Social networks-based alt-metrics and the unethical use of AI

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Abstract: *A thorny issue in the research community, especially in the last decade, is the criteria for career advancement. In Romania and internationally, the indicators specific to academic promotion have been radically modified over the years. Their permanent refinement has been natural because research activity has changed radically, for instance, in terms of the way partnerships are formed and organised. Moreover, research data are made available and distributed openly, and the valorisation of scientific results in the form of articles and/or patents is actively encouraged. The world has continued to change, and the need to remove barriers to accessing research results is increasingly being questioned, with open science being a topic encouraged by policymakers. This new paradigm impacts the sphere of value indicators of research, and the subject of alt-metrics, i.e., alternative ways of measuring the quality of research, has also become a topic of interest. Many current proposals for considering research impact in line with the specificities of the contemporary world are derived from measuring interactions on social networks, which may or may not be dedicated to research activity. In this paper, we aim to explore the possibility of introducing sociometric alternatives that include indicators based on metrics specific to social networks in the context of evolving artificial intelligence (AI) technologies, which may influence the field in unethical ways. Therefore, we will identify and present how AI can influence alt-metrics, especially those based on social network activity such as Twitter, and explore the possibilities for detecting such actions, especially with bot identification.*

Keywords: alt-metrics, social networks, ethics, social bots.

1. Introduction

The problem of evaluating the impact of research carried out in a world of unlimited access to the latest scientific discoveries and of technologies capable of assuming important roles in the research team is a thorny issue. In recent decades, this has been achieved according to a series of quantitative indicators based mainly on the researcher's ability to access scientific publications with recognized prestige

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in the academic world (Bazelay, 2010, Gingras, 2016, Gutiérrez-Salcedo, Martínez, Moral-Munoz, Herrera-Viedma & Cobo, 2018).

But information and communication technologies drove the change of the world, and access to information became an increasingly valued variable in any community, even more so in the scientific one, where access to scientific novelty is a guarantee that one's own results have the particle of originality. That is why, researchers are increasingly aware that research results should not be restricted to a small, elitist number of people with access to scientific publications, but that they should be available to the general public. The implementation of this principle gave rise to the emergence of new concepts such as citizen science, civic science, crowd-sourced science, participatory monitoring (Fraisl, Campbell & See, 2020, Wehn & Almomani, 2019) and so on, which, in summary, designate a category of scientific research carried out by the nonprofessional scientists.

Making research data accessible is not an easy process, but a marked by a whole series of difficulties one, resulting from the inertia of traditional research management, the habits of financing access to specialised journals, from fears regarding data sharing and assuming intellectual ownership or from fears determined by the possibility that the data provided will be misinterpreted (Biagioli & Lippman, 2020, Bornmann, Tekles, Zhang & Ye, 2019, De Rijcke & Rushforth, 2015). Still, all these are problems that must be solved, because open science is an unstoppable phenomenon, a result of nowadays world.

In this paper, we analyse the main classical ways of evaluating research results based on traditional indicators and then review the considerations that have led to the emergence of a new generation of metrics that attempt to encompass new ways of communicating and using research results that are based on online tools such as social networks. This new category of metrics called alt-metrics has, besides obvious advantages, several risks that need to be taken into account to ensure their integrity and relevance. In particular, the current problems related to the proliferation of fake news and online misinformation make alt-metrics susceptible to targeted manipulation campaigns, especially in the case of scientific works that may have a significant social, economic or political impact. In this regard, we will present a series of results of studies that have highlighted such campaigns of manipulation of public opinion using social media and AI-based tools such as conversational agents. Thus, due to the use of AI tools in an unethical way to amplify or create false narratives to influence an individual, the issue of identifying and eliminating these software agents becomes essential to preserve the usefulness of alt-metrics.

