0.988	0.172	0.945
Empirical design	-0.526*	0.589	0.212	0.014
Resource paper	-0.663*	0.516	0.280	0.019

5 DISCUSSION & CONCLUSIONS

In this paper, we studied the collaboration patterns of CHIIR authors through co-author analysis as well as the citation impact of CHIIR papers based on Google Scholar data and across several dimensions identified through extensive annotation of all CHIIR papers.

The co-author analysis of all 742 CHIIR authors shows that most CHIIR papers are collaborative with 3.4 authors per paper on average. A network analysis shows that a third of the CHIIR authors are directly connected in a central connected component with many author links across countries and institutions. Several disconnected, smaller components exist alongside this, some with clusters of ten or more researchers making frequent CHIIR contributions.
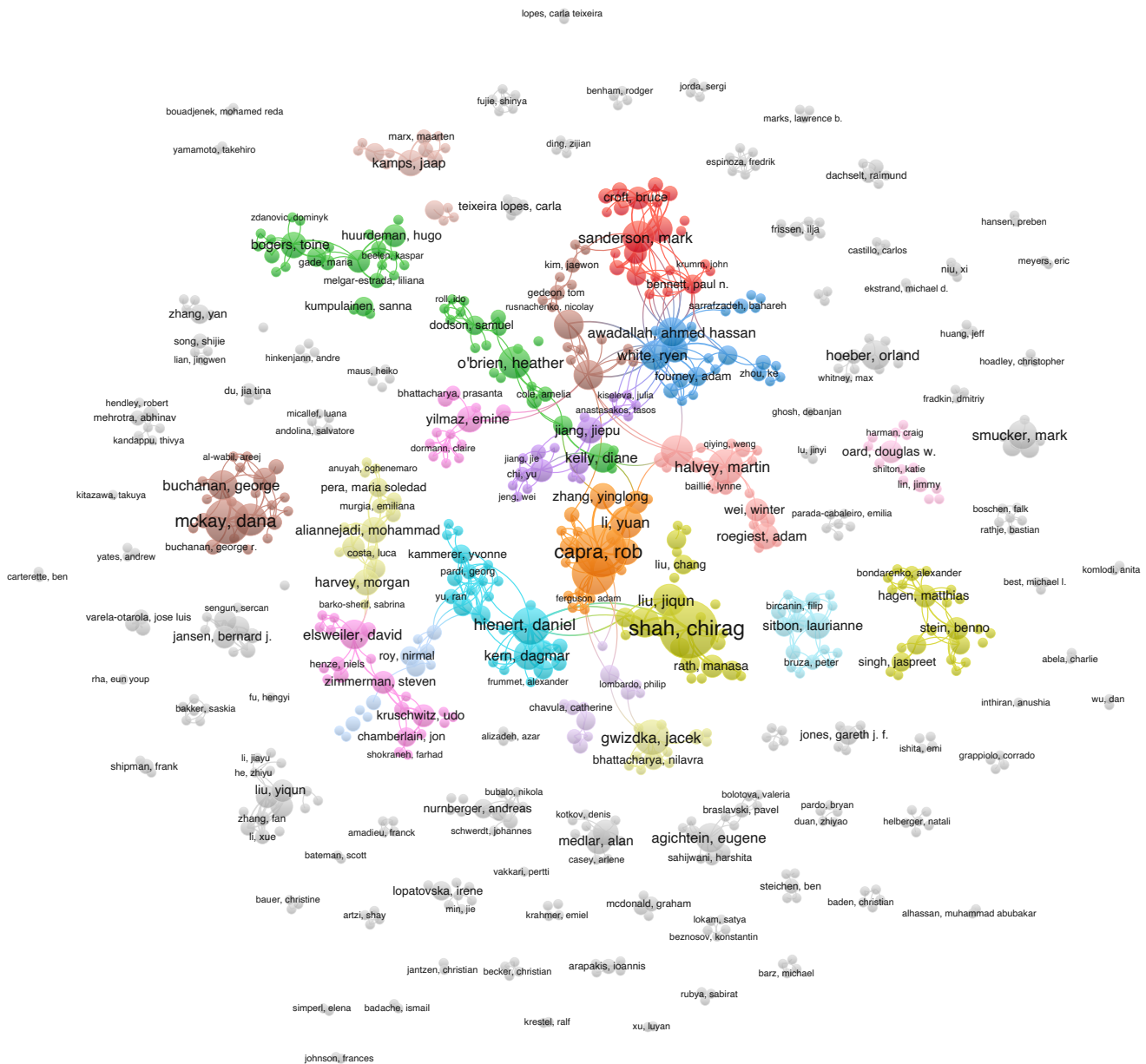
Figure 5: Co-author network map of all 742 authors. Colors of central component correspond to those in Figure 4.

