Computing Education Research in Social Media, News, Blogs, Patents And Blogs: Capturing The Impact And The Chatter with Altmetrics

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Abstract

Research impact goes beyond academia and exists in the multiplicity of digital platforms that we use to read, share, and discuss knowledge. Computing education research (CER) is no exception: it is created in academia and typical research institutions but is talked about widely on social media, blogs, and news websites. The aim of this study is to have a comprehensive analysis of how research in CER has been received, talked about in social media, discussed on blogs, and spread to the news and media. In addition to common analysis of trends of growth, we analyze trends of usage of social media and quantitative analysis of platforms, articles, and venues. The analysis also includes which articles in which subfields had a wide impact, and for whom (i.e, which platforms had more impact). The results show that Altmetrics adoption is weak, yet increasingly growing fast. Gender and diversity issues made it to popular news sites e.g., Scientific American, Los Angeles Times and Christian Science Monitor. While articles about ethics, programming education, introductory courses as well as computational thinking and inclusion have captured the attention of social media users. There was weak –or no correlation between article, author or topic impact and the traditional impact measures e.g., citation count.

Introduction

Altmetrics was conceived over a decade ago as *alternative metrics* to the commonly used sciento-*metrics* for the evaluation of research impact, e.g., citation counts and H-index (Priem et al. 2011; Priem, Groth, and Taraborelli 2012; Piwowar 2013). The main driver behind the initial idea was to help researchers use the wisdom of the web and social media crowds as curators of relevant research, given the burgeoning number of research published every day (Priem et al. 2011). Another reason was to capture the online scientific conversations as scientists and the public engage in discussions about academic scholarly work (Priem et al. 2011; Piwowar 2013). Such conversations take place on a wide array of non-scholarly platforms which include Twitter, Facebook, blogs, LinkedIn, etc.. Altmetrics also capture other sources such as mentions by Wikipedia**,** policy websites, syllabi, as well as Mendeley readers (Ortega 2020). In doing so, Altmetrics captures the attention an article gets from the wider community, the public's reactions to it (likes, retweets, saves, page views, downloads etc.) and the exposure (page views or hits) (Ortega 2020; Nuzzolese et al. 2019; Hassan et al. 2017). Taken together, Altmetrics offers a measure of dissemination of scholarly works, as well as an indication of their influence and impact across the Internet audience at large (Erdt et al. 2016).

While Altmetrics have been around for over a decade, little – if any at all – is known about how CER researchers have embraced the idea or how spreading the word about research helps attract the attention of other researchers or boost research impact. What is more, no previous study has captured the conversation on social media, blogs and news about CER. A gap which this article aims to bridge. We take advantage of the latest advanced in analytics and offer a comprehensive analysis of Computing Education Research (CER) in social media, news and patents. This article is structured as follows: First, we offer a background about Altmetrics, then, we review the main sources of Altmetrics data and later, we

describe the motivation of the study. The background section is followed by the methods, the results and the discussion.

Background

Compared to traditional scholarly metrics such as citations, Altmetrics are faster to curate; in traditional scholarly journals, when a paper cites a given paper, it takes time until the citing paper gets published and the citations are recorded (Piwowar 2013). Conversely, web mentions —the subject of Altmetrics— are immediately available and therefore, they are easier to accumulate and monitor as soon as they are online (Ortega 2020). Another advantage of Altmetrics is the diversification of how we measure research impact and influence which allows us to understand —in real time— if and to which extent a paper has succeeded in garnering attention as well as by whom and when (Piwowar 2013; Thelwall 2020). Such advantages in diversity, speed and scale have made Altmetrics a valuable tool used by the public, policy makers, funders as well as the academics (Nuzzolese et al. 2019). Nowadays, most publishers embed Altmetrics within their platforms or have alternative solutions that offer similar functionality, e.g., Plumx and ImpactStory (Ortega 2020). Libraries —the traditional curators of knowledge— have started to capitalize on the potential of Altmetrics and the insights it offers into what could be of interest to curate or subscribe to.

As a quantitative tool, Altmetrics suffers from the same drawbacks of traditional citation counts and metrics (Thelwall 2020; Hassan et al. 2017). Quantifying research work —as numbers of impact— is an oversimplification of a complex reality that both Altmetrics and citation counts suffer from (Hicks et al. 2015; Schöbel, Saqr, and Janson 2021). Furthermore, Altmetrics —being collected— from the wider web are more subject to manipulation by, e.g., Twitter bots (Haustein et al. 2016). In the case of blogs, it is unclear how credible the mentions that Altmetrics collect are, e.g., is every blog site a legitimate site? If so, how can we weigh the evidence we get from such a blog given its nature as a non-peer reviewed site? (Ortega 2020; Erdt et al. 2016). What is more, not all articles make it to the social web; many authors are not social media users, and only a fraction of journals has social media presence. Consequently, Altmetrics information are available about just a “slice” of the scholarly works (Ortega 2020). It should be noted that absence of social media presence can be mistakenly –and should not be– considered as a sign of lack of impact. Researchers may share their articles using non-standard links (shortened links), or links to online repositories, e.g., the University version of the article or ResearchGate. These links are not collected or curated by Altmetrics.

