Clinical and Translational Imaging (2025) 13:231–239
https://doi.org/10.1007/s40336-025-00688-x

RESEARCH

Social media for scientific research: the impact of publicization on citations in diagnostic imaging and radiation oncology publications

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Received: 3 November 2024 / Accepted: 26 February 2025 / Published online: 12 May 2025

Abstract

Purpose The impact of social media dissemination on the citation of scientific papers in the field of diagnostic imaging and radiation oncology has not yet been established. We aimed to evaluate the impact of alternative metrics on citation counts and to identify the most influential predictors of citation impact across social media platforms.

Methods We selected original papers published between 2015 and 2019 in six reference journals in the field of diagnostic imaging and radiation oncology. Social media attention was quantified using the Altmetric Attention Score (AAS) and its indicators (mentions in news, blogs, Facebook posts, Twitter posts and accounts, and any online document that links to one or more research objects), provided by Altmetric. Citation counts were retrieved from Scopus. Descriptive analysis was used to extract essential information for subsequent regression analysis to predict citations. We tested three models to assess the relationship between AAS and citations. A p-value below 0.05 was considered statistically significant.

Results We analyzed 4778 papers. AAS alone did not predict citation counts. The time since publication had the strongest influence on the number of citations. Among social platforms, Facebook emerged as the most influential, but it was surpassed by Twitter when considering Twitter accounts and Twitter posts collectively.

Conclusion AAS and its indicators cannot be considered sole predictors of citation counts.

Keywords Social media · Altmetric Attention Score · Medical imaging · Radiation oncology · Citation metrics · Bibliometrics

Introduction

Since the early 2000s, the use of social media has skyrocketed, revolutionizing various sectors, including scientific communication and research impact assessment [1, 2]. The influence of scientific publications is increasingly measured by their visibility on social media, among both experts and the general public. Traditional bibliometric indicators—such as the number of citations, impact factor, and h-index—are no longer the sole evaluation tools [3, 4]. In 2010, the term 'altmetrics' was introduced to describe non-traditional metrics [5]. Specifically, the Altmetric Attention Score (AAS) is "an automatically calculated, weighted count of all the attention a research output has received" [5]. Altmetric assesses an article's influence beyond the realm of academia, by quantifying the online activity surrounding it. This score is

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provided by the homonymous data science company Altmetric [Altmetric.com] [6, 7].

In recent years, several studies have investigated the relationship between citation counts and various altmetrics [8–12]. Social media-derived metrics have been shown to exhibit significantly different temporal patterns compared to citation-based impact metrics. Indeed, while the latter may continue to grow for years after a study's publication, alternative metrics tend to accumulate rapidly after publication but plateau soon thereafter [13]. Overall, the relationship between traditional and alternative metrics remains inconsistent. A linear relationship has been observed only in high-impact factor journals that focus on the internet and social media [11], or cover topics of broad public interest [13]. Furthermore, a number of additional factors, such as open access status, journal reputation, authors' scientific authority and prior production, may affect the dissemination and citation of scientific papers [14–16], alongside the strength of the study's results and the significance of its findings. The influence of authors' social media presence on the dissemination and citation of academic papers is still undefined. While some articles have found a positive relationship between increased visibility through social media and higher citation rates [17, 18], others have reported no significant effect of social media exposure on article downloads and citations [19, 20]. It should also be mentioned that social platforms have introduced new figures such as influencers and bloggers who have reshaped perspectives, interactions, trends, and modes of dissemination [21, 22]. Additionally, social media has amplified the Dunning–Kruger effect in various fields including politics and marketing [23, 24]. All these factors could also be relevant to the dissemination of scientific research. Therefore, it could be relevant to determine whether social media exposure significantly contributes to the success of a publication and whether researchers who are inactive on social media may undermine their own work by limiting its dissemination and potentially its citations. To the best of our knowledge, no studies have assessed the impact of social media exposure on the dissemination of scientific papers in the field of diagnostic imaging and radiation oncology. To fill this gap, we conducted an in-depth investigation on the influence of social media use on citation counts in the field of diagnostic imaging and radiation oncology The specific aims of our work were to evaluate the impact of alternative metrics on citations and to identify the most influential predictors of citation impact among social media platforms.

