

Measuring the impact of scientific publications and publication extenders: examples of novel approaches

Item Type	Journal article
Authors	Pal, Avishek;Portegies, Wesley;Schwinn, Jennifer;Taylor, Michael;Rees, Thomas J.;Thomas, Sarah;Brown, Kim;Morrell, Gareth;Nicholson, Josh;Falcone, Brian;Juneja, Renu
Citation	Pal, A., Portegies, W., Schwinn, J. et al. (2024) Measuring the impact of scientific publications and publication extenders: examples of novel approaches. Current Medical Research and Opinion, 40(4), pp. 677-687.
DOI	10.1080/03007995.2024.2320849
Publisher	Taylor & Francis
Journal	Current Medical Research and Opinion
Download date	2026-05-19 15:32:00
License	https://creativecommons.org/licenses/by-nc-nd/4.0/
Link to Item	http://hdl.handle.net/2436/625470



Measuring the impact of scientific publications and publication extenders: examples of novel approaches

Journal:	<i>Current Medical Research & Opinion</i>
Manuscript ID	CMRO-2023-ST-0851.R1
Manuscript Type:	Commentary
Date Submitted by the Author:	n/a
Complete List of Authors:	Pal, Avishek; Novartis Pharma AG, Cell & Gene Therapy Portegies, Wesley; MedComms Experts, New York, NY, USA, Medical Communications Schwinn, Jennifer; Immunovant Inc, Medical Affairs Taylor, Michael; Digital Science, University of Wolverhampton, Advanced Data Insights Rees, Tomas; Oxford PharmaGenesis Ltd, AI and Data Science Thomas, Sarah; Ipsen, Global Medical Publications and Communications Brown, Kim; Novo Nordisk, Rare Diseases Morrell, Gareth; Madano, Insights Nicholson, Josh; scite, scite Falcone, Brian; Fingerpaint Group, MedThink SciCom Juneja, Renu; Janssen, US Medical Affairs Oncology
Keywords:	altmetrics, article-level metrics, bibliometric indicators, peer-reviewed publication, publication extender metrics

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Title Page**Measuring the impact of scientific publications and publication extenders: examples of novel approaches****Article type: Commentary****Authors (ORCID):**

Avishek Pal (0000-0002-2213-3336)^{a*}, Wesley Portegies^b, Jennifer Schwinn^c, Michael Taylor (0000-0002-8534-5985)^d, Tomas J Rees (0000-0003-0221-0098)^e, Sarah Thomas^f, Kim Brown^g, Gareth Morrell^h, Josh Nicholson (0000-0002-1111-1828)ⁱ, Brian Falcone (0000-0001-8506-0915)^j, Renu Juneja^k

^a*Novartis Pharma AG, Basel, Switzerland*

^b*MedComms Experts, New York, NY, USA*

^c*Immunovant Inc., New York, NY, USA*

^d*Digital Science, University of Wolverhampton, Wolverhampton, UK*

^e*Oxford PharmaGenesis, Oxford, UK*

^f*Ipsen, Wrexham, UK*

^g*Novo Nordisk, Zurich, Switzerland*

^h*Madano, London, UK*

ⁱ*scite, Brooklyn, NY, USA*

^j*MedThink SciCom, Cary, NC, USA*

^k*Janssen, Horsham, PA*

*corresponding author: Avishek Pal (avishek.pal@novartis.com)

Measuring the impact of scientific publications and publication extenders: examples of novel approaches

Abstract

Different stakeholders, such as authors, research institutions, and healthcare professionals (HCPs) may determine the impact of peer-reviewed publications in different ways. Commonly-used measures of research impact, such as the Journal Impact Factor or the H-index, are not designed to evaluate the impact of individual articles. They are heavily dependent on citations, and therefore only measure impact of the overall journal or researcher respectively, taking months or years to accrue. The past decade has seen the development of article-level metrics (ALMs), that measure the online attention received by an individual publication in contexts including social media platforms, news media, citation activity, and policy and patent citations. These new tools can complement traditional bibliometric data and provide a more holistic evaluation of the impact of a publication. This commentary discusses the need for ALMs, and summarizes several examples – PlumX Metrics, Altmetric, the Better Article Metrics score, the EMPIRE Index, and scite. We also discuss how metrics may be used to evaluate the value of ‘publication extenders’ –educational microcontent such as animations, videos and plain-language summaries that are often hosted on HCP education platforms. Publication extenders adapt a publication’s key data to audience needs and thereby extend a publication’s reach. These new approaches have the potential to address the limitations of traditional metrics, but the diversity of new metrics requires that users have a keen understanding of which forms of impact are relevant to a specific publication and select and monitor ALMs accordingly. (240/250 words)

Keywords: altmetrics; article-level metrics; bibliometric indicators; Journal Impact Factor; peer-reviewed publication; publication extender metrics.