Several studies have evaluated the concordance between Altmetrics and traditional metrics (citation counts and H-index) in the measurement of impact. For such a purpose, most researchers have performed correlations between the Altmetrics indicators (e.g., Mendeley reads, Twitter posts) and traditional indicators (citations count and H-index). While the results vary, there is an agreement that a correlation exists between the number of citations and Altmetrics indicators. Some studies have found that blog count is the best predictor of citation count (e.g., Hassan et al. 2017), while other studies have pointed to Mendeley reader count as the best predictor of citations and the H-index of the author

(Nuzzolese et al. 2019). Most of the studies, however, also agree that social media usage correlates weakly with citation count (Nuzzolese et al. 2019; Hassan et al. 2020, 2017). A meta-analysis of forty metrics found an overall moderate to weak correlation between Altmetrics and citation counts. The authors of the meta-analysis concluded that results “do indeed measure a different kind of research impact, thus acting as a complement rather than a substitute to traditional metrics” (Erdt et al. 2016).

Our review of the literature leads us to some important conclusions regarding Altmetrics that are relevant to the current study. Altmetrics offers a different approach to measure reach impact and reach over the social web at large. Altmetrics data is a complementary piece of the story, an enhancement to our knowledge of how research has been part of the public discourse. In the next section we offer an overview of the main sources of information in Altmetrics which we will cover in our research.

Twitter

Twitter is a social media platform launched in 2006 as a microblogging website where users could use their phone text messaging to post brief blogs. Soon after its launch, Twitter usage grew to include all aspects of life including scholarly work (Kwak et al. 2010). Today, Twitter stands as the most studied metric in the Altmetrics literature (Ortega 2020). Among researchers, Twitter usage ranges from 5 to 32% including personal and professional use (Sugimoto et al. 2017). Yet, it is also well-known that regular activity is low in Twitter and therefore, the actual activity of tweeting or interacting about research work could be far lower. Altmetrics coverage of articles on Twitter increased from 10–15% in 2012–2014 to about 40% in 2018 (Ortega 2020). Several studies have confirmed the correlation between Twitter mentions and traditional citation count. Yet, correlation was mostly weak in general (Erdt et al. 2016). However, to what extent tweeting causes or leads to article citations is controversial, i.e., has tweeting caused the citations or is it the impact of the article that resulted in tweeting?

Mendeley

Mendeley was launched in 2008 as an attempt to allow researchers to share their favorite scholarly work with their colleagues. Since then, Mendeley has grown in adoption, functionality, and importance. Mendeley offers a cross-platform application, a website, and a smartphone application which allow users to share their curated papers, annotate as well as to handle their references (Elsevier 2013). Mendeley is known to have the highest coverage by Altmetrics of articles among all social media platforms, reaching up to 90% of all published articles (Sugimoto et al. 2017). Yet, Mendeley is used by just 5–10% of all researchers and is mostly dominated by early-stage researchers. Therefore, the number of Mendeley readers should be viewed as only an indication of readership representing a certain demographic, not the actual number of readers at large (Thelwall 2020; Ortega 2020). Nonetheless, as discussed earlier, Mendeley readership is one of the strongest and most consistent predictors of article impact (Erdt et al. 2016).

News

Mentions by news outlets as the name implies capture the attention an article gets from news sources, e.g., mainstream media and press releases. Unlike Twitter and Mendeley, news mentions are based on multiple sources (Sugimoto et al. 2017; Ortega 2020). The list of outlets and the scope of coverage are not clear and Altmetrics announces expansion to the list overtime. Thereupon, news can be viewed as a relative proxy indicator rather than a concrete measure of news attention. Still, attention by news is a good indication of how news outlets engage with research findings. Altmetrics' coverage of research articles remains low with a range from 0.1% in 2012 to 3.8% in 2017 (Ortega 2020), which can be attributed to the idea that not all articles receive news coverage or trigger the attention of news outlets.