To suit the aim of this work, we considered the AAS, a weighted measure of the attention a publication receives across various alternative channels, including Facebook, Twitter, YouTube, blogs, and online news [5]. To properly reflect the influence of each social media platform, we included both the total value AAS and its single indicators in the analysis, providing a comprehensive view of all possible dissemination channels. Additionally, factors such as open access, the behavior of the interquartile population, and journal impact factor were also considered, as these variables could potentially influence dissemination and, ultimately, citation counts.

Materials and methods

Dataset

Our dataset was compiled using the Python platform. We included papers published in high-impact, peer-reviewed international journals in the fields of radiology, nuclear medicine, and radiation oncology. Specifically, for each discipline, we focused on the official journals of the European and American Societies, respectively. These comprised *European Radiology* (ER); *Radiology* (Rd); *European Journal of Nuclear Medicine and Molecular Imaging* (EJNMMI); *Journal of Nuclear Medicine* (JNM); *Radiotherapy and Oncology* (RO); *International Journal of Radiation Oncology, Biology, Physics* (IJROBP). The Embase biomedical literature database was used to generate the article list. We considered a 5-year observation period from 2015 to 2019. It was assumed that this period would allow the impact of the published articles (in terms of citations and indicators) to be fully observed. Reviews, meta-analyses, guidelines, recommendations, editorials, letters, conference papers, notes, and erratum contributions were excluded, as these types of articles may present with extremely high or extremely low citation counts respectively, potentially introducing bias. The titles and abstracts of the remaining articles were manually screened to ensure that only original research articles were considered. For each paper, we extracted a number of variables listed in detail in the Supplementary Material.

Altmetric Attention Score, its' indicators and citations' extraction

The DOI list obtained from Embase was used to query the bibliographical archive Medline [MedlinePlus.gov] to gather all available information related to the listed papers, including the Altmetric key, which provides access to the AAS through the Altmetric application programming interface (API). In addition to AAS, we considered other indicators (i.e. mentions in news, blogs, Facebook posts, and Twitter as stand-alone variables). In particular, we selected "mass media" (number of news outlets mentioning them), "feeds" (number of blogs that have mentioned the publication), "Facebook" (number of pages that have shared on Facebook), "Twitter posts" (number of Twitter posts mentioning them), "Twitter accounts" (number of

Twitter accounts mentioning them), and “number of posts” (number of posts—any online document that links to one or more research objects—mentioning them). The variable “reader” was excluded as it refers to the number of individuals who save a paper in their personal Mendeley and CiteULike libraries, which does not necessarily reflect its impact on the community at large. Google Plus, Reddit, Mainstream Media, and Videos—initially excluded from the analysis due to their values being reported as zero for most publications,—were subsequently retained in supplementary and exploratory analyses to evaluate potential relevance in specific contexts. Additionally, the variables Google Plus, Reddit, Mainstream Media and Videos were also eliminated because their value was reported as zero for most published works. Finally, articles for whom any of the previously mentioned features contained missing data points were excluded.

The number of total citations was extracted through Scopus API. The AAS, its indicators, and the number of citations were extracted on March 4th, 2022.

Statistical analysis

Descriptive analysis of the dataset was carried out to extract the basic information required for the subsequent regression analysis. For all statistical tests, a p-value below 0.05 was considered statistically significant.

Firstly, the distribution of each variable was estimated, along with its correlation to scientific impact, expressed in terms of paper citations. A Shapiro–Wilk test was employed to verify normal distribution. Spearman correlation coefficients were calculated to test the bivariate non-parametric correlation between variables. Subsequently, the relationship between other factors (i.e. open access and high AAS) and citation values was assessed, to determine whether different publication characteristics might affect the behavior of papers on social media. In particular, the Wilcoxon rank sum test was used to test the effects of open-access publishing (i.e. open-access versus subscription papers) and to evaluate whether papers with higher impact on social media exhibit different citation patterns. For this latter analysis, we distinguished between papers with a high AAS value (greater than the third quartile AAS, defined as “outliers”) and those having AAS within the third quartile (the “main population”).