2. Evaluation of research quality and alt-metrics

Traditional research quality metrics are evaluating each type of research object (researcher, research organisation or a country) based on indices such as the number of publications, citations, appearances in bibliometric databases (Web of

Science, Scopus, Google Scholar), on the basis of which additional scientometric indicators were built, especially for articles (Journal Impact Factor – JIF, Eigenfactor, CiteScore (Elsevier, 2016), SJR, SNIP,) and for authors (h-index (Hirsch, 2005), g-index, i10-index).

Although traditional methods of evaluating research are extremely widespread and used in many countries of the world (Gutiérrez-Salcedo, Martínez, Moral-Munoz, Herrera-Viedma & Cobo, 2018) they have received a series of criticisms from the research community. Each index has been evaluated from different points of view. For example, it was considered unfair to equate the impact of the journal with the impact of its articles (DORA, 2012) or incorrect for the H-index do not consider older but perhaps still very relevant works of senior researchers.

Thus, it was noted that traditional indicators to evaluate research are insufficient or irrelevant when comparing research objects having different characteristics or which are emerged in different scientific areas (Lesenciuc, 2012). Many critics referred to traditional indicators that assess research as a correlation of some data that is easy to collect, not a real and strong indicator of the quality of research (Bazeley, 2010). Currently, voices saying that the evaluation of research is based on a small but easily measurable number of metrics (such as publications, citations and the level of contracted funding) are more and more frequent, while elements at least as important are less used (peer review, contribution to the development of the research infrastructure, design of policies in the field, involvement in mentoring, supporting activities of other researchers to advance in their careers or assuming the role of reviewer or editor) (Moher et al., 2018, 27).

These considerations led to the emergence of a new generation of metrics, which are based on the understanding that science made accessible for everybody is impossible to be evaluated through the lens of a single category of metrics specific for times when only elites had access. Therefore, a multidimensional set of indicators are needed especially focused on the link between the product of research and its author, but also on the receptivity of society as a whole to new scientific perspectives. These metrics should reflect the evolution over time of interest in the topics under discussion. They are designed to evaluate research and also to support open science by 1. Monitoring scientific systems towards transparency at any level and 2. Measuring performance in order to reward individual or group research activities.

Several approaches to official regulate this subject took place in the last decade, suggesting the novelty and effervescence of this concern:

- Alt-metrics Manifesto 2010 led to the birth of alt-metrics through the already well-known phrase *'No one can read everything. We rely on filters to make sense of the scholarly literature, but the narrow, traditional filters are being swamped. However, the growth of new, online scholarly tools allows us to make new filters; these alt-metrics reflect the broad, rapid impact of scholarship in this burgeoning* *ecosystem. We call for more tools and research based on alt-metrics*.' (Priem & Hemminger, 2010);

- The San Francisco Declaration on Research Assessment (DORA, 2012) calls for the assessment of research by its merits and not by using journal impact factors (signed by 156 countries, over 21300 individual signatories and organisations by 2022);
- Science in Transition (2013, https://scienceintransition.nl/english) argue for evaluating research from the perspective of societal impact, not strictly from bibliometric point of view;
- The Leiden Manifesto (2015, http://www.leidenmanifesto.org/) proposed a set of 10 principles for the use of quantitative indicators for research evaluation (Hicks et al., 2015);
- The Metric Tide (2015, 2022) evaluates the role of metrics in the evaluation and management of research in the UK, which also includes recommendations for a responsible metric (Wilsdon et al., 2015);
- Next-generation metrics: responsible metrics and evaluation for open science (2017) (Wilsdon et al., 2017);
- Science Europe Study on Research Assessment Practices (2020, https://www.scienceeurope.org/our-resources/science-europe-study-on-research-assessment-practices/) which aims to optimise the quality of research by adjusting its framework.

