Altmetrics and Citation Counts: An Empirical Analysis of the Computer Science Domain

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ABSTRACT

Background. Researchers, funding agencies, and institutions involve bibliographic data to assess the impact or reputation of papers, publication venues, researchers, and institutions. Particularly citation counts, and metrics that build on these (e.g., impact factor, h-index), are widely used, despite extensive and rightful criticism regarding, for instance, their meaning, value, and comparability. Moreover, such metrics require time to accumulate and do not represent the scientific impact outside of academia, for instance, on industry. To overcome such limitations, researchers investigate and propose altmetrics to complement or provide a more meaningful alternative to traditional metrics. Altmetrics are based on user interactions in the internet and especially social-media platforms, promising a faster accumulation and to represent scientific impact on other parts of society. **Aim.** In this paper, we complement current research by studying the altmetrics of 18,360 papers published at 16 publication venues of the computer science domain. **Method.** Namely, we conducted an empirical study to understand whether altmetrics correlate with citation counts and how they have evolved over time. **Results.** Our results help understand how altmetrics can complement citation counts, and which represent proxy metrics that indicate the immediate impact of a paper as well as future citations. We discuss our results extensively to reflect on the limitations and criticism on such metrics. **Conclusion.** Our findings suggest that altmetrics can be helpful to complement citation metrics, potentially providing a better picture of overall scientific impact and reducing potential biases of focusing solely on citations.

CCS CONCEPTS

• **Information systems** → **Social networks**; *Social recommendation*; • **General and reference** → *Empirical studies.*

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Altmetrics, Citation Count, Computer Science, Research Impact

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1 INTRODUCTION

The constantly expanding corpus of research papers makes it harder for everyone to judge the quality and impact of a single paper, publication venue, researcher, or research project. So, many researchers, funding agencies, institutions, social-media platforms (e.g., ResearchGate), and other websites (e.g., Google Scholar[1]) rely on bibliographic data, and particularly citation metrics, to approximate scientific impact. As a result, citations are now widely used as a means to indicate the performance and reflect on the quality of research [2]—despite extensive criticism on using such metrics (e.g., due to misinterpretation or manipulation) [4, 5, 13, 45, 49]. In parallel, researchers aim to make their work more visible to various audiences by using new communication channels, such as blogs, social media (e.g., Twitter), and collaborative tools (e.g., Mendeley). Such communication channels are often still aimed at the scientific community, but they can expand towards other parts of society. Moreover, they create new opportunities to measure the impact of research, leading to the introduction of altmetrics [31].

Altmetrics have been introduced in 2010 to assist researchers with tracking the impact of papers beyond traditional bibliographic data [17]. They provide quantitative data of user interactions over a wider range of communication channels, for instance, Wikipedia, Twitter, Facebook, Youtube, CrossRef, and Amazon. Altmetrics comprise usage data (e.g., downloads and views), and indicate how well the target audience engages with a paper through these platforms. The primary reason for the increasing popularity of altmetrics is the immediate feedback through interactions on the internet that can be gathered rather quickly, unlike traditional citation metrics that accumulate over years. Even though altmetrics are not as accurate

[1] https://scholar.google.com/citations?view_op=top_venues&hl=de

as citations for indicating the impact of a paper on research, they can potentially predict future citations [8, 28]. Also, they can help to measure a paper's impact outside of the scientific community and may tackle some of the problems of citation metrics. For instance, if a paper receives a number of tweets and mentions, it is likely that the paper will also be cited in the future, providing an early indicator that can also reflect on other parts of society. With the growing interest in altmetrics, several tools have been developed to aggregate data from diverse sources, for instance, Plum Analytics,[2] Altmetrics Explorer,[3] and ImpactStory.[4]

Problem Statement. Citation metrics have been proposed as measures of scientific impact and are often considered as quality indicators [1, 24]. Altmetrics have been introduced to address some of the shortcomings of citation metrics, and researchers heavily debate their potential for that purpose [11, 16]. Particularly, some studies investigate correlations between altmetrics and citation metrics to understand whether and how altmetrics can be used to measure scientific impact [15, 51]. Unfortunately, such studies have not been extensively conducted explicitly for computer science, yet. Computer science (or at least parts of it) is driven by applied research and strongly connected to engineering, providing and using modern communication channels that are relevant for altmetrics—and many users of these channels discuss (computer) science (e.g., on Reddit[5] and StackExchange sites[6]). Consequently, altmetrics may be more relevant for computer science than for other communities [37].

To explore the usefulness and limitations of altmetrics in computer science, we defined three research questions for this paper:

- RQ_1 *Do citations and altmetrics correlate for computer science?* With this question, we aimed to understand to what extent altmetrics are only proxies or can actually complement citation metrics in computer science. For this purpose, we extracted a dataset of citation counts and altmetrics for 18,360 papers using Plum Analytics' PlumX[2] tool and investigated the correlations within that dataset.
- RQ_2 *How have citation counts and altmetrics evolved over time?* With this question, we explored whether altmetrics exhibit the same temporal evolution as citation metrics. To this end, we summed up the metrics for all papers in our dataset for each year and compared the resulting distributions.
- RQ_3 *Can tweets reflect on future citations of papers?* With this question, we intended to understand whether tweets can be used to predict the impact of a paper, thus reflecting on possible future citations. We focused on tweets, because we identified them as the most interesting altmetric from our previous questions.

Note that we contribute our raw dataset and analyses scripts in an open-access repository to allow other researchers to validate and replicate our study.[7]

Contributions. Overall, we provide two core contributions by tackling our research questions: First, we analyze how different communication channels can increase and reflect on the visibility of research in computer science. Second, we discuss which altmetrics can be helpful to tackle the limitations of, and biases caused by, citation metrics. Thus, our results help researchers understand the impact of altmetrics in computer science, which can help in designing, reviewing, and evaluation processes. Moreover, our findings can be helpful in literature analyses that build upon metrics, for instance, during the identification or selection of papers [38, 40].

2 BACKGROUND

In this section, we briefly outline the concepts of traditional metrics (i.e., citations) and altmetrics (i.e., PlumX).