Blogs

Blogging started as early as 1990 before most other social networking sites and contributed —at least partially— to the rise and spread of social networking. Many scientists blog continuously about their research, or science in general and enjoy the rich conversations blogging brings. Blogging enables scientists to summarize their research, disseminate it to the public, comment on other's work or criticize research or academic life in general. Blogging can be performed on dedicated web sites or services, e.g., WordPress, Blogspot or LiveJournal or as part of University personal web pages or research networking sites such as ResearchGate. Such diversity and source fragmentation has led to the rise of blog aggregation, i.e., sites that help collect different blogs of interest. However, systemic aggregation of blogs is a difficult task and the list and extent of coverage by Altmetrics is unclear and probably underestimates the full breadth of academic blogging. Yet, blogs are a good proxy indicator of academic dialogue or an "alternative" platform for summarizing research findings. Altmetrics coverage of articles ranged from 0.6% in 2012 to 8.8% in 2018. The coverage varies by discipline and demographic, i.e., socio demographics affect blogging and engagement with blogs (Sugimoto et al. 2017; Ortega 2020).

Other sources

Altmetrics also monitors a wide range of public policy documents that mentions public research, Wikipedia mentions (or references) of a public article, patents, data from the Open Syllabus Project regarding usage of the published research in syllabi as well as peer-reviewed reporting sources, e.g., Publons. In addition, Altmetrics monitors other social media sites, e.g., Facebook pages, LinkedIn, YouTube, Reddit and the popular questions and answers site Stack overflow (Ortega 2020).

The motivation for this study

Research impact goes beyond academia and exists in the multiplicity of digital platforms that we use to read, share, and discuss knowledge. Computing education research (CER) is no exception: although research is created in academia —the typical research institutions—, it is talked about widely on social media, blogs, and news websites. The literature review presented earlier shows that Altmetrics have become a mainstream platform for measuring research attention and dissemination on such platforms. While not perfect, it tells an important part of the story. Therefore, the aim of this study is to have a

comprehensive look at how research in CER has been received, talked about in social media, discussed on blogs, and penetrated to the news and media.

Methods

The data for this chapter were obtained from the Altmetrics website using two methods. First, Altmetrics data of all Digital Object Identifiers (DOI) of the 16,383 articles from the CER dataset described in Chap. 4 of this book (López-Pernas, Saqr, and Apiola 2023) were retrieved from Altmetrics.com using its API. Second, a search for titles, keywords, and venues (dedicated journals and conferences of CER) was performed to retrieve articles that do not have a DOI or may have been recorded by title or without their DOI.The first method retrieved 1,712 articles, and the second resulted in 1,360 articles. The two datasets were combined, and duplicates were removed, resulting in a final dataset containing 2,336 articles (13.9% of the CER articles) with at least one Altmetrics data field (e.g., Twitter mentions). The data were analyzed and visualized using the R programming language (R Core Team 2018). In addition to common analysis of trends of growth, we analyze trends of usage of social media and quantitative analysis of platforms, articles, and venues. The analysis also includes which articles in which subfields had a wide impact, and for whom (i.e., which platforms had more impact). Furthermore, such analysis include the themes of research that have garnered more attention from social media users. Such results are discussed with an in-depth qualitative analysis that reflects on the value and importance of the findings.

Results

Although Altmetrics was launched in 2011, some 728 of the papers published before this year had Altmetrics data (representing 31.2% of all the papers with Altmetrics data, which makes around 8.7% of the papers published to that date). Of all Altmetrics sources, Mendeley had the highest coverage. The average number of tweets per article in the pre-Altmetrics era (before 2011) was 0.39 compared to 3.98 in the post-Altmetrics era; such a large difference was statistically significant $t(1715.89) = 11.81$, $p < .001$). The average number of Mendeley readers for the pre-Altmetrics era was 37.7, compared to 45.6 in the post-Altmetrics era and the difference was statistically insignificant. The descriptive statistics for papers with Altmetrics data are presented in Table 1. As the table shows, except for Mendeley and Twitter mentions, the numbers were very low. The average number of Twitter mentions was 2.87 on average (SD = 10.11, Median = 1.00). News mentions were low (mean = 0.07, SD = 0.64, Median = 0.00) and so were blog mentions (mean = 0.06, SD = 0.29, Median = 0.00). The mean number of Mendeley readers was 43.17 (SD = 91.64, Median = 21). Wikipedia mentions (mean = 0.09, SD = 0.42, Median = 0.00), and Facebook mentions (mean = 0.03, SD = 0.21, Median = 0.00) were also very low.