Thus, new concepts such as alt-metrics and usage indicators have appeared in the discourse of specialists and aims to cover the area not evaluated by traditional research indicators, based to the greatest extent on social media (e.g., Twitter, ResearchGate, Mendeley), on the principle of quantifying the number of distributions, likes, followers, posts, mentions and comments (Wilsdon et al., 2017, 9-10). These metrics have the advantage of being able to constantly measure an ever-changing digital environment - while new platforms may emerge (e.g., Loop, WhatsApp, Kudos) and old ones may fall into obsolescence (e.g., MySpace, even Facebook), alt-metric principles can be used further with new inputs.

An attempt to reconcile traditional bibliometric indicators with alt-metrics generated a new category of assessment indicators – usage indicators that aim to measure the attention a research object benefits from (Usage impact factor, Libcitation). Starting from the premise that a work read with interest is not always cited later, usage indicators use the number of downloads or views of a product. Open access publications provide information on usage (PLoS), some indicating the number of downloads and reads of an article (e.g. Springer Nature, IEEE, ACM, Elsevier's Science Direct in cooperation with Mendeley). More advantage of usage indicators relate with the possibility to use them also for non-traditional but modern publications such as blogs (Shema, Bar-Ilan & Thelwall, 2014), open software or data (Peters, Kraker, Lex, Gumpenberger & Gorraiz, 2016).

The importance of alt-metrics was also highlighted in order to promote and support the Open Science paradigm - a global movement that aims to improve the accessibility and reusability of research outputs by providing unrestricted access to research publications and data, engaging citizens in research activities, and using open resources in education or software development. In this regard, in 2016, a study was conducted in 13 EU countries on the implementation of the Open Science strategy according to the EU agenda (European Commission. Directorate General for Research and Innovation., 2018). The focus of the study was on the potential of alt-metrics (as an alternative to traditional metrics) to support the development of the Open Science domain, i.e., the possibility of using alt-metrics as an incentive or reward for researchers. In addition, the study addressed recommendations for implementing national policies to promote Open Science. For example, in Romania's case, the alignment with the European Open Science Cloud objectives was achieved through the establishment of the RO-NOSCI national initiative, supported by participation in the NI4OS-Europe consortium (Vevera et al., 2020).

There are a number of indisputable advantages of the introduction of metrics for evaluating scientific products in accordance with the specifics of the modern technological revolution, as the metrics of future should:

- Evaluate research products communicated in new format: blogs, open software and applications;
- Measure not only scientific influence, but also audience impact;
- Diversification of the criteria for career advancement, considering several new possible dimensions of the research career;
- Evaluate faster research objects from several different perspectives.

Despite the importance of the subject, as in the case of any innovation, this desired change of research evaluation is accompanied by a series of unclear elements and challenges that must be overcome, derived both from the infrastructure supporting the new metrics, as well as from the specifics of the data collection. For example, the fact that alt-metrics are based on social platforms, whose territorial distribution is uneven, represents an obstacle for the unitary evaluation of research products. On the other hand, the behaviour behind alt-metrics is also not fully understood, especially since the collection algorithms are the property of the providers, and the used standards are under construction.

3. Alt-metrics challenges and the unethical use of AI

A comprehensive review on the use of social media and alt-metrics in research work was conducted by Sugimoto et al. (2016), which provided a very detailed literature review on practices in the field, focusing on the role that certain online platforms play in research work and then in the dissemination of results, i.e., it highlighted the strengths but also the limitations of alt-metrics. An important aspect that should be highlighted refers to the non-homogeneity of the results obtained, which differ from study to study depending on the methodology used, but also due to the fact that each online platform has other indicators, as well as collection and processing methods so that the results obtained are difficult to generalise. For example, in their study, several social media platforms were analysed, such as those offering social networking services, social bookmarking, video, blogs, referral management, recommendations, and ratings, but since these services are constantly developing and introducing new facilities and features to users, it is expected that the results obtained will not be relevant in the near future due to the technological evolution of these platforms.