2.1 Citation Metrics

Researchers rely on the number of citations, and metrics building on such numbers (e.g., h-index), to obtain an overview of the impact of papers, venues, researchers, and research in general. Citations are derived from the references a paper receives from other papers, and thus citations have become a widely accepted measure of research performance. Even though there are important and various criticisms of citation counts, they are commonly used and, along with several sub-metrics (e.g., author h-index, Field-Weighted Citation Impact of papers, CiteScore of venues) even provided by various digital libraries [39]. Many criticisms of citation metrics can be easily illustrated by the drastic variations in citation numbers across different sources that result from each source's characteristics and coverage. For instance, Google Scholar automatically indexes all documents that appear scientific (e.g., pre-prints, academic opinions, dissertations) and are available on the internet, whereas some digital libraries build only on their own dataset—leading to varying citations that can easily be manipulated in some sources and that may not be representative. As a result, Google Scholar and Scopus are mostly used for citation analyses, since they have a comparatively broad coverage [18, 21].

When measuring the citations of a paper, it is particularly important to consider the temporal dimension [2]. Usually, recently published papers are hardly cited, as citation counts start to accumulate later on. Researchers are also not completely convinced and question the credibility of citations and their use as quality indicators, mainly due to self-citations and the possibility of bias as well as manipulations [4, 5, 35, 45, 49]. Still, there is adequate evidence that supports the use of citation counts for assessing the impact or relevance of papers [6, 24].

2.2 Altmetrics

Since the introduction of altmetrics, they have been considered a new method to complement citation counts, and for determining the societal as well as social impact of papers. Due to the increasing importance of altmetrics within the scientific community, one of the largest multidisciplinary publishers, Elsevier, has recently partnered with the Plum Analytics tool developers to provide researchers with altmetrics data in addition to the standard bibliometrics available publicly. For our study, we use the PlumX API to collect citations and altmetrics from two important Elsevier products, namely Scopus and Science Direct. Generally, the PlumX metrics consist of the following five categories:

[2] https://plumanalytics.com/
[3] http://altmetric.com/
[4] http://impactstory.org/
[5] https://www.reddit.com/r/science/
[6] https://stackexchange.com/sites#science
[7] https://doi.org/10.5281/zenodo.6506966

Captures. Captures aim to track the interest of the audience in a paper by considering how users act on the digital library. Precisely, capture metrics accumulate the readership size by determining how often a paper is, for instance, bookmarked, read, liked, or added to a reference manager. Several sources are used to track this information, for example, Slideshare, YouTube, GitHub, Vimeo, Mendeley, and EBSCO.

Citations. The citation counts accumulated within PlumX are not limited to Scopus, they also cover other sources, such as CrossRef, PubMed, and SciELO.

Mentions. This category tries to indicate how often other people engage with a paper through blog posts, comments, and peer reviews. For instance, blogging acts as a bridge between the research community and other parts of society. However, accumulating such data is challenging, due to a lack of standardization and accessibility [41].

Social Media. This category intends to measure interactions on platforms, such as Facebook, Twitter, Amazon, and Youtube, based on the number of likes, tweets, and shares. The argument for this category is that social-media platforms broaden the coverage and provide an alternative way of measuring the impact of a paper.

Usage. Usage is a publication statistic summarizing several values, such as abstract views, full-text downloads, and the number of URL clicks. Usage metrics ideally reflect the immediate visibility of a paper and the attention it receives.

The four altmetrics in the above five categories have the potential to extend and complement the citation count, and to measure impact that goes beyond citations on their own.

3 RELATED WORK

Since the introduction of altmetrics, several studies have been conducted to examine their usefulness for measuring the impact of a paper [19, 22, 46]. Particularly, Eysenbach [15] and Xia et al. [50] analyzed the relations between interactions on Twitter and citations, while Priem et al. [32] and Thelwall et al. [43] investigated the association of Mendeley readers with citation counts. In general, these studies have found a positive moderate correlation between the variables. These results are further confirmed through the meta-analysis performed by Bornmann [9], which concluded that the correlation of citations with micro-blogging (e.g., Twitter and Facebook), blog counts, and bookmarks from online reference managers (e.g., Mendeley) is negligible, small, and moderate, respectively.

In addition to correlation analysis, the study performed by Thelwall and Nevill [44] also employed regression modelling to analyze data from altmetric tools, such as Altmetric.com, to investigate their ability to predict the scientific impact of papers. They found that Mendeley reader counts are consistent predictors of future citation impact, and most other Altmetric.com scores can be useful as performance indicators. So, the findings of Thelwall and Nevill align with the previous observations. Another recent study by Luc et al. [25] reports a comparative analysis to determine the impact of tweets on citations, considering results of a prospective randomized medical trial. They analyzed 112 papers published between 2017 to 2018 in two medical journals, and draw similar conclusions regarding the usefulness of tweets as Thelwall and Nevill. Their results demonstrate that tweeting helps increase the number of citations received by a paper, validating the scholarly impact of social media interactions. However, Luc et al. suggest that more comprehensive social media strategies should be tested rigorously for further validation of their results. Finally, we are aware of a recent study by Lamba et al. [23], investigating altmetric attention score and citation counts to examine the productivity of research groups working in certain sub-domains of computer science. Based on Spearman's rank correlation, Lamba et al. observe a weak to moderate positive relationship between citations and altmetric attention scores. However, the authors highlight some limitations of their study, such as the dependency on selected research groups and a single altmetric tool, namely Altmetrics Explorer. Since PlumX has gained a lot of popularity in recent years and with its recent integration into Elsevier tools, more extensive investigations of the usefulness of altmetrics for determining impact in computer science are possible.

Based on the aforementioned related work, we observe that researchers are actively investigating the significance of altmetrics as a performance measure, and their association with citations. However, we also see that such studies are limited in the area of computer science, since most studies analyzed literature from medicine or for multiple disciplines, including education and sciences. So, in this paper, we are focusing on computer science literature and model the behavior of altmetrics, focusing particularly on PlumX metrics and their ability to predict future scientific impact of a paper. To provide an in-depth understanding of the related work and mitigate the threat that we may have missed relevant papers, we performed an automated search on Scopus to determine any existing papers that utilize PlumX as their source of information and determine its respective metrics' association with citations. We employed a focused search string: "*(altmetrics and citations and correlations and 'PlumX or Plum Analytics')*", and we restricted our results to papers published in English from 2012 until 2021. Our search returned 35 results, and through the first screening (titles and abstracts) we found 19 papers. After we performed all full text reviews, we kept eight papers as closely related to our study—which partly overlap the papers we already discussed.