Table 1
Mention statistics per source (n = 2336)

	Median	Mean	Std. Deviation	Minimum	Maximum
Twitter mentions	1.00	2.87	10.11	0	313
Number of Mendeley readers	21.00	43.17	91.64	0	1836
Facebook mentions	0.00	0.03	0.21	0	4
Blog mentions	0.00	0.06	0.29	0	6
News mentions	0.00	0.07	0.64	0	16
Patent mentions	0.00	0.19	2.62	0	118
Policy mentions	0.00	0.03	0.18	0	2
Q&A mentions	0.00	0.01	0.08	0	2
Video mentions	0.000	0.004	0.062	0.000	1.000
Wikipedia mentions	0.000	0.086	0.422	0.000	6.000

The trend of growth of Altmetrics data in Fig. 1 shows that only Twitter mentions are up-trending while all other trends are irregular or trending down. It is noteworthy to mention that each service has different time dynamics. For instance, in Mendeley, it is conceivable that the older a paper is, the more likely it is to be read by more readers and therefore, the trend should not be interpreted as a decreasing *number of readers*, but rather that older papers have been read more times overall. Similar to Mendeley, the patents, policy and Wikipedia mentions are expected to cite highly regarded or well-established papers. On the other hand, in news and blogs, recent papers are expected to make it to the news or be blogged about by authors. Similarly, Twitter mentions are expected to grow with time as researchers turn to Twitter to discuss the emerging research. Yet, it is hard to infer any future trends from other services, as the number of paper mentions is small and current trends are irregular.

Twitter mentions

The oldest paper that has Altmetrics data in our dataset was published in 1968 (Kuno and Oettinger 1968). The paper was tweeted by the account of Teaching NLP Workshop “How long have folks been thinking about #TeachingNLP? Here's a paper from more than 50 years ago by Susumu Kuno and Anthony G. Oettinger (CACM 1968).” (Teaching NLP Workshop @NAACL2021 2021). Articles with Twitter mentions were 1391 (59.5% of all articles with Altmetrics data, 15.3% of all articles in the post-Altmetrics era and 8.3% of all the articles in the dataset). The average number of Twitter mentions for any article in the whole dataset (16838 articles) was 0.39, while the average number of tweets for the articles was 4.81 (SD = 12.75, Median = 2, range: [1, 313]). The average age of articles that have received Twitter mentions was 5.8 years, compared to 15.8 in the non-mentioned articles. Such difference was statistically

significant, and large (difference = 9.97, 95% CI [9.61, 10.33], t(2915.89) = 54.74, p < .001; Cohen's d = 2.03, 95% CI [1.94, 2.12]). Similarly, the tweeted articles received an average of 2.9 citations/article/year compared to 0.7 in the non-tweeted articles, the difference was statistically significant, and large (difference = -2.19, 95% CI [-2.45, -1.93], t(1410.09) = -16.56, p < .001; Cohen's d = -0.88, 95% CI [-1.12, -0.77]). Articles with Twitter mentions were more likely to have more Mendeley readers (mean = 48.57) compared to 35.22 for the articles with no Twitter coverage. This difference was statistically significant and the effect size was small t(1779.40) = -3.35, p < .001; Cohen's d = -0.16, 95% CI [-0.25, -0.07]).

The correlation between the number of Twitter mentions and total citations was statistically insignificant, while the correlation between Twitter mentions and number of citations per article per year was weak r = 0.17, p < 0.001. Furthermore, the correlation between Twitter mentions and number of Mendeley readers, policy mentions, Wikipedia mentions, patent mentions, and Facebook mentions were either trivial or statistically insignificant.

In summary, articles on Twitter tended to be more recent, with slightly more citations per article per year, as well as more Mendeley readers. It is important here to emphasize that we make no assumptions of any causal relationship, i.e., we do not imply that Twitter mentions increased the citations or readership. In fact, it is possible that the mechanism that made the article receive more citations (e.g., interesting, or novel findings) caused both Twitter mentions and citations. In all cases, such differences were very small.

Table 2
Correlation between Twitter mentions and other social media

Source	***r***	**p**
Number of Mendeley readers	0.163	< .001
Policy mentions	0.106	< .001
Q&A mentions	0.052	0.055
Wikipedia mentions	0.069	0.010
Patent mentions	-0.048	0.071
Facebook mentions	0.099	< .001
Total Citations	0.033	0.216
Total Citations per year	0.167	< .001
Age of publication	-0.252	< .001

The most mentioned topic on Twitter was *computational thinking* which garnered 2,384 mentions (9.7% of all Twitter mentions), followed by *computational theory* (1,943 mentions, 8%), *programming* (1861, 7.6%), *introductory courses* (1443, 5.9%) and *pedagogy* (1416, 5.7%) and *education psychology (*1,347,

5.5%). The order of the most mentioned topics and the timeline of tweets per year of publication is shown in Fig. 2. We see that topic of pedagogy, assessment, and introductory courses as well as games were early mentioned on Twitter. As the graph shows, there is no certain pattern that we can discern from the graph, and the timeline looks rather irregular. We also see that the year 2022 had witnessed a large increase in Twitter mentions for the first five topics (*computational thinking, computational theory*, *introductory courses, pedagogy, and education psychology).*