Nowadays, more and more researchers are using various online tools such as social media platforms, blogs, or reference management systems, i.e., using platforms such as Faculty of 1000, Mendeley, Twitter or Facebook to disseminate information that is relevant not only to the academic and research community but also to the general public. This has led to a significant increase in scientific papers' impact in areas as diverse as health, education, technology or the environment.

However, it is also necessary to consider the risks, i.e., the possible downsides that can arise when the data used are affected by a series of attacks designed to artificially increase or decrease the impact of a scientific result or an individual researcher. Even if there is no specific intention to influence the relevance score of an article, certain aspects related to certain biases or stereotypes may lead to a subjective alteration of alt-metrics. For example, Chapman et al. (2022) systematically examined how alt-metrics for approximately 10,000 articles that have been published in journals may be relevant to highlight outstanding or impactful results. A surprising finding of their study was that there was an unbalanced distribution of alt-metrics scores, i.e., most articles scored so low that they could not be considered relevant, and furthermore, for articles that scored well, it was obvious a gender bias - when the first author was male, there was a higher score than for an article that had a female first author.

Social networks can thus be seen as influencing the way in which certain works are promoted, i.e., ideas are amplified or moderated, but also currents of public opinion formed based on results that rely on scientific research. Thus, Priem et al. (2012) analysed 20,000 articles published in the Public Library of Science to compare various metrics associated with them in social media. Their study revealed that both citation counts and alt-metrics have some degree of correlation but need to be considered together to determine the full impact of academic output. For example, there is a moderate degree of correlation between Web of Science citations and Mendeley citations, but most alt-metrics show an impact that is not reflected by citation counts (i.e., some articles may have a very high number of reads or saves in a citation management system such as Mendeley but will not then also have a significant number of citations).

Also, as the use of social media platforms to promote scientific articles increases, it is important to note that, especially in the case of public-sensitive topics such as the COVID-19 pandemic, many articles were withdrawn.

Nevertheless, the degree of attention given to them was similar to those that remained published. Khan et al. (2022) analysed the website retractionwatch.com in relation to the articles that had the COVID-19 pandemic as their theme, i.e., they calculated the Altmetric Attention Scores (AAS) metric to highlight the role that social media plays in amplifying misinformation and manipulation. Thus, out of a total of 196 articles that were identified within the Retraction Watch website, 175 papers had an identifying DOI number, and of these, only 30 articles were pre-prints. Subsequently, after calculating the AAS score and eliminating publications with an incomplete score, 22 papers remained published but were retracted, yet were promoted and disseminated on social media, having a significant role in misinforming public opinion. Furthermore, it was observed that retracted articles receive significantly more attention online, especially in the case of the Twitter platform, which, together with Mendeley, was the most popular media for disseminating retracted articles.

Another aspect worth considering relates to how metrics extracted from different online platforms are collected and aggregated. For example, different methodologies are used to extract information and metrics data for each online platform, and respectively different tools are needed to aggregate alt-metrics. This issue was highlighted by Zahedi & Costas (2018), who studied discrepancies related to data and metrics published by several tools using different methodologies for accessing, collecting, processing or summarising metrics extracted from the online environment.

It is widely accepted that modern society relies on social media for the smooth functioning of interpersonal relationships or to share information or sustain debates on important issues that concern an individual, a group or a community. It is all the more important to ensure the accuracy and integrity of news sources or participants in social media interactions. Twitter is a platform that specialises in the sharing and disseminating information and is one of the primary media used by the academic community to promote research results. One of the main features of Twitter concerns the implementation and use of bots, i.e. software agents that can interact and participate in a conversation with a human individual just like an average person. These conversational agents can perform different tasks (e.g., generate content, initiate discussion topics and sustain a conversation).