Plain language summary

Different readers have different ways of deciding how important scientific articles are. The usual methods used to measure the impact of research, like the Journal Impact Factor or the H-index, are not meant to measure this for individual articles. These methods mainly look at how many times the articles are mentioned by others, and it can take a long time to see the impact.

But in the past ten years, new tools called article-level metrics (ALMs) have been created. These tools measure how much attention an article gets online, like on social media, in the news, or when other researchers talk about it. ALMs are better in explaining of how important a specific article is. They can work together with the usual methods to measure impact.

This paper talks about why ALMs are important and gives examples of these tools, like PlumX Metrics, Altmeter, the Better Article Metrics score, the EMPIRE Index, and scite. It also explains how these tools can help us see the value of animations, videos, or summaries in simple language. These make it easier for more people to understand and learn from the articles.

These new ways of measuring impact can help us see how important articles are in a more complete way. But because there are many different ways to measure this, it's important for users to understand which methods are relevant for a specific article and keep track of them.

Note to editorial team: The first draft of the above PLS was developed using an AI/LLM, following which it was revised by the authors for accuracy and readability.

Main text

(Word count of main text inclusive of subheadings, references and tables: 6197)

Introduction

Understanding the impact of a peer-reviewed publication, in both the research community and in wider society, is an important goal for various stakeholders. A key challenge is that the concept of ‘impact’ may vary considerably among different stakeholder groups. How publications are received and understood by interested groups is an important consideration for both authors in academia and those in the pharmaceutical and medical device industries. Patient support groups may wish to share publications to improve public awareness of disease. Some peer-reviewed publications are practice-changing; in particular, they can have a widespread impact on healthcare decision-making by the incorporation of relevant study results into guidelines, treatment protocols, and public policies. Studies have estimated the lag from publication to inclusion in clinical guidelines is approximately 8 years, and the lag until impact on clinical practice may be even longer [1-3]. A better understanding of how biomedical research publications lead to changes in medical practice may ensure that beneficial research findings receive appropriate and timely attention, and thus translate into improvements in patient care sooner.

The limitations of traditional bibliometric analysis

Bibliometric analysis – the statistical analysis of publications in a particular field – can assist with the evaluation of research impact and has a history stretching back over a century [4]. One of the established examples, the Journal Impact Factor, was developed

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3 in the 1960s and measures the citation frequency of articles published in the journal
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5 within a given year [5]. Another frequently encountered example is the H-index, which
6
7 quantifies an author's publication output and citation rate [6]. Because these systems are
8
9 based on citations, they take years to accumulate and their measures are specific to the
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11 authors and readership at the level of the scientific and medical journals themselves and
12
13 are not specific to individual articles. Furthermore, because these traditional metrics
14
15 were developed to describe the impact of journals and researchers, they have many
16
17 serious limitations when used to understand an individual publication's impact (Table 1)
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19 [7,8,9]. The low granularity of traditional metrics, such as the H-index and Journal
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21 Impact Factor, means they cannot be used to compare a publication with an established
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23 benchmark (i.e., a publication that achieved a 'good' score). There is thus a need for
24
25 metrics that can rapidly provide faster, richer, and more actionable insights into the
26
27 impact of a specific article itself, beyond that provided by counting citations.
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37 *The rise of article-level metrics*