Preliminary results allowed for the selection of predictor variables, which were useful for building statistical models able to foretell the number of citations. Three such models of increasing complexity were tested: multivariate linear regression (MLR), random forest (RF), and boosted regression tree (BRT) models. All the statistical analyses were conducted using the R studio software.

Multivariate linear regression model. A standard MLR model was employed to predict the number of citations as the outcome variable. The predictor variables included the number of news sources mentioning the publication, the number of Facebook pages sharing it, the number of tweets, the number of Twitter accounts involved, and the total number of posts. The standard MLR was implemented in R-Studio using a fitting linear model package (function *lm*). The linear regression coefficients were used to measure the association between the predictor variables and the outcome, while the model fit was evaluated in accordance with the adjusted R-square value.

Random forest. The RF model is a machine learning algorithm that selects the best predictive criterion from a randomly generated subset of variables at each decision tree node, rather than considering all variables at each step [25]. We used this method as it helps to reduce estimator variance and improves overall performance compared to MLR by eliminating the need for manual variable selection. The RF attributes unique weights to each tree, and through a majority vote process, the most heavily weighted tree provides the most accurate prediction [25, 26]. Before implementing RF model, we split our data into two subsets, using a bag fraction of 75% to train and test the algorithm performance. The Out of bag (OOB) score was used for validating the Random forest model.

Boosted regression tree. BRT models combine regression methods with boosting techniques which generate a single output improving predictive accuracy [27]. Similar to the RF model, BRTs sequentially build large amounts of single decision trees, with each tree being dependent on the previously generated one. As a third step, we adopted sequential learning to improve the overall predictive accuracy [27]. As opposed to the Random Forest model, where no variable selection was performed, the BRT model included only variables that significantly correlated with the number of citations via Spearman correlation coefficient. These were Facebook, number of posts, feeds, mass media (MSM), Twitter accounts and Twitter posts. We also included some confounding variables such as open access, source title, and months since publication.

Results

Descriptive results of the dataset

We collected an initial pool of 9649 articles. Applying the criteria mentioned above, 4871 articles were removed resulting in a final dataset of 4778 articles. The number and percentage of articles eliminated per year are detailed in Table 1. Table 2 summarizes articles subdivided per journal and per year.

Over the observed 5-year period, the number of citations of papers published in the reference journals of medical imaging and radiation oncology had an average

Table 1 Number and percentage of articles eliminated (total and per year)

Year	Initial articles	Removed articles	Removal percentage	Remaining articles
2015	1677	724	43.2	953
2016	2009	972	48.4	1037
2017	1935	932	48.2	1003
2018	1976	1070	54.1	906
2019	2052	1078	52.5	974
Total	9649	4871	50.5	4778

value of 28, ranging from a minimum of 0 to a maximum of 3033. Although citations could not be considered normally distributed according to a Shapiro–Wilk Test (p-value < 0.001), we found that they increased considerably as the number of months since publication increased.

The average AAS value varied across publication years. Specifically, the mean AAS was 6.18 in 2015, 15.41 in 2016, 23.89 in 2017, 14.45 in 2018, and 13.79 in 2019 (Supplementary Table 1). No significant trend was observed between AAS value and the number of months since publication. Similarly to citations, the AAS did not result normally distributed (p-value < 0.001). Descriptive statistics such as the minimum, the 1st quantile, the median, the mean, the 3rd quantile, and the maximum value of input data subdivided by year of publication for the indicators of the AAS are reported in Supplementary Table 1. The normality distribution test conducted on the indicators showed that normal distribution cannot be assumed for any of them (Supplementary Table 2). Non-parametric tests were thus employed for the statistical analysis, in accordance with the distribution of the variables.

Relationships between citations and AAS, and identification of the most influential indicators

Neither the total AAS nor the single indicators had a Spearman rho correlation coefficient greater than 0.3, indicating a weak correlation (Supplementary Table 3).