The top articles mentioned on Twitter in Table 3 come from different themes, e.g., ethics, programming education, introductory courses as well as computational thinking and inclusion. The top cited article in the list discusses the state of ethics education in computer science education. The authors claim that the field has an “ethics crisis” that needs to be addressed to avoid what they call “exclusionary pedagogy” where there is lack of interdisciplinarity and collaboration with other fields to improve the ethics curricula (Raji, Scheuerman, and Amironesei 2021). Five other papers addressed programming education discussing diverse topics. McGowan et al. (2017) reported a positive correlation between seating in the front row during programming classes and performance. Stefik and Siebert (2013) investigated the intuitiveness of the syntax of different programming languages. Drake and Sung (2011) used board games to introduce computer science topics to university students. Salac and Franklin (2020) found a weak correlation between performance and quality indicators calculated from school children’s Scratch artifacts. In the same token, Chen et al. (2019) found a positive correlation between prior programming experience and attitudes towards programming as well as academic achievement, and concluded that it is more effective to teach young students using a graphical language than a text-based one. Two articles among the top mentioned articles discussed political aspects of computer science education (Williamson 2016; Malazita and Resetar 2019). The last article in our list (Kemp, Wong, and Berry 2020) discusses female participation and attainment in CS; where the findings indicate that females score higher than their male peers but lower than their average score in other courses. The article also argues that the introduction of CS into the national curriculum might “decrease the number of girls choosing further computing qualifications or pursuing computing as a career”.

It is worth noting that six of the top Twitter mentioned articles have received less than 5 citations, emphasizing the discord between Twitter publicity and academic interest (as measured by citation count). Nonetheless, it is not difficult to discern where there has been a conversation about these articles on Twitter. For instance, two articles' titles have chosen thought provoking titles “You can't sit with us” and “choose your lecture seat carefully”. One article addresses the programming language war, and two articles address policy and politics, and an article cautions against introducing CS into female education. Lastly, the remaining of these articles addresses graduate students' dissertations which would be expected to be shared among doctoral students who are social media users.

Table 3
Top mentioned articles in Twitter

Title	Year	Twitter mentions	Citations
"You Can't Sit with Us": Exclusionary Pedagogy in AI Ethics Education	2021	313	3
Learning to Program - Choose your Lecture Seat Carefully!	2017	139	3
An Empirical Investigation into Programming Language Syntax	2013	123	139
Teaching Introductory Programming with Popular Board Games	2011	115	20
The Organization and Content of Informatics Doctoral Dissertations	2016	104	1
Infrastructures of Abstraction: How Computer Science Education Produces Anti-Political Subjects	2019	103	4
Political Computational Thinking: Policy Networks, Digital Governance and 'Learning to Code'	2016	67	31
If they Build it, Will they Understand it? Exploring the Relationship between Student Code and Performance	2020	67	4
The Effects of First Programming Language on College Students' Computing Attitude and Achievement: A Comparison of Graphical and Textual Languages	2019	65	23
Female Performance and Participation in Computer Science: A National Picture	2019	61	4

A total of 3044 authors had at least a paper mentioned on Twitter: 75.6% of them had a single paper and around 97.2% of the authors had five papers or less. The median year of the first publication of the authors with Twitter mentions was 2016 (compared to 2011) which reflects the recency of the Altmetrics and Twitter. There was a weak correlation between the mean number of tweets an author has and the mean number of citations their article gets; Spearman's rank correlation was statistically significant and medium ($r = 0.21$, $p < .001$). Yet, while the correlation is weak, it should not be interpreted as causation.

The top authors with Twitter mentions were not the most cited or the most productive authors. Nonetheless, they were mostly among the top 50 authors. On top of the list was Brett A. Becker, an assistant professor at the School of Computer Science at University College Dublin who had 30 of his papers mentioned on Twitter, each receiving an average of four mentions. Aman Yadav, a professor of educational psychology & educational technology at Michigan State University, had 24 of his papers discussed on Twitter, with a total of 202 mentions and an average of 8.4 mentions per paper. Amy J. Ko, professor of informatics at University of Washington, Seattle, and the Editor-in-Chief of TOCE had 22 of her articles discussed on Twitter, with an average of 6.2 mentions per paper. Table 4 has the full list of authors with most discussed papers on Twitter.