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39 The internet era has seen the rise of additional channels for communicating peer-
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41 reviewed publications that stretch far beyond the traditional outlets such as scientific
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43 journals and the popular press, notably discussion of a peer-reviewed publication on
44
45 social media, blog posts, HCP education websites, and other forms of online attention.
46
47 These new channels allow the audience to not only access content, but to discuss and
48
49 further communicate key findings. The development of data analysis tools that can
50
51 evaluate the digital attention an individual article receives has led to a proliferation of
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53 article-level metrics (ALMs) or 'altmetrics' (a generic term not to be confused with the
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55 Altmetric Attention Score) [10].
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3 Although the Altmetric Manifesto of Priem et al. in 2010 is considered the birth of
4
5 altmetrics [10,11], earlier efforts to understand internet-based attention to research had
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7 been conducted and described using the term ‘webometrics’, focused on the analysis of
8
9 hyperlinks, search engine results and web citations [12-14]. With the growing
10
11 importance of social media for the dissemination of research [15], ALMs have evolved
12
13 to include attention data from social media networks such as Facebook and
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15 ResearchGate, microblogging services (e.g. Twitter), reference management software
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17 (e.g. Mendeley), and diverse sources including news, policy and patent citations (**Table**
18
19 **2**) [9,16]. The availability of metrics for large-scale analytics is restricted by technical
20
21 limitations and policy. For example, online platforms may lack application processing
22
23 interfaces (APIs) to facilitate the capture of data [9], or the data may not be available
24
25 publicly (for example, discussion on closed forums and readership data for many
26
27 journals). Despite this limitation, PlumX Metrics offers 40 individual metrics across
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29 five categories [17].
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39 ***The potential benefits of altmetrics and ALMs***

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41 Altmetrics and ALMs address one of the major shortcomings of citation-based metrics
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43 by incorporating measures of attention from diverse sources, they offer insights into the
44
45 impact of the peer-reviewed publications on audiences not reflected in citation activity
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47 (Table 1) [10]. Some altmetrics and ALMs can provide information on the impact of a
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49 publication within weeks or months, rather than the months or years required with
50
51 citation-based approaches [10]. The type of engagement that ALMs evaluate is highly
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53 heterogeneous. This arises from the differences between audiences among online
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55 platforms and their different motivations for their activity in relation to the publication.
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3 This is useful because the intended impact may differ greatly for different types of
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5 research studies, such as clinical trials versus real-world studies. A publication on a
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7 preclinical study of a new drug candidate will have a very different intended impact to
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9 that of a large phase III randomized clinical trial of the same drug. The availability of
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11 ALMs may allow stakeholders to select and monitor metrics that align specifically with
12
13 communication objectives for an individual publication, rather than monitoring less
14
15 meaningful ‘one size fits all’ metrics. Thus, ALMs give authors and other stakeholders a
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17 chance to evaluate the impact of their publication, both in academia and broader society
18
19 in a more refined manner than journal- or author-level metrics. This richness of
20
21 information can create difficulty in conveying to stakeholders the impact of a peer-
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23 reviewed publication in a clear and concise manner, and so a variety of approaches have
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25 been proposed that involve selecting, aggregating and weighting metrics to provide
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27 simplified scores.
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34 ***Broadening the metrics horizon: Publication extenders***

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37 Estimates suggest one new publication is added to PubMed every 30 seconds [18]. An
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39 analysis of the volume of medical literature relevant to primary care published in a
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41 month concluded that HCPs would need to read for 29 hours a day to keep up [19]. In
42
43 reality, an international industry survey found HCPs have only 2 hours of learning time
44
45 per week [20]. These circumstances have led to a strong preference for short-form
46
47 content among HCPs and visualizations over long-form text, even though HCPs still see
48
49 journal publications as the most important information source [21]. Understanding
50
51 HCPs’ preferences for new information is important, as information gathering is a
52
53 crucial first step in reaching a clinical diagnosis [22].
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59 A notable trend in biomedical publishing is the development of publication extenders
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3 (also known as publication enhancers). Publication extenders deliver content derived
4
5 from a publication's key data in smaller, bite-sized, formats such as short videos,
6
7 infographics, visual abstracts, short-form text summaries, interactive dashboards,
8
9 animations, and podcasts. By using a variety of formats to deliver information in a form
10
11 convenient for HCPs, publication extenders may extend the reach of a publication to a
12
13 wider audience, and subsequently achieve a greater level of engagement and impact
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16 **(Figure 1)**. Metrics suitable for evaluating publication extenders are called content
17
18 performance metrics and can include the number of visitors, time on page, video view
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20 duration, downloads, traffic sources, organic search traffic.
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25 In the scientific publication landscape, each medium demands a distinct set of metrics
26
27 **(Table 3)**. There is a need for widespread education regarding suitable metrics for peer-
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29 reviewed publication and content performance metrics for publication extenders.
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31 Furthermore, due to the extremely detailed nature of content performance metrics, there
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33 is a need to develop comprehensive models that aggregate the metrics, making it easier
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35 to extract actionable insights.
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43 **Examples of article-level metrics**