Effects of open access publication

A total of 43% of analyzed papers were published as open access. Open-access papers had both higher citation values and higher publicization scores compared to the papers published with the subscription option. In particular, the average citation value for open-access publications was 36, whereas it was 22 for subscription-based papers. The average AAS for open-access publications was 25, while for subscription-based publications, it was 8. Wilcoxon rank-sum tests showed a significant difference in both citation counts and AAS indicators' between open access and subscription publications. Open-access papers were cited significantly more frequently than papers requiring a subscription, as demonstrated by the results of the Mann–Whitney test (p < 0.001).

Correlations between Altmetric Score indicators and social media activity in "Main Population" and "Outliers" Groups

Within each subset ("outliers" and "main population"), Spearman Rho correlation coefficients showed significant correlations between AAS and the following variables: Facebook, Twitter posts, Twitter accounts, and number of posts (Supplementary Table 4). Although positive correlations were detected in both groups, the Rho correlation coefficient was greatest for the "main population" group.

Models' results

The preliminary analyses showed that AAS and its indicators cannot be considered unique predictors of citation counts

Table 2 Included papers detailed per journal and per year

Journal	Year					Total
	2015	2016	2017	2018	2019	
European Radiology	89	142	172	206	259	868
Journal of Nuclear Medicine	124	125	89	94	63	495
Radiology	144	222	223	260	209	1058
European Journal of Nuclear Medicine and Molecular Imaging	41	59	44	49	67	260
International Journal of Radiation Oncology, Biology, Physics	180	193	199	257	232	1061
Radiation Oncology	146	231	204	207	248	1036
Total	724	972	931	1073	1078	4778

(Supplementary Table 3). Therefore, we built multiple-predictor models to determine the extent to which mass media, feeds, Facebook, Twitter posts and accounts, as well as the number of posts contribute to the impact of papers. Here, we tested three models. Since AAS is obtained as the linear combination of the other predictors, we didn't include it amongst the independent variables of the models.

Multivariate linear regression model

Our initial approach to predicting citation counts involved fitting a MLR model. The MLR model proved AAS had a significant influence over the values of citations (number of citations, number of news, number of Facebook pages, number of Tweets, number of Twitter accounts, number of posts). However, the model yielded a very low adjusted R square value (adjusted-$R^2 = 0.01512$), indicating a poor ability to explain the variance in citation behavior.

To improve the model, we applied a stepwise elimination approach to identify a subset of predictors that maximized the model's adjusted R^2 while minimizing redundancy among variables. While all predictors were statistically significant individually (Table 3), some became less impactful when analyzed in the multivariate context.

After completing the stepwise elimination process, "Twitter accounts" and "months since publication" emerged as the strongest and most consistent predictors of citation counts across all years, consequently, only these two variables were retained in the final model.

The refined model achieved a slightly improved adjusted R^2 value (Adjusted $R^2 = 0.1264$), but it remained low, highlighting that even these two predictors could not fully explain citation variability. This suggests that the underlying nonlinearity of the data may require more sophisticated modeling. To address this, we implemented machine learning models to try to predict more effectively citation counts.

Random forest model

The RF model offered some advantages over MLR including reduced estimator variance and improved overall performance by eliminating the need for manual variable selection. A preliminary model was built adopting standard values—500 trees and 3 variables selected at each split—while including all variables. Resultant error was high with only 7.7% of variability being explained. To improve the model, we optimized the number of randomly selected per split by performing an empirical search. Specifically, we conducted two splits per loop to determine the optimal number of variables and trees for enhanced performance. The minimum out-of-bag (OOB) error, a metric that evaluates how well a model generalizes to unseen data, was achieved when the RF model considers only one variable at a time (Supplementary Fig. 1). The optimal number of trees was found to be 800.

Overall, the RF model with the optimal number of trees and variables for each split resulted in a poor predictive outcome (Supplementary Fig. 2).

In detail, the number of Twitter accounts, and months since publication were the most influential variables in predicting the number of citations. However, the RF model, as a whole, failed to correctly predict this number, as it generally underestimated the citations, and its error was found to gradually increase with the number of observed citations.