We summarize the eight papers in Table 1, and can observe that the studies found different results. When reading the full texts, we found that this is likely caused by the different datasets used and variations in the experimental settings. The studies performed by Nuzzolese et al. [28], Saberi and Ekhtiyari [36], and Ram et al. [34] build on multiple metric categories defined in PlumX and mostly perform Spearman's rank correlation test. In contrast, the remaining studies focus mostly on the social media impact and its association with citation counts. Most of these studies analyze papers published within a specific year and their accumulated metrics for the next years, using mostly a time window of 1–3 years and varying data resources for citation counts. For example, Eysenbach [15] measures the impact of tweets on citation counts gathered from Scopus and Google Scholar. Such differences in the experimental settings lead to variation in the correlation coefficients. Note that we did not find a paper reporting a study within the computer science domain. Consequently, we complement the related work with such a study, providing detailed insights on the usefulness of altmetrics for assessing impact in our research domain.

Table 1: Overview of the existing related work, summarizing the covered domain, source, metrics, and correlation results.

Reference	Year	Domain	Source (Test)	Metrics	Correlation
Eysenbach [15]	2011	Medicine	Twitter (Spearman)	Tweets (GS; Scopus)	0.39; 0.20
Thelwall et al. [43]	2013	Medicine	Twitter (Spearman)	Tweets	-0.19
Ortega [29]	2016	Diverse	Scopus (Spearman)	Tweets	0.18
Xia et al. [50]	2016	Natural Sciences	Twitter (Spearman)	Tweets	0.16-0.35
Erdt et al. [14]	2018	Diverse	WoS, Scopus (Spearman)	Social media; Usage	0.12-0.38; 0.13-0.21
Ram et al. [34]	2018	Diverse	Scopus (Spearman)	Capture; Mention; Social media; Usage	0.38; 0.04; -0.01; 0.07
Nuzzolese et al. [28]	2019	Education	Scopus (Pearson)	Capture; Mention; Social media; Usage	0.54-0.57; 0.06-0.2; 0.09-0.15; 0.1-0.12
Saberi and Ekhtiyari [36]	2019	Information Science	Google Scholar (Spearman)	Capture; Mention; Social media; Usage	0.68; 0.37; 0.16; 0.45

4 METHODOLOGY

In this section, we first describe the overall design of our empirical study before detailing how we created our dataset.

4.1 Study Design

Considering RQ_1, we hypothesize that altmetrics can complement citation counts and have the potential to reflect the impact of a paper. To test this hypothesis, we analyze whether our dataset reveals correlations between a paper's accumulated altmetrics and its citation count. For this purpose, we compute Spearman's rank correlation coefficient (ρ) between each PlumX metric and the citation count as implemented in the R statistics suite [33]. Spearman's ρ expresses the strength of a correlation from -1 to +1, either implying a negative or positive correlation between both variables, respectively. We use a confidence interval of 0.05 and use test correction (Bonferroni method) to account for multiple hypotheses that we test on the same data. Since correlations can easily be misinterpreted and may be misguiding (e.g., assuming a non-existing causation) [3, 47, 48], we use the correlations we identify only to guide our actual study. Consequently, we build upon visualizations to observe relations in our dataset and qualitative discussions to analyze them.

To address RQ_2, we analyze the temporal evolution of the metrics in our dataset. Through our analysis, we aim to understand how altmetrics have evolved over time, especially considering the information sources used for the metrics, such as Twitter and Mendeley. Since each altmetric is influenced by different factors and behaviors of the scientific community, it is important to understand similarities and differences between such information sources. For this purpose, we illustrate the temporal evolution of all metrics and discuss how different patterns may indicate which altmetrics are a suitable alternative or complement for citations.

For RQ_3, we investigate one particular altmetric of the social-media category of PlumX metrics, namely tweets. We focus on the social-media category to determine the use of such platforms in the computer science community as a communication channel for disseminating papers. Since we found that tweets are a major proportion of the values accumulated within the category social media, we specifically consider these for our analysis. The idea is to obtain the tweet counts of all papers within our dataset and understand whether these can reflect on potential future citations. We focus on the more recent years from 2018 to 2021 in particular, since our data shows that the number of tweets increased —while the number of citations decreased. This can be expected, since Twitter gained more attention in recent years, while new papers could not get as many citations, yet.

4.2 Data Sources

To address our research questions, we considered the data available through PlumX, including the four categories of altmetrics we described in Section 2. In addition, we elicited the citation counts of each paper from Scopus. We remark that the citation counts are based on Scopus only, and thus the values can differ compared to other sources, such as Google Scholar or the ACM Digital Library. However, Scopus covers a broad range of venues from various publishers, while also excluding publications that have not been peer reviewed (e.g., bachelor theses, technical reports). So, Scopus has become widely used to recover citation counts, since it provides an adequate data basis.

Besides the main PlumX categories, we also examine a subcategory of social media in more detail, namely tweets. Twitter has recently become an important social media platform for disseminating information, allowing its users to communicate ideas, promote their work, and receive feedback from a broader audience [12]. Similarly, researchers extend the visibility of their work through the network of followers and connections by tweeting and re-tweeting to create a flow of information. Thus, maintaining a digital presence allows researchers to add to their prestige and to the impact of their papers [27]. Although it is used by a small proportion of researchers, Twitter remains the most popular social media platform, especially in disciplines related to computer science [10]. Still, some researchers are not convinced to use social media, due to the issues of authenticity [42]. Through an online survey, Black et al. [7] determined whether social media platforms are used by software developers and how successful Twitter is for scientific communication. Their results show that 91% of 31 participants use social media, with Twitter being one of the most popular platform. Although their sample size is limited to a small number of participants, their observations indicate the increasing use of social media by researchers. Due to these findings and our own results indicating an increasing importance of Twitter, we focused on this social media platform for RQ_3.