Although the use of intelligent agents to support online activities such as user interaction and support or to provide information are use cases with obvious benefits, there is still a significant risk in using them for malicious purposes such as misinformation or influencing public opinion, as was the case in the 2016 US election (Bessi & Ferrara, 2016). This problem can be attributed to the unethical way in which Artificial Intelligence (AI) is used, i.e., exploiting stereotypes and social biases to exacerbate the polarisation of public opinion, radicalization of groups and generation of conflict. From this point of view, it is essential to study how software agents can be used to amplify fake news or to promote themes or viewpoints that aim to manipulate public opinion in an unethical way.

Consequently, it is becoming increasingly important that the activity of bots within Twitter can be monitored and analysed, i.e., tools are needed to detect software agents that aim to misinform or manipulate public opinion, including by disseminating specific scientific results online. This is particularly important, including the impact on metrics using social media data, i.e., how scientific work is promoted through alt-metrics. A review of detection methods for identifying bots as well as the datasets used to do so was conducted by Samper-Escalante et al. (2021). Bot identification requires both the design and implementation of efficient methods but then also the explanation of the decision to identify such a software agent. Kouvela et al. (2020) present a bot detection solution that integrates an ML framework that offers the possibility to explain the results obtained, and additionally, it includes the user's feedback. A dataset for training the detection algorithms is also provided, and the bot identification tool is made available as a web service.

Traditional bot detection methods use supervised machine learning algorithms, but this technique has several drawbacks as it cannot identify changes in real-time. In this regard, an adaptive method of characterizing users based on their behaviour was explored by Minnich et al. (2017). The technique is based on both the use of metadata and features related to the content of messages and connections within the count graph within the ensemble of unsupervised models that are trained for anomaly detection in a multi-dimensional space. The bot identification accuracy was evaluated to 90% from a learning sample of 15 bots.

Also related to the performance of detection algorithms, Fonseca Abreu et al. (2020) presented an evaluation of four bot classification methods using simple features related to a user's profile statistics, obtaining homogeneous results with a mean of 0.85 and a standard deviation of 0.18. Also, for multi-class classifiers, an AUC score of over 0.9 was obtained which provides higher confidence for detecting Twitter bots.

Particularly in the case of events that have major implications for society as a whole, such as presidential or parliamentary elections, referendums such as Brexit, riots or popular movements such as the Arab Spring or Occupy Wall Street, social media platforms have been instrumental in generating and supporting public participation. While at first, this involvement was natural and quite limited, as society gradually adapted and was even encouraged to use these new technologies, their maturity increased as well. Thus, the risk that social media could be used to manipulate public opinion and amplify disinformation campaigns has been widely acknowledged. In addition, due to the new technical facilities offered by social media platforms, such as the filtering and selection of the target population susceptible to a particular message or communication and to the possibility of integrating software applications or conversational agents into social networks, it has become increasingly evident that algorithmic-based manipulation techniques are compelling in influencing society at the individual level. In this regard, numerous studies have analysed this phenomenon, e.g., influencing the 2016 US elections (Bessi & Ferrara, 2016), the Brexit referendum campaign (Howard & Kollanyi, 2016) or other topics with societal implications such as climate change (Marlow et al., 2021).

4. Conclusions

Taking into account the current challenges related to the evaluation of the research activities, we have presented both traditional methods and the new metrics that rely on the use of data extracted from social networks, reference management tools, or other online platforms, so-called alt-metrics.

In a democratic system, civic involvement is fundamental to sustaining an open environment that encourages citizens to engage in public debate on important issues. In this respect, social media and social networks are the main avenues through which social and political issues are debated, narratives on issues of interest are created, and communities coordinate their online and offline activities. In the context of science which has become a public and open phenomenon, a review of the criteria that are the basis of the evaluation of research and researchers by identifying new ones is not only recommended but necessary considering the paradigmatic changes we are going through.

The increasing performance of machine learning methods and artificial intelligence may represent a problem that needs to be understood and solved to create the necessary framework for implementing metrics related to the research results evaluation.

In this paper we described the main landmarks of this new era of evaluating research, underlining a few examples in the area of unethical use of AI to influence alt-metrics.

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