Boosted regression tree model

BRT models merge regression methods and allow for the combination of multiple models. As a third step, we adopted this type of learning based on sequential learning to improve

Table 3 Multiple linear regression results, considering mass media, feeds, Facebook, Twitter posts and accounts, as well as number of posts as predictors[a] for citations

Coefficients	Estimates	Standard error	p-value
Intercepts	− 2.74145	2.84445	0.335202
AAS	− 1.52364	0.35888	2.22e−05
Number of Facebook pages	− 18.00011	1.30517	< 2e−16
Number of blogs	− 14.03693	3.10377	6.26e−06
Number of Google + accounts	− 23.35464	3.19344	3.04e−13
Number of the news	− 9.12885	2.57005	0.000386
Number of Reddit threads	− 20.05139	6.44508	0.001875
Number of the twitter accounts	− 19.47665	1.14313	< 2e−16
Number of the Youtube/Vimeo channels	36.66126	7.92517	3.83e−06
The sum of all "cited_by" entries	20.97277	1.21003	< 2e−16
Months since publication	0.40662	0.04725	< 2e−16

[a]Google Plus, Reddit, mainstream media, and videos—variables initially excluded from the analysis due to their values being reported as zero for most publications,—were subsequently retained to evaluate potential relevance in specific cases

the overall accuracy of the predictive model. To build the BRT model, 10.000 iterations were performed, and each of the 7 considered predictors had a non-zero influence on the model's outcome. In particular, "months since publication" had the most influence (30%), followed by "number of Facebook pages" (18%), "number of the posts" (13%), "number of the news" (11%), "number of the Twitter accounts" (10%), and "number of blogs" (5%). Careful analysis of the model's root-mean-square error (RMSE) with respect to the number of iterations showed that the model did not overfit (i.e., the training error does not continuously decrease as the number of iterations increases). However, when trying to predict the number of citations, the error increased significantly. This behavior showed the model partially failed in both describing and predicting, similar to the RF model's outcome. Summarize in Fig. 1 summarizes the relative influences of each AAS indicator.

In detail, the BRT determined that months since publication had the largest effect on the number of citations, achieving a score of 25 which was nearly double the score of the other indicators. This further confirmed what the Spearman coefficient had previously suggested. Additionally, Facebook was the most influential, among the analyzed social media platforms. However, when considering the partial effects of "Twitter accounts" and "Twitter posts", the total influence of Twitter as a social platform exceeded that of Facebook. Although less significant than the other platforms, the total number of posts also showed a relative influence on the number of citations. Finally, the BRT model found that the journal name and the open-access status had a marginal influence on the number of citations.

Partial dependence plots (PDP) were employed to illustrate the marginal effects of the most influential variables identified—Facebook and Twitter posts—on the predicted outcome of the BRT model (Supplementary Fig. 3). The indicator "Facebook" showed an increasing number of citations up to 7, as illustrated by the peak reached in the corresponding PDP plot, followed by a plateau. This behavior may be explained by the fact that few papers had large values of the Facebook variable (15 papers had a Facebook value larger than 10 and 2 papers had a Facebook value above 30), making the estimation unreliable. The Twitter posts variable showed a constantly increasing number of citations, except for a few small deflections in the curve that slightly decreased and finally saturated. Both the initial deflections and the final decrease in value were presumably given by the small number of corresponding papers at the indicated Twitter post values.