4.3 Data Collection and Processing

To construct our dataset, we first identified the most popular (as of January 2022) conferences and journals via Guide2Research,[8] a public database that uses well-established indicators, such as h-index and citations, to rank venues within the computer science domain. Based on this search, we selected 16 venues that were also included in Scopus to retrieve the data we needed to answer our research questions. Our dataset comprised

- eight conferences:
  - ACM Conference on Computer and Communications Security (CCS)
  - ACM International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS),
  - ACM International Conference on Information and Knowledge Management (CIKM),
  - IEEE International Conference on Distributed Computing Systems (ICDCS),
  - ACM Special Interest Group on Management of Data Conference (SIGMOD),
  - ACM SIGPLAN Conference on Programming Language Design and Implementation (PLDI),
  - Society for Industrial and Applied Mathematics Annual Meeting (SIAM AN),
  - ACM/IEEE International Conference on Software Engineering (ICSE),
- and eight journals:
  - Computing Surveys (ACM),
  - Empirical Software Engineering (Springer),
  - Transactions on Parallel and Distributed Systems (IEEE),
  - Transactions on Software Engineering (IEEE),
  - Pattern Recognition (Elsevier),
  - Information Fusion (Elsevier),
  - Science Robotics (AAAS),
  - Transactions on Pattern Analysis and Machine Intelligence (IEEE).

As we can see, we cover a broad range of venues from the computer science research community, which are among the ones received as the best venues and include all major categories from the 2012 ACM Computing Classification System.[9] Consequently, we argue that the papers and authors in our dataset represent a broad sample of highly visible research, and will arguably also have accumulated an appropriate number of altmetrics for our study.

Afterwards, we used Scopus to retrieve the bibliographic data for all papers published at the sixteen venues from 2015 until 2021 (last updated in January 2022). We chose this more recent time period because altmetrics have only been introduced in 2010, and required time to become established enough to observe how they behave compared to citations. In detail, we extracted the title, publication year, source, digital object identifier (DOI), and citation count for each paper. We gathered this data in a single Comma-Separated Values (CSV) file.

To obtain the altmetrics of each paper, we have implemented a prototype in Python that allows us to automatically extract PlumX metrics from Scopus, building on our generated CSV file to identify each paper. Our prototype uses the DOI to specify a paper and initiates the extraction of PlumX data using the Scopus PlumX Metrics API.[10] For each paper, we extended our CSV file with the number of captures, usages, social media counts, and mentions. All the extracted metrics (i.e., citation counts and altmetrics) are as they have accumulated until January 2021. To process and visualize our data, as well as for hypothesis testing (cf. Section 4.1), we used R and Python based on the open-source IDE RStudio.

[8]https://www.guide2research.com/

[9]https://dl.acm.org/ccs

[10]https://dev.elsevier.com/documentation/PlumXMetricsAPI.wadl

Table 2: Coverage of altmetrics for the 18,360 papers in our dataset.

PlumX metrics	Number of papers	% proportion
Captures	18,306	99.71
Usage	4,840	26.36
Social media	3,312	18.04
Mentions	930	5.07

5 RESULTS

In the following, we present our results for each of the research questions we defined in Section 1. We summarize the coverage of each PlumX metric within our dataset in Table 2. Considering the coverage of altmetrics, it is important to notice that not all papers have each of the PlumX metrics, since these are evolving and yet to be completely adopted in the scientific community. Particularly, the problem of missing data is evident for older papers, which we have to be aware of during our analysis. By default, R removes records with missing values for each metric. Since the problem of missing altmetrics inevitably exists, we examine each metric on their individual capability of correlating with citations, which we analyze and discuss further.

5.1 RQ_1: Correlations

Our dataset comprises metrics of 18,360 papers, and in Table 3 we present the results of Spearman's rank correlation test between each almetric and citations counts, along with their p-values. We defined the confidence interval as 0.05 and adapted it to perform the Bonferroni correction, thus the corrected p-value is 0.01. We observe that a statistically significant correlation exists for all the PlumX categories (p-value < 0.01), meaning that the test correction does not imply misinterpretations of our results due to testing multiple hypotheses. Most metrics have a weak positive correlation with citation counts. So, the positive correlation coefficients indicate that all the metrics tend to associate with citations. The main exception is the strong correlation we can observe between captures and the citation count (i.e., +0.70).

In Figure 1, we present the scatter plots for our entire dataset. We indicate the pattern for each PlumX metric with respect to the citation counts, which suggest that, although not perfectly linear, some positive relationship between the variables exists—which we quantified in Table 3. The blue line in each plot within Figure 1 represents the average correlation values. Particularly, we can see that the association of mentions with citation counts is

Table 3: Spearman correlation coefficient (ρ), for each PlumX metrics and citation counts.

Reference	PlumX metrics	$\rho\downarrow$	p-value
Figure 1 (a)	Captures	+0.70	<0.01
Figure 1 (d)	Usage	+0.11	<0.01
Figure 1 (c)	Social media	+0.07	<0.01
Figure 1 (b)	Mentions	+0.07	<0.01

the weakest (due to the smaller sample size), and remains weak for social media and usage—while it is strong for captures. Still, our overall results indicate that altmetrics are positively associated with citation counts; and thus, if used appropriately, altmetrics should provide meaningful insights into the future impact of a paper.

RQ_1: Correlations

Altmetrics are weakly positively (mentions, social media, usage) correlated with citation counts, with an exception of captures being strongly positively correlated. This indicates that papers with higher altmetrics are more likely to gain more citations.

5.2 RQ_2: Temporal Evolution

In Figure 2, we present the temporal evolution of the PlumX categories along with citation counts. We remark that the modeling is based on our dataset, and thus for the years ranging from 2015 to 2021. For captures, we can observe the highest peaks for 2018 and 2019, but not for earlier years. Although the numbers decrease for 2020 and 2021, they still still remain higher than that of 2015–2017. This trend aligns with the assumption that papers gain visibility over time, and thus keep accumulating reads and views over the years. High values for captures also indicate that users have different motives for marking and reading a paper, which can be caused by their research interests, papers they save for reading later, or deciding whether they need to cite a paper in the future. Through their study, Maflahi and Thelwall [26] have determined that Mendeley reader counts occur shortly after the publications are available online, and gradually build over time. Our results confirm their findings, since we can observe a significant difference in capture counts, for example, by comparing the numbers for 2017 with 2021. However, regarding the temporal evolution, we can also see that the capture counts for 2015 and 2016 are comparatively low in contrast to those for 2020 and 2021. This implies that, although the papers have been published earlier, the technologies captured by these metrics were still developing and gained more popularity in recent years—thus newer papers benefited more.