The analysis of citation impact shows that in relation to research design type, theoretical and empirical papers tend to receive more citations than resource papers. With regards to sharing and re-use, papers that share at least one resource tend to have significantly higher citation impact—in particular when sharing data resources and design resources. Re-using resources does not significantly increase citation impact in itself.

There are some limitations to our analysis. Our analysis is based on accepted papers and therefore represents a pre-selected percentage of the actual research in this field. It might be interesting to extend the analysis to all submitted papers. Another limitation

is the annotation of each paper by a single author, despite regularly scheduled discussions during the coding process to align our coding practices. The main area where we identified inter-annotator disagreement was annotation of research design types. Post-annotation discussion highlighted significant disagreement in how the exploratory, descriptive, explanatory, and predictive research types were annotated, even though these were based on explicit definitions from the literature. There are likely to be multiple factors driving this, including overlaps in the definitions of the different research types as well as a lack of clarity in the authors'
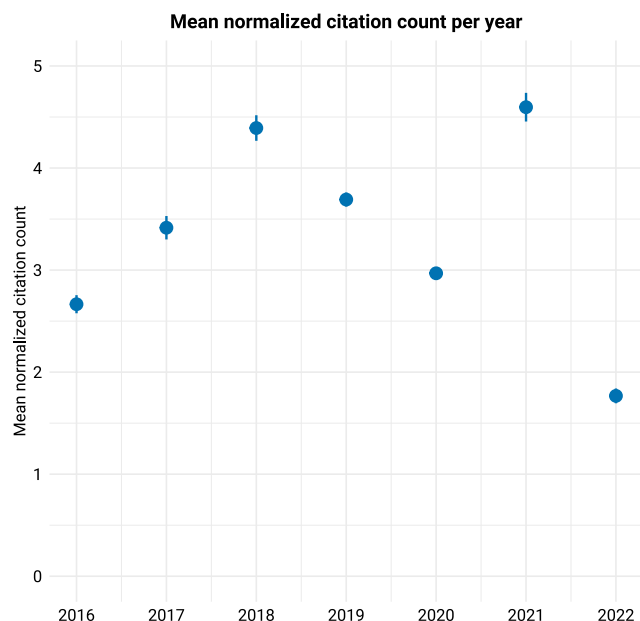
Figure 6: Normalized citation counts with standard error bars for all CHIIR papers grouped per year.

descriptions of their research designs. How to address this remains a question for future work.