Finally, we performed residual analysis (Fig. 2) which showed a linear trend indicating that, as citations rise, so

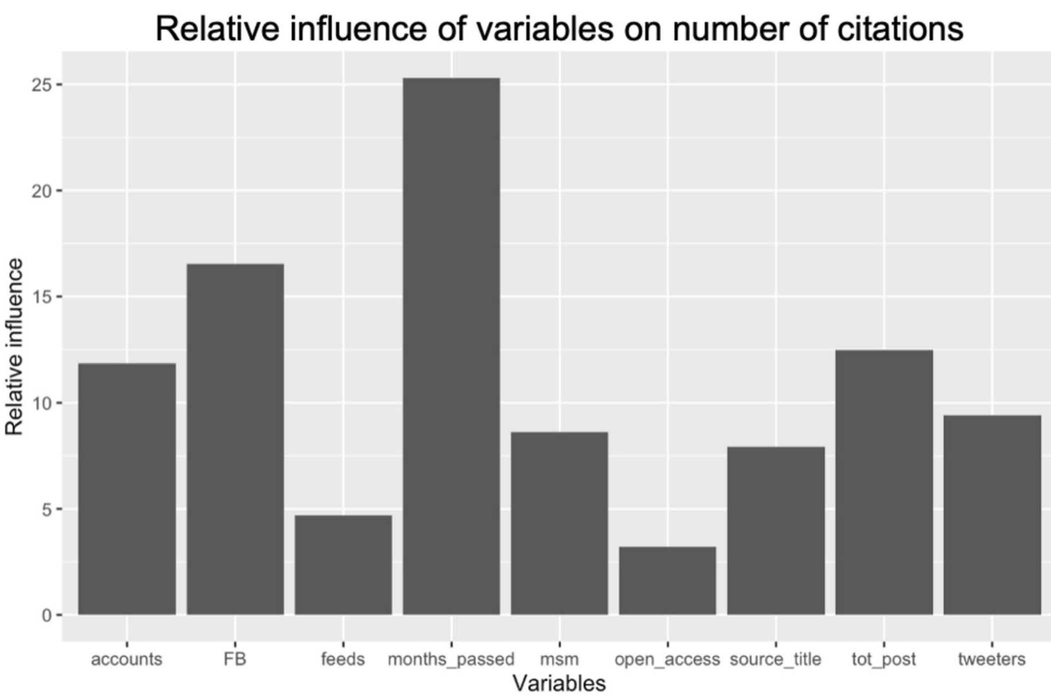

Fig. 1 Relative influence of variables on number of citations—"accounts": the sum of all "cited_by" entries; "'cited_by' entries": number of sources or works that have cited a given article; "FB": number of the pages that have shared on Facebook; "feeds": number of blogs that have mentioned the publication; "months_passed": months since publication; "msm": number of the news sources that have mentioned the publication; "open_access":open access status of the publication; "source_title": Journal name; "tot_post": number of the posts (any online document that links to one or more research objects) that have mentioned the publication; "tweeters": number of the Twitter accounts that have tweeted this publication

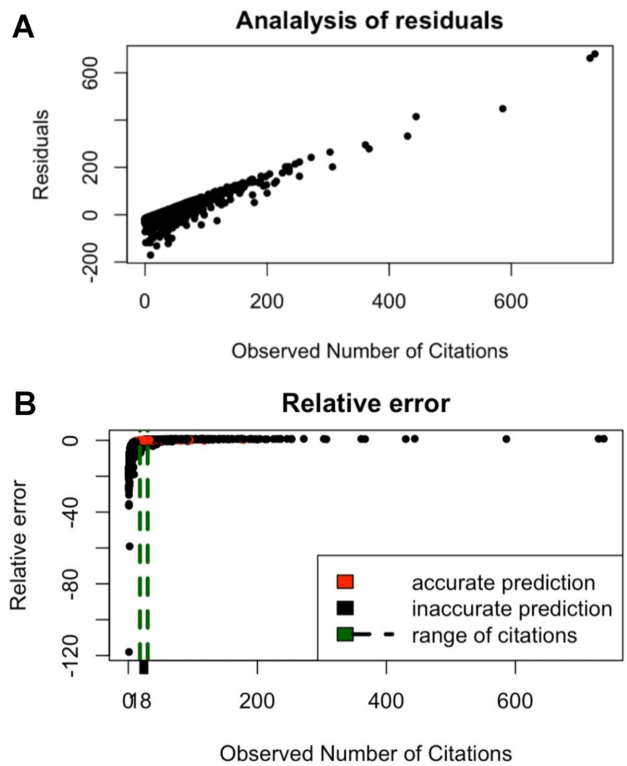

Fig. 2 **a** Residual analysis reveals a clear linear trend, indicating that as the number of citations increases, the absolute error also increases. **b** Relative error investigations demonstrate that our model tends to overestimate the number when there are low citations and underestimate it when there are high citations

did the absolute error (Fig. 2a). Figure 2b shows the relative error which trend demonstrates how our model tended to overestimate the number in case of low citations and underestimate in case of high citations.