An exception to this pattern represent mentions, which remain almost insignificant over all years we observed. This clearly indicates that researchers in the computer science domain lack active involvement in writing blog posts or comments on platforms regarding research and artifacts. While the constantly increasing usage of social media platforms, such as, Twitter, is evident in Figure 2, other platforms, such as Slideshare, are still less popular for such interactions. The overall increasing pattern of the social media counts indicates that, although their usage in the years from 2015 until 2017 is smaller, social media keeps developing over the years. In our dataset, social media counts are especially high in 2020, reflecting on the fact that the community is using such platforms and social media networking more and more. While we can see a slight decrease in 2021, we can explain this by the fact that we constructed our dataset in January 2022. So, it is likely that more data is still being accumulated for very recent papers, which will likely be visible in some time.

While the trend we can observe for usage counts seems quite random in our dataset, it still indicates the accumulation of many user interactions (e.g., abstract views, downloads), which will likely result in future citations. However, it is surprising to see lower values for usage compared to the citations for papers published more recently, namely in 2020 and 2021. One reason for this could be that the sources accessed by PlumX to accumulate this metric are still limited, and there may be other more popular resources researchers use for viewing papers, which may not be covered by PlumX currently. Another reason is the passage of time, since the longer a published paper is available online, the more often it can be and is accessed, resulting in an evident increase of usage counts.

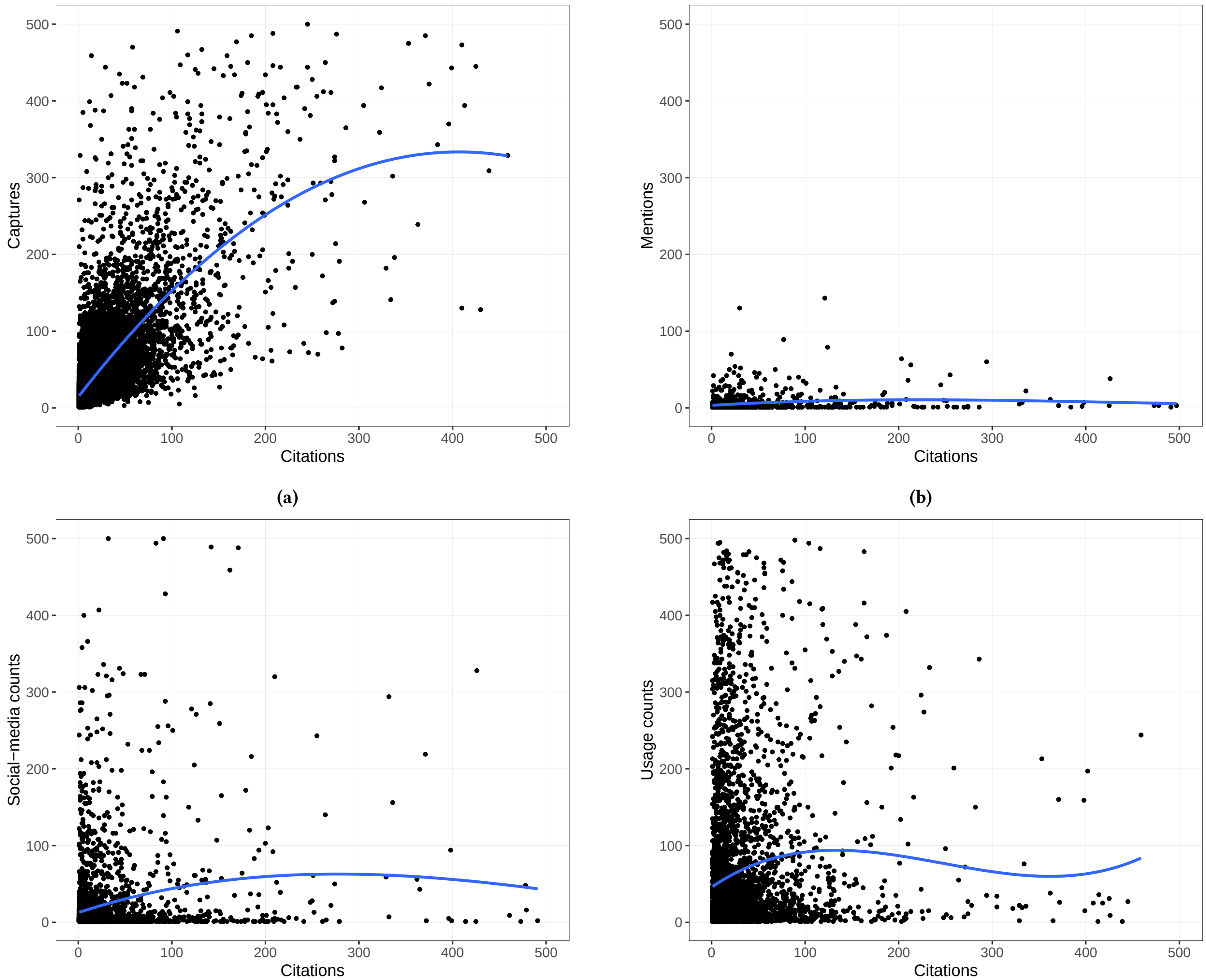
Considering the trend for citations, we can see the highest peak for papers published in 2018, with an overall increasing pattern from 2015 forwards. This trend can be expected, since the longer a paper has been published online, the more time it has to gain citations over the years. Also, since it takes time to accumulate, the number of citations are constantly becoming lower for more recent papers (i.e., published during 2019–2021). Based on our observations, the high peaks for captures and usages (cf. Figure 2) would eventually result in possible future citations, especially with their positive association with citations (cf. Table 3). Still, we can see an interesting pattern for social media in relation to citations. Over the years, as the citation counts keep getting lower, the peaks for social media are increasing, making it clear how altmetrics could complement the assessment of the impact and popularity of more recent papers—which are yet to be cited by others.