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45 This commentary will examine selected examples of ALMs for the evaluation of peer-
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47 reviewed publications. The examples of ALMs included are PlumX metrics, Better
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49 Article Metrics (BEAM) score, the Altmetric Attention Score (AAS), the EMpirical
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51 Publication Impact and Reach Evaluation (EMPIRE) Index, and scite.
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1. *PlumX Metrics*

PlumX Metrics evaluates the online attention given to peer-reviewed publications (and various other items such as conference proceedings and book chapters, collectively referred to as ‘artifacts’) in Elsevier’s Scopus abstract and citation database using metrics distributed across five categories (citations, usage, captures, mentions, and social media) [23]. These metrics are visualized in simplified form as a ‘Plum Print’, a five-armed graphic in which the circle on each arm represents the relative magnitude of that category [23]. PlumX metrics can also be presented in a more detailed table form for each artifact, and the types of attention an article receives can be compared to other articles in the same journal expressed as a percentile. PlumX metrics can also be used to aggregate information for individual researchers or institutions, and benchmarking tools have been developed to allow institutions to compare their metrics to those of their peers [23].

2. *The Altmetric Attention Score*

Altmetric, established in 2011, is the most widely-used source of ALMs [24]. The Altmetric Attention Score (AAS) is a weighted count of online attention a piece of research output has received, using default weightings based on the amount of attention each source is likely to achieve (**Table 4**) [25]. The AAS is presented as a number inside a colored circle, with area of each color representing the different sources of attention (**Figure 2**) [26]. with demographic and geographic data being provided for different types of mention. An analysis of 100 highly-cited peer-reviewed publications on surgery topics found that that articles with higher AASs are associated with higher citation counts [27], and a follow-up analysis of this same cohort of publications

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3 concluded that AAS was a better predictor of future citations than historical Journal
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5 Impact Factors [28].
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10 11 **3. The EMpirical Publication Impact and Reach Evaluation (EMPIRE)** 12 13 **Index** 14

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16 The EMPIRE Index is a multi-component metric framework developed (with support
17
18 from Novartis) to allow authors in the medical and pharmaceutical research fields to
19
20 assess the impact of publications.[29] It is intended to monitor long-term impact, predict
21
22 likely impact with early indicators and identify the effectiveness of communications
23
24 related to publications. The Index summarizes ALMs to provide three scores reflecting
25
26 the impact in different domains – social (social media and news), scholarly (journal
27
28 citations and reference libraries), and societal (guidelines, policy documents and
29
30 patents; **Figure 3**) [30]. – and are averaged to provide a total impact score [29].
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34 EMPIRE Index scores are calculated using metrics obtained from Altmetric Explorer,
35
36 PlumX, Pubstrat Journal Database, CitesScore and Scimago Journal Ranking. These
37
38 data commonly include news, blog, twitter, and Facebook mentions, Mendeley readers
39
40 and Dimensions citations, as well as rarer forms such as policy and guideline citations
41
42 and patents. The grouping and weighting of the metrics were informed by statistical
43
44 analysis of 2,891 Phase 3 clinical trial publications and are calibrated such that a score
45
46 of 100 equals the mean scores of Phase 3 clinical trial publications in the *New England*
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48 *Journal of Medicine* in 2016.
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57 The Empire Index can be used to analyze the impact of a publication over time. An
58
59 example included by Pal and Rees assessed the publication of a Phase 3 study of a type
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3 2 diabetes drug, vildagliptin. At 6–7 months post publication, it had achieved a high
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5 Early Predictor Score associated with press releases and a congress presentation that
6
7 accompanied its publication [29]. This publication was selected for early inclusion in
8
9 treatment guidelines, with subsequent evaluation (approximately 1 year after
10
11 publication) showing increases in the societal impact score [29]. Additionally, *New*
12
13 *England Journal of Medicine* articles selected by the editors for being “notable” also
14
15 scored higher on social and societal components [29]. These findings suggest that the
16
17 EMPIRE Index can be used to identify publications that have a higher or lower than
18
19 expected impact, and thereby inform communication strategies around research topics.
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21 Further investigations using the EMPIRE index have revealed the importance of
22
23 selecting a suitable benchmark publication, when using ALMs. In a 2023 analysis by
24
25 Rees and Pal, the impact of a publication measured by the EMPIRE index varied
26
27 significantly by disease area and publication type [30]. This finding supports the notion
28
29 that there is no universal benchmark for measuring the impact of a peer-reviewed
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31 publication. Rather, when using ALMs, each publication should be assessed in the
32
33 context of publication type, disease area and other factors.
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44 An adapted form of the EMPIRE index has been developed by Ipsen and Oxford
45
46 PharmaGenesis to understand the real-world impact of medical publications [31]. The
47
48 adapted EMPIRE index uses weighted ALMs, grouped into three scores: reach (short-
49
50 term, e.g. news articles and Tweets), engagement (medium-term, e.g., blog and
51
52 Facebook posts) and impact (long-term, e.g. guideline and policy citations) [31]. This
53
54 index has been used to compare the impact of different publications, determine why
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56 some publications are associated with greater impact and to support processes and
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3 publication planning. The approach has enabled targeted analyses to be conducted, for
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5 example investigating the impact of publication enhancements, as well as comparing the
6
7 article metrics associated with simultaneous congress presentation vs asynchronous
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9 congress presentation [32]. This analysis found that simultaneous congress presentation
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11 and article publication was associated with more article views and twitter activity
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13 compared with asynchronous publication [32]. Following internal feedback and
14
15 discussions, as well as crucial insights gained from evaluating metrics over recent years,
16
17 the metrics approach has recently evolved. The weightings of the metrics in the
18
19 component score have been revised following review of historical metrics data. Journal
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21 Impact Factor, used in the original scoring system as a component of the Reach score,
22
23 has been excluded. Rather than taking quarterly snapshots, automated report cards are
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25 generated at consistent time points following the date of publication and combined with
26
27 internal publication details. These report cards facilitate an easy comparison of
28
29 publications and allow better insights to be obtained by viewing the data in the context
30
31 of different publication types, therapy areas, and other factors. These summaries have
32
33 proved useful to the wider company, and the additional detail captured is useful to a
34
35 smaller team. A limitation is that congress publications are currently excluded from
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37 analysis as it has been difficult to find an approach that gathers meaningful metrics.
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48 ***4. Better Article Metrics (BEAM)***