Indeed, the red dots in the graph represent those predictions that we defined as 'accurate' (having a relative error lower than 0.3). Empirically, we were able to identify a citation range within which the number of accurate predictions exceeds that of inaccurate ones, with 63% accurate predictions. The chosen relative error (0.3) was relatively high, meaning that even in this range our model's accuracy remained low.

Discussion

The results of this study, based on 4778 articles published in 2015–2019 in the most recognized journals of diagnostic imaging and radiation oncology, proved that the use of social media as a research dissemination primer might determine an early-term benefit in terms of citation counts. However, the attention was no longer retained once a paper reached a certain "maturity" in its citation lifecycle. We assumed that the robustness and meaningfulness of a study would also impact its citability, although we did not explore these aspects. We found that the AAS and its indicators cannot be considered unique predictors for citation counts. More likely, research dissemination relies on various channels both traditional and social media. As previously shown, results obtained from studies investigating the influence of multiple potential factors on citation counts are more reliable than correlation analysis investigating the relationship between citation counts and individual factors. This was because the former approach accounted for interaction between factors [16].

In this study, among models we built, the MLR and the RF were deemed unable to properly predict citation counts. The main issue in describing and predicting citation behavior with these models was likely due to the intrinsic nonlinearity of the relationship between variables. Differently, the BRT model resulted in the most well-suited for the data at hand, as it effectively mitigated the issue of multi-collinearity. The most remarkable outcome of the BRT model was its identification of the temporal dependence of social media dissemination and its impact on citations. Specifically, we found a direct correlation between the number of citations and the number of months since publication. When citation counts were low, they were more strongly correlated with diffusion on social media channels. However, when the number of citations surpassed a certain threshold, or when the number of months became larger, such a positive relationship between citation and social publicization was lost. This suggested that a high number of citations becomes less dependent on publicization over time. We confirmed this hypothesis using the Wilcoxon signed-rank test after splitting the dataset into high- and low-cited subsets, allowing us to ascertain how the positive correlation truly held only for the low-citation subgroup. Furthermore, the BRT model identified Facebook as the most influential social media platform. However, when considering the combined effects of Twitter accounts and Twitter posts, Twitter's overall influence exceeded that of Facebook. Although not as significant, the total number of posts was also found to be a defining criterion.

Open-access status, initially hypothesized to be strong a confounding factor [14], had only a marginal influence on citation counts in our analysis. A recent study reported significant disciplinary and platform-specific differences in the advantage offered by open access, highlighting the complexity of assessing its effect on Altmetrics, especially given the dynamicity and the heterogeneity of both web and Altmetrics [28]. Nevertheless, we cannot exclude the possibility of model prediction failures a priori.

Traditionally, medical sciences have relied on scientific journals, academic conferences, and scientific meetings as the primary means of disseminating research. However, over the past two decades, with the rise of digital technology and the internet, the scientific community's the scientific community's exclusive control over knowledge dissemination has diminished, leading to its more widespread accessibility. Consequently, researchers have increasingly relied on social media platforms to promote their work to colleagues and the public on an international scale [29]. The most popular platforms such as Facebook and Instagram, are designed to meet general user goals [30], while others, such as LinkedIn and Twitter (now named x.com), are more business-oriented. Platforms like ResearchGate and Academia.edu specifically target researchers, academia, and educators [29]. Unfortunately, it is not possible yet to automatically retrieve the number of posts or shares received by an article on each platform. The AAS, as a composite metric incorporating multiple variables, is emerging as a new stand-alone indicator of research impact. However, it has several shortcomings. The most critical of these is its exclusion of multiple data sources (e.g. LinkedIn, ResearchGate, and Academia.edu among others), the potential for artificial inflation by authors promoting their own research, and the lack of data normalization. Although no metric is 'perfect', certain adjustments, if properly implemented, could partially overcome well-known limitations and improve the accuracy and reliability of research impact assessments. Other social-media research impact data providers, such as PlumX [31], are now available however different platforms may capture and weigh inputs differently, preventing direct comparison between metrics.