RQ_2: Temporal Evolution

For altmetrics, we have observed a contrasting association between social media and citations over time. While we can see a reasonable temporal pattern for captures, it is quite random for usage counts and almost irrelevant for mentions.

5.3 RQ_3: Tweets Reflecting on Future Citations

To understand how the citation behavior of researchers may be affected by the increasing use of Twitter, we investigated the tweet counts of each paper in our dataset in more detail. We gathered tweet counts by using DOIs to initiate the Scopus PlumX Metrics API for our dataset of 18,360 papers, and found only 3,210 papers (i.e., 17.48%) that were mentioned in tweets at least once. This indicates that only a small fraction of papers is mentioned on Twitter, which makes their use as a representative for monitoring social impact of scientific papers debatable. However, since social media platforms help the scientific community reach out to other parts of society (e.g., industry, institutions), they are being used more and more often This trend is evident in Figure 3, where we display how the tweet counts gradually, but constantly, increases over time; illustrating that more papers from recent years are mentioned on



(a) (b) (c) (d)

Figure 1: Scatter plots for the correlation analysis for each altmetric category and citation counts using our dataset: (a) captures, (b) mentions, (c) social media, and (d) usage.

Twitter. Ideally, a high number of tweets would mean that a paper is popular within the scientific community (and other parts of society), and thus gets cited in the future. For instance, for papers published in 2021 (cf. Figure 2), tweets are almost comparable with citations, and eventually increase more quickly—thus making them useful for assessing recent papers, since citations appear much later.

We calculated Spearman’s correlation coefficient for tweets and citation counts, which is almost identical with social media in general (ρ = 0.06, p-value < 0.01). This resemblance can be expected, since a major proportion of the social media counts are accumulated from Twitter. Overall, we can see that tweets are associated with citation counts in a similar manner as other PlumX metrics with a positive weak correlation (cf. Figure 3). Since the scientific community is actively using Twitter with increasing numbers of tweets and mentions, these have the potential to become strong indicators of the immediate impact of scientific papers, irrespective of the research discipline. So, tweets could become meaningful predictors of future citations as well. However, further research must be performed to improve the reliability of using tweets for this purpose, for instance, designing novel techniques to effectively accumulate organic tweets and not only acceptance once.

RQ_3: Tweets

Twitter is actively being used by the computer science community for networking and gaining visibility. Our results indicate that tweets have the potential to indicate future citations of papers.

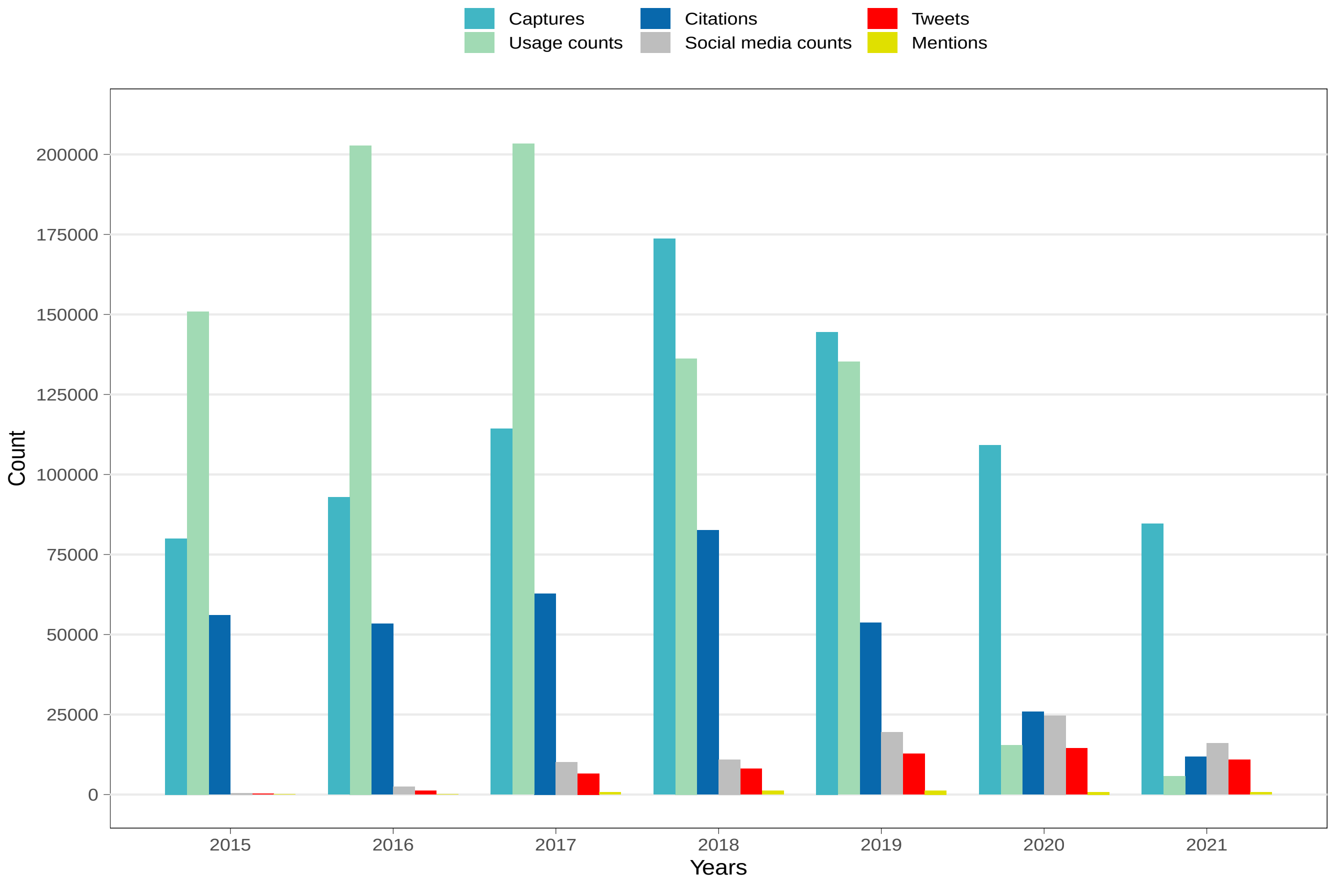


Figure 2: Overview of the temporal analysis for each altmetric category: captures, mentions, social media, and usage compared to citation counts.