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51 BEAM is a framework and methodology developed by Madano and Novo Nordisk to
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53 measure and benchmark the reach, engagement and impact of peer-reviewed
54
55 manuscripts across 10 therapeutic areas of interest. BEAM collects data on a daily basis
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57 on 12 key metrics for all peer-reviewed publications in a given therapeutic area since
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3 2016. In diabetes and obesity, this equates to over 400,000 articles; in hemophilia this is
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5 approximately 10,000 articles. The 12 metrics for every publication are combined and
6
7 then weighted to reflect their frequency and qualitative relevance to Novo Nordisk's
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9 publication objectives (**Figure 4**). After weighting, the metrics are normalized by the
10
11 age of the manuscript (i.e., compared to other manuscripts published within a 6-month
12
13 window) and therapy area. The weighted and normalized metrics are then combined
14
15 into a single percentile – the “BEAM Score”.
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23 This normalization process, adjusting for age and therapy area, and the use of a simple
24
25 percentile score is intended to enable comparison of the impact of manuscripts at a
26
27 glance. The data from each individual article and their BEAM score over time is
28
29 available to Novo Nordisk publications teams in a ‘live’ BEAM dashboard (**Figure 5**).
30
31 Data can be queried within the BEAM dashboard to display the average BEAM Score
32
33 based on groups of articles (e.g., identifying study types of high impact), as well as
34
35 comparing BEAM Scores of individual articles (e.g. tracking an individual article's
36
37 impact over time since publication, or comparing the impact of all recent articles
38
39 publishing Phase 3 data in a given therapeutic area). Artificial intelligence is also used
40
41 to analyze publications impact by topic. Large language models are used to categorize
42
43 publications based on titles, keywords and abstracts. Manual human labelling of these
44
45 categories then takes place, enabling high impact topics to be identified, as well as
46
47 highlighting low frequency topics. Finally, BEAM also serves as an information source
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49 on the impact of journals and specific social media influencers within a therapeutic area.
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3 The information gathered from BEAM allows publications professionals within Novo
4 Nordisk to identify the reach, engagement and impact of their publications. This
5 information can be used to evaluate and update publications strategies and plans and
6 inform future publications. BEAM has been developed for internal Novo Nordisk use
7 only.
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18 **5. *scite***

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21