As proven by our work, establishing a causal link between publicization and citation counts is not straightforward. This may be related to the fact that social media posts target a broader audience, while citations come from scientific literature. Additionally, we can speculate that social media reactions may not be related to the methodology's soundness and solidity of results. Currently, it is not possible to determine whether a social media user who shares or engages with a post has actually read the full-text paper or at least the abstract. Nonetheless, many researchers actively promote their achievements by posting them on social media. The benefits of social media use extend far beyond merely increasing citation rates, it fosters peer group engagement on an international scale [13, 30]. Thus, a key challenge for the scientific community moving forward will be to optimize social media use in a more precise and engaging manner.

Some limitations of our work should be acknowledged. Firstly, the investigation focused on a very specific field—diagnostic imaging and radiation oncology. As a result, our findings cannot be automatically translated to other disciplines. However, they provided a current snapshot of the research dissemination landscape in this field. Moreover, to the best of our knowledge this is the first case study within this domain. Its focused and specific nature allowed us to set up a rigorous methodology and apply sophisticated modelling approaches, which could be adapted for use in other settings. Future research on different topics might yield additional insights into research communication practices, particularly given that citation patterns vary depending on study topics—more attractive and novel topics tend to receive more citations—the field of study, and the subfields within a discipline [16]. Another potential limitation of our study stems from the exclusion of articles with missing data. This decision was made to ensure data quality and avoid misclassification, as missing values could indicate tracking gaps rather than a true absence of interactions. However, we recognized that this approach might introduce bias by omitting articles that may have had significant engagement on alternative platforms.

In conclusion, in the fields of diagnostic imaging and radiation oncology, scientific publications reach the readers not only through traditional channels such as in-person meetings and scientific literature databases but also through social media posts. We found that low citation counts were significantly correlated with "publicization"; however, once the number of citations surpassed a certain threshold, this relation was lost. Moreover, the Altmetric Attention Score and its indicators cannot be considered sole predictors for the number of citations suggesting that even if authored by 'socially inactive' researchers, high-quality investigations can achieve sufficient recognition and visibility through 'traditional' channels to be cited.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s40336-025-00688-x.

Author contributions AC, MK, and MS conceptualized and designed the study; MS screened and collected data, AFB, GC, SDG, MCG, BM, SMT, and AA; performed analysis; MS, MK, and AA critically interpreted results; AFB, GC, SDG, MCG, BM, SMT, and MS, AA and MK drafted the paper. AC critically commented and revised the paper. AC supervised the project's activities. All the authors approved the submitted version of the manuscript.

Funding None.

Availability of data and material The manuscript represents valid work, and neither this manuscript nor one with substantially similar content under the same authorship has been published or is being considered for publication elsewhere. Arturo Chiti had full access to all the data in the study and takes responsibility for the data integrity and the accuracy of the data analysis. Raw data are available on specific request to the corresponding author.

Code availability Code is available on specific request to the corresponding author.

Declarations

Conflict of interest AC: past editor-in-Chief of the EJNMMI, Editor Emeritus of the EJNMMI Reports, and member of the CATI editorial board MS: member of the EJNMMI editorial board and associate editor for the "Artificial intelligence, machine learning and radiomics" section of cancer imaging MK: member of the EJNMMI editorial board, member of the CATI editorial board, member of the EJNMMI Reports editorial board, and associate editor for the "Artificial intelligence, machine learning and radiomics" section of cancer imaging. All the authors do not report any relevant financial conflict of interest related to the present work.

Ethics approval Not applicable.

Consent to participate and consent for publication Not applicable.

Compliance with ethical standards Not applicable.

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