6 DISCUSSION

Our results indicate that there are weak and strong positive correlations between each of the four PlumX metrics and citation counts. The strongest correlation exists for captures, while we can observe the weaker ones for mentions, social media, and usages. Since altmetrics are used more often in recent years, they are particularly useful and valid for more recent papers. For our dataset, only a certain fraction of papers includes altmetrics, with the highest proportion for captures. In contrast, mentions have the lowest coverage of all altmetrics with small proportions of papers having data for the remaining altmetrics (≈18%–26%). However, we realize that altmetrics are a rather new concept and are still evolving. Thus, while we do not expect that all papers will gain altmetrics values, we encourage researchers to actively engage in interactions with a wider community and expand their communication channels. In fact, we do observe more complete data for more recent papers, indicating the increasing popularity of altmetrics (and the channels they measure), but problems with the data quality do still exist and must be addressed to allow researchers obtain a better understanding. The completeness of the data must be ensured and constantly updating systems must be employed to keep track of changes over time. Additionally, administrators of tools aggregating altmetrics should also consider standardizing the method of accumulating data and advancing their resources for this purpose. Eventually, standardization would also encourage tool development to automate accumulation and interpretation of altmetrics, especially during a literature analysis for searching, selecting, and evaluating papers.

A key limitation of citations is the time that is required for a paper to be cited, which may take months or years. This problem is especially concerning for recently published papers and younger researchers. Still, researchers are inclined by methods that provide immediate feedback from the community once the paper has been published. This led to the exploration and increased popularity of communication channels that are covered by altmetrics, with constantly developing tools and technologies. However, there are still concerns from the scientific community regarding their use as performance indicators, including some obvious overlapping issues compared to citations. For instance, the increased possibility of bias and manipulation since both types of metrics are quantitative methods for accumulating information. Generally, altmetrics are quickly accumulated for papers immediately after being published, and do most likely not change significantly over the years. On the

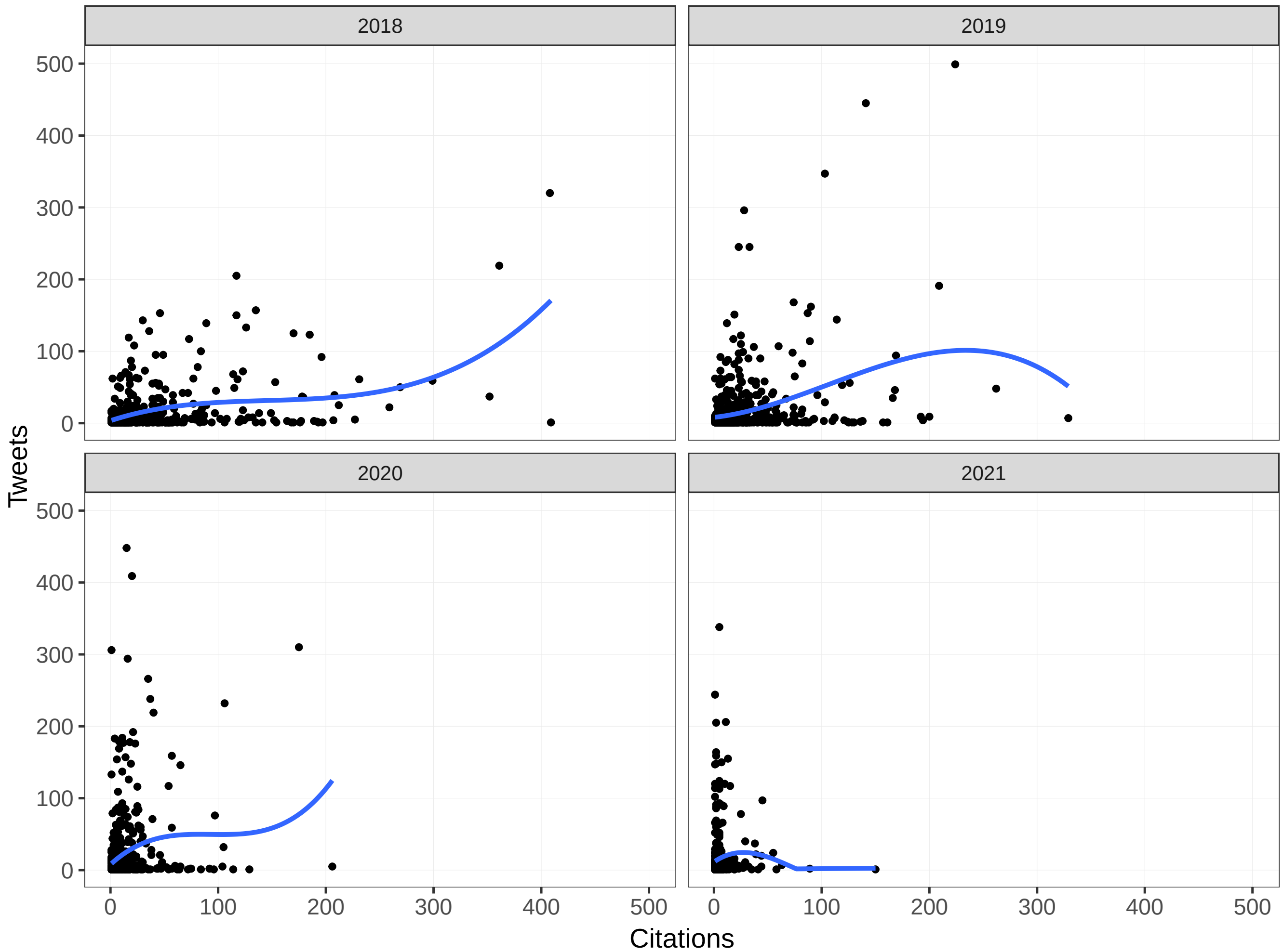


Figure 3: Scatter plots illustrating the correlation of tweets with citation counts for recent years (i.e., 2018–2021).

contrary, citations take time to accumulate, but increase constantly over the years. So, if we need to rely on such metrics, both types can complement each other.