ACKNOWLEDGMENTS

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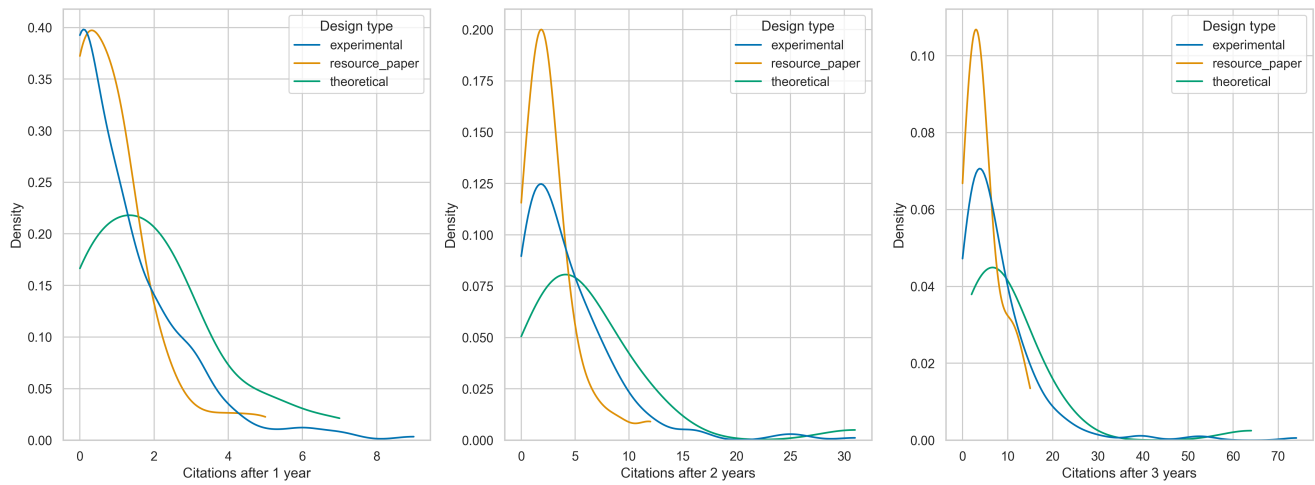
Figure 7: Kernel density estimation of the number of citations per research design type after 1 year (left) 2 years (middle) and 3 years (right)
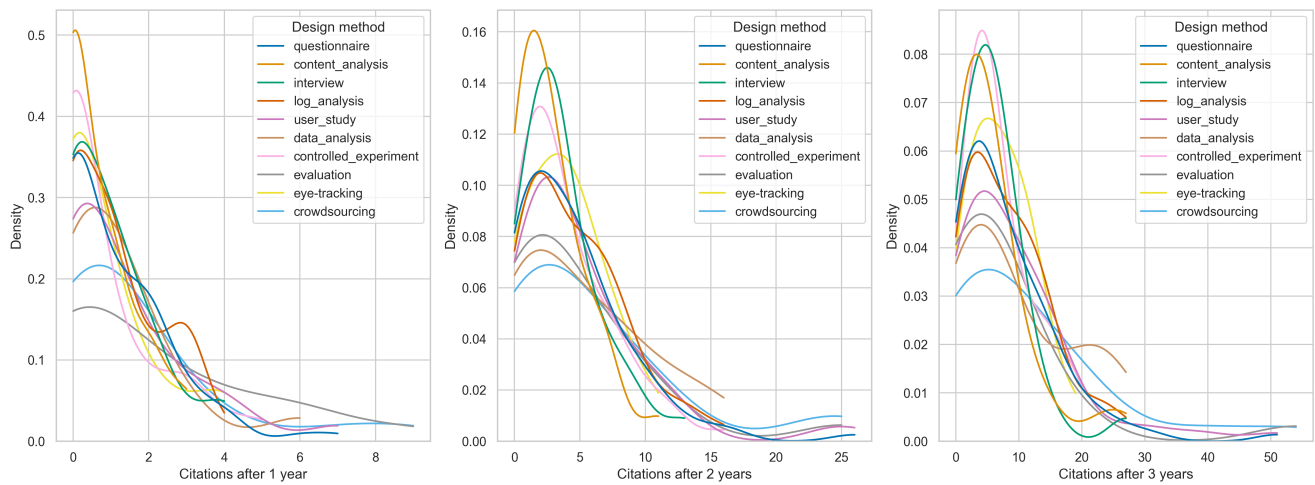

Figure 8: Kernel density estimation of the number of citations per research design method after 1 year (left) 2 years (middle) and 3 years (right)