Table 4
Top mentioned authors on Twitter

Author	Oldest	# of papers	Proportion	Rank	Mean mentions	Mean citations
Becker BA	2016	30	0.682	36	4.1	17.2
Yadav A	2011	24	0.667	64	8.4	26.75
Ko AI	2009	22	0.611	61	6.2	22.36
Petersen A	2011	20	0.4	23	3.5	19.95
Porter I	2010	19	0.333	14	2.2	20
Franklin D	2011	18	0.409	38	9.9	11.67
Cutts Q	2007	16	0.432	55	11.6	9.62
Hellas A	2016	16	0.356	35	4.7	10.19
Sentance S	2011	16	0.364	39	11.6	14
Falkner K	2009	15	0.375	47	5.4	13.93
Guzdial M	1994	15	0.172	1	1.5	23.6
Simon	1997	15	0.174	2	3	23.4
Luxton-Reilly A	2005	14	0.2	6	3.4	27.36
Kafai YB	2008	13	0.325	48	3.3	23.23
McGill MM	2009	13	0.277	32	4.6	11

Mendeley

Some 2,268 articles had Mendeley data, which is 97% of all articles with Altmetrics data and 13.46% of all the articles in the dataset. The mean number of mentions was 43.17 (SD = 91.64, Median = 21), and the mean age of publication (time since published) was 9.21 (SD = 8.37, Median = 7.00) which is older than the mean age on Twitter. The presence of Mendeley data and the number of readers per article are well known to correlate with the number of citations across several studies (e.g., Erdt et al. 2016), which was the case in our study. Articles with Mendeley data were more likely to be cited with a mean of 19.51 citations compared to 6.00 in articles without, the difference was statistically significant and medium (difference = -13.51, 95% CI [-15.39, -11.63], $t(2331.86) = -14.08$, $p < .001$; Cohen's d = -0.58, 95% CI [-0.76, -0.50]). Within articles with Mendeley data, correlation between number of readers per article and citation count was statistically significant, positive and very large ($r = 0.64$, 95% CI [0.61, 0.66], $t(2266) = 39.14$, $p < .001$). There was also a weak correlation between the number of Mendeley readers and policy, news, blogs, Facebook, or Wikipedia mentions.

Regarding authors, the number of articles with Mendeley readers was correlated with citation count, which was statistically significant, and effect size was very large ($r = 0.68$, 95% CI [0.66, 0.69], $t(4327) = 60.86$, $p < .001$). Similarly, the number of Mendeley readers was highly correlated with citation counts which was statistically significant with a very large effect size($r = 0.78$, 95% CI [0.77, 0.80], $t(4327) = 83.35$, $p < .001$). In summary, there is a very strong association between Mendeley mentions and citation counts for either papers or authors, which reflects the paper importance or impact rather than has caused the citation.

The top CSE papers with the highest number of readers (Table 5) are expected to also reflect highly cited papers since we have established that correlation was high. Our top papers include seven papers that address issues related to computational thinking of CSE in schools. The other three papers address game-based learning, an instructional computer laboratory and computer curriculum. Most of the top read Mendeley papers are highly cited with six papers having over 100 citations. The top read paper about game-based learning (Papastergiou 2009) is also the top cited paper in our complete dataset; the fifth paper about bringing computational thinking to K-12 (Barr and Stephenson 2011) is the second most cited paper, and the seventh top read paper about Scratch is the third most cited paper (Maloney et al. 2010).

Table 5
Top read papers in Mendeley

Title	Year	Mendeley readers	Citations
Digital Game-based learning in High School Computer Science Education: Impact on Educational Effectiveness and Student Motivation	2009	1836	984
Progress Report: Brown University Instructional Computing Laboratory	1984	1763	16
Computational Thinking	2007	1509	63
Design Patterns: An Essential Component of CS Curricula	1998	1466	42
Bringing Computational Thinking to K-12: What is Involved and What is the Role of the Computer Science Education Community?	2011	817	658
Which Cognitive Abilities Underlie Computational Thinking? Criterion Validity of the Computational Thinking Test	2017	786	215
The Scratch Programming Language and Environment	2010	727	640
Computational Thinking in Elementary and Secondary Teacher Education	2014	613	191
Computational Thinking for All: Pedagogical Approaches to Embedding 21st Century Problem Solving in K-12 Classrooms	2016	587	133
Constructivism in Computer Science Education	1998	584	140

The list of authors with a high number of articles in Mendeley (Table 6) show interesting findings that are different from those of Twitter. Most of the authors in the list are among the top publishing authors in the general dataset. The top authors were also well-established authors who started their careers during the last century or in the early 2000s, the mean years in publishing about CSE was 19.93 [6, 32]. Each of the top authors had an average of 53.41 Mendeley readers [18.83, 118.72]; each of their papers received a mean number of citations per paper of 27.26 [11.47, 48.92]. Such numbers were not much different from other authors who are not on the top list.

Table 6
Top read authors on Mendeley

Author	Oldest	# of papers	Proportion	Rank	Mean mentions	Mean citations
Guzdial M	1994	49	0.56	1	38.06	38.37
Rodger SH	1993	42	0.78	16	18.83	18.48
Astrachan O	1990	34	0.65	17	55.74	11.47
Becker BA	2016	33	0.75	36	37.36	17.12
Simon	1997	33	0.38	2	36.09	17.30
Ben-Ari M	1996	28	0.57	26	76.36	38.18
Ko AI	2009	27	0.75	61	55.04	23.00
Lister R	2000	25	0.37	9	53.88	48.92
Sheard J	1997	25	0.33	4	52.88	27.16
Yadav A	2011	25	0.69	64	118.72	30.48
Edwards S	1998	24	0.35	8	47.71	36.04
Porter I	2010	24	0.42	14	32.08	20.50
Luxton-Reilly A	2005	23	0.33	6	55.04	29.65
Petersen A	2011	23	0.46	23	51.22	20.91
Armoni M	2004	22	0.49	34	72.14	31.36

News and blogs

Computing education research has appeared rarely in the news where only 79 (0.46%) articles were mentioned across the whole dataset, with a total of 136 mentions in total. The most mentioned articles by the news (Table 7) seem to address diversity and gender issues, which made more than half of the news mentions. The top article in the list was discussed by, e.g., Scientific American, Los Angeles Times, Christian Science Monitor, Houston Chronicle and SF Gate. Christian Science Monitor presented the

article and concluded “Children need to be engaged in STEM before they start to lose interest. The image of STEM as solitary and isolating is strong in our culture. If we make STEM social, we can help inspire more students to discover their interest in STEM” (Master 2016). The second article with a significant number of news mentions has also discussed gender diversity and was mentioned by Business Insider, World Economic Forum, and The National Interest. For instance, Business Insider titled their story “Women are just as capable as men in computing skills —but they're not as confident. Here's how that's contributing to the gender gap in tech” (The Conversation 2021). The authors of the paper concluded that “many have made the case that companies need better participation of women in the STEM workforce for greater innovation and productivity. These efforts have had some success, but other avenues are needed to promote STEM careers to women and help them to believe in their abilities.” The World Economic Forum presented a similar story with the title “Computing has a gender problem – and isn’t about talent.”

Table 7
Top mentioned papers in the news

Title	Year	Citations	News mentions
Computing Whether She Belongs: Stereotypes Undermine Girls' Interest and Sense of Belonging in Computer Science	2016	173	16
Fostering Gender Diversity in Computing	2013	13	16
Multiple Case Study of Nerd Identity in a CS Class	2014	5	9
They Can't Find Us: The Search for Informal CS Education	2014	22	9
Gender Neutrality Improved Completion Rate for All	2016	1	6
What Is AI Literacy? Competencies And Design Considerations	2020	51	6
Computer Science Trends and Trade-Offs in California High Schools	2021	1	6
History of Logo	2020	9	5
A Growth Mind-Set Intervention Improves Interest but not Academic Performance in the Field of Computer Science	2020	23	5
Collaborative Strategic Board Games as a Site for Distributed Computational Thinking	2011	99	4

Some 134 papers (0.8%) had blog mentions with 150 blog appearances in total. The highest blogged about paper (six times) was also the paper that received the top news mentions and addressed the stereotypes about girls interest in computer science (Master, Cheryan, and Meltzoff 2016). The blog named “Scienceblog” published a blog post titled “To Get Girls More Interested In Computer Science, Make Classrooms Less ‘Geeky’”. All other blog mentions were two mentions or less and therefore, will not be discussed in detail here.

Patents

A total of 131 (0.78%) articles received patent mentions and received a total of 434 mentions combined. Table 8 shows the articles with the most mentions. The article that received almost one third of all patent mentions describes an online computerized testing system called “QUIZIT” which supports adaptive and standard testing, automatic grading, and storage of results (Tinoco, Barnette, and Fox 1997). The paper was mentioned by several patents across a wide range of applications that include systems and methods for automatic scheduling of a workforce, discovering customer center information, recording audio as well as by a web service for student information and course management systems. The next article on the list discusses the development of a programming project where Java applets can be dynamically updated in an undergraduate programming course (Yang, Linn, and Quadrato 1998). The paper was mentioned by several patents (30) mostly covering access to database and software design. The remaining papers with patent mentions revolve around the same themes, i.e., either enhancement to an online teaching system or teaching programming.

Table 8. Top papers mentioned by patents

Title	Year	Citations	Patent mentions
Online Evaluation in WWW-Based Courseware	1997	19	118
Developing Integrated Web and Database Applications Using Java Applets and JDBC Drivers	1998	5	30
A Reusable Graphical User Interface for Manipulating Object-Oriented Databases Using Java and XML	2001	6	11
A Constructivist Approach to Object-Oriented Design and Programming	1999	30	11
The KScalar Simulator	2002	9	11
Interactive Hypermedia Courseware for the World Wide Web	1996	6	9
On-Line Programming Examinations Using WebToTeach	1999	9	9
Teaching Web Development Technologies In CS/IS Curricula	1998	8	8
Using a Model Railroad to Teach Digital Process Control	1988	9	8
Using Java to Teach Networking Concepts with a Programmable Network Sniffer	2003	10	8

Other Altmetrics sources

Other services had very few mentions. Only two articles had six mentions by Wikipedia (Mounier-Kuhn 2012; Osborne and Yurcik 2003), where the first discussed computer science education in French

Universities and the second discussed visual simulation. Facebook mentions were also very scarce: the highest mentioned article received only four mentions and discussed computational thinking (Yadav, Hong, and Stephenson 2016). On the questions and answers website Stack Exchange, the mentions were even fewer, with only a single article mentioned two times (Liberal Arts Computer Science Conso 2007). The article was mentioned as a reply to the question “Which math classes should be included in an undergraduate computer science program?”.

Discussion And Conclusions

Altmetrics’ vision was to establish an alternative way of evaluating science, capturing the conversation across the social media and the web at large, and presenting an immediate record of the attention a scholarly work gets. We offer a discussion of this vision in light of the results we had and the review of computing education research within Altmetrics.

The results of this study showed that correlation between citation counts and the social media mention of articles, or other sources of mentions e.g., news, blogs or Wikipedia was weak in the former or negligible in the latter. The case was also true for the authors where a direct correlation was not possible to establish. Therefore, social media cannot be viewed as a measure of scientific impact in the traditional scholarly way. These conclusions are further supported by the finding that articles that received most mentions on Twitter were not highly cited, also, authors with most mentions on Twitter were not the highest cited. While some differences exist between articles or authors who received mentions and those that do not, the differences were small. Furthermore, a causal relationship between mentions and citation count is impossible to establish given the weak associations and the fact that the mechanism that led an article to receive Altmetrics mentions (i.e., important findings) could be the same reason for receiving citations. These findings might be disappointing to researchers who may resort to the social media to increase attention, attract readership, or disseminate their research. Nonetheless, the results are indeed a reflection of a different impact that is not essentially correlated to citations but possibly complementary to the traditional scientometrics and leads to engagement of a relatively different audience.

The case was different for Mendeley, where the correlation between the number of Mendeley readers and citation counts were strong for papers and authors. Yet, Mendeley is not a social media platform — despite the fact that it was designed to be so— as it currently stands. Mendeley’s focus is to offer citation management and archival of papers, rather than any true social dialogue about the scholarly work. Therefore, Mendeley numbers should be viewed as predictors of paper impact on the scholarly work in the same way citation counts are, rather than being “alternative metrics”.

The second vision that Altmetrics sought was to capture the web dialogue about scholarly work. Altmetrics has proven to collect a wide array of web sources. Given the small numbers on most platforms including social media, it seems that CER has not yet endorsed social media to its full potential. The social media uptake within the CER community has just started to take off in the last year. Yet, it is too early to conclude that the uptake will continue to grow. Furthermore, it is early to reach firm conclusions

given the small numbers. Despite the fact that the speed of Altmetrics curation has proven to capture the immediate reactions and mentions of scholarly work as they are published online, they have not been used to their full potential within the CER community.

The analysis has shown that the chatter about CER on social media is more focused on topics that are essentially of public interest rather than the academic or pedagogical priorities. Topics that received more mentions on Twitter were computational thinking and programming in schools, ethics, diversity and gender issues (e.g., Raji, Scheuerman, and Amironesei 2021; Kemp, Wong, and Berry 2020; 2020). Topics of news interest were particularly focused on gender issues, inclusivity and how to narrow the gender gap. Papers that addressed stereotypes about girls and computer science were more likely to resonate across the news and blogsphere (e.g., Master, Cheryan, and Meltzoff 2016). In the case of Mendeley, the topics of interest tended to be of scholarly interest and therefore, we can say that Mendeley offers just another way to measure —or possibly predict the future of— academic impact and interest. Patents were rather few and, thus, solid conclusions cannot be drawn, although there seems to be a trend towards learning tools or educational technology.

In summary, Altmetrics reflect a different chatter, a dialogue that may be dominated by academics but not about academics, or their interests but rather geared to public concerns at large. Thereupon, Altmetrics can be viewed as a melting pot of dialogue that could help two seemingly distant communities —academics and the public— recognize each other's aspirations and perhaps awes too. Reading the Altmetrics with the lens of citation counts is simplistic, reductionist and defeats the purpose as Alternative metrics.

Declarations

The authors declare no competing interests.

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Figures

Figure 1

Evolution of mention statistics per source

Figure 2

Evolution of Twitter mentions by topic