We also observe that altmetrics are helpful in filtering papers with higher citations, but not every highly cited paper will be accurately identified by only considering altmetrics data. For example, if a researcher aims to gather most cited papers within a certain area in less time, analyzing only the altmetrics would be helpful, however, not all highly cited papers will be retrieved. This is because not all highly cited papers necessarily gain high altmetric values. This leads to another observation, although we obtain high values for usage and captures, the values accumulated for social media, tweets, and mentions is relatively small, indicating that only a limited proportion of papers are tweeted about or being discussed on the Web. Despite their advantage of increasing visibility and maybe result in additional citations, a large proportion of researchers are still currently inactive on digital platforms.

When considering Twitter data, it is also meaningful to determine who tweets or re-tweets, what is the purpose of the tweet, and how does the network of connections for a profile impact the communication. There are different types of Twitter accounts, as identified by Ortega [30], including those owned by journals, publishers, individual authors, and other research community members (e.g., novice researchers, teachers, students). Not surprisingly, Ortega identified that journals with own Twitter handles obtained more tweets and citations compared to those without one. However, the authors encourage further research to confirm their findings with a larger sample size and in-depth analysis. Java et al. [20] have explored the intentions of researchers tweeting, and identify four main purposes: (1) daily chatter, (2) start a conversation regarding a topic by asking or answering questions, (3) share information they find interesting that is usually indicated using links, and (4) reporting news, such as, any new published work or project, including self-promotion [10]. In their analysis, Singer et al. [42] highlight the importance of building a network by following profiles of expert researchers, projects, and leaders to stay aware of current advancements and practices. Also, being involved in conversations and making the own profile more visible leads to followers, and this helps in effectively disseminating information and build communities. For altmetrics, such insights imply that there are various different connections within Twitter data that may indicate, or bias, their implications for future scientific impact.

The results we obtained through our study align with some previous papers (cf. Section 3) performed to analyze the correlation between altmetrics and citation counts. Based on the dataset we compiled considering the most important venues in the computer science domain, we observe a positive, but often weak, relationship between PlumX categories (mentions, social media, usage, and tweets) and citations; with the exception of captures being strongly positively correlated. We expect this situation to evolve over time, since altmetrics are constantly advanced and may be well established in the near future. Still, to analyze their proper use and appropriate selection, we need more studies. Particularly, we believe that social media platforms, such as Twitter, have the potential to become effective tools for reflecting the impact of papers published in computer science, or any other domain, and act as meaningful predictors for future citations that are accumulated later over the years. While this could help younger researchers when evaluated against more senior ones, there are some limitations and potential biases that must be mitigated.

7 THREATS TO VALIDITY

There are certain limitations with respect to our study that we separate as internal, external, and conclusion threats to validity.

Internal Threats. How we constructed our dataset can impose some threat to the internal validity of our results. Although we use a large sample size for our dataset, it is still confined to a fraction of the entire dataset of papers available within the computer science domain. However, to reduce this threat, along with discussing explicit observations based on our dataset, we discuss our findings by also considering related studies from other domains. Additional problems with the data quality (e.g., missing DOIs of papers) led to issues concerning inconsistencies and missing data, which particularly affected the retrieval of altmetrics. Therefore, to provide a better picture of the availability of metrics within our dataset, we provide an overview of the coverage of all metrics in Table 2. In the future, we would encourage better support from administrators of digital libraries to help reduce this problem, and address such issues with the data quality.

External Threats. Another threat originating from our dataset is its limitation to specific publication venues only. However, we aimed to mitigate this external threat by first identifying a suitable sample of the most important venues in computer science and gathering the published papers to form our dataset. Similarly, our analysis is also limited to certain tools, even though there are other tools that aggregate altmetrics data. Precisely, we selected PlumX, because it is well integrated into Scopus. In turn, that limits the metrics to be accumulated based on Scopus only, which may differ across other digital libraries. Nevertheless, our results provide an overview of the temporal evolution and correlations between the metrics, which is still meaningful. Lastly, since digital libraries evolve over time, with the available information being updated, our data and observations can only capture the current status. However, it is still important to conduct such studies to provide a foundation for identifying problems and guiding future research, indicating that we need to explore the relevance of altmetrics in more detail.

Conclusion Threats. We observed and drew conclusions in this paper based on our knowledge and understanding of the data we elicited as well as the computer science domain. However, other researchers may interpret the results differently than we did. Even though we have analyzed the results to the best of our knowledge, there can be a conflict of opinions, which is why we publish our dataset and scripts that we used for the analysis in an open-access, persistent repository[7] to allow other researchers to conduct further studies (e.g., refinements, replications) using our artifacts.

8 CONCLUSION

In this paper, we investigated the correlations between altmetrics and citation counts over time to interpret the significance of altmetrics in computer science and understand whether these can predict future citations. We present first insights through our current analysis, and intend to perform further research in this regard. Our current results indicate that altmetrics have the potential to reflect the immediate impact of papers, which is more evident for those papers that have been published more recently. However, the limitations of using altmetrics as an indicator of impact and performance of a paper are debatable, and our effort is aligned with investigating the importance and association of each altmetric category with citations. For this purpose, we have particularly focused on the situation of the most important venues within computer science, which are more likely to be selected as a source of papers for secondary studies, such as systematic literature reviews. Although we found positive correlations of altmetrics with citations, they are mostly weak. To improve the arising problems with altmetrics, we encourage administrators of digital libraries and developers of altmetric tools to improve standardization of the accumulated data and ensure organic numbers for such metrics. We believe that an appropriate use and accumulation of altmetrics can offer several benefits, for instance:

- Reduce the time required for analyzing a large set of papers, especially for literature analyses.
- Accumulate data from various platforms, and thus reflect on the impact of papers in a more structured manner before the first citations occur.
- Provide a possibility for researchers to understand different communication channels, improving the visibility of their work and potentially adding to their future citations.

In the future, we plan to perform extensive experiments to further investigate the significance of altmetrics in computer science, especially the impact of tweets on citations. Furthermore, we intend to evaluate these metrics to understand their usefulness as quality indicators [38]. This particularly applies for systematic literature reviews, as researchers are actively involved in exploring methods to facilitate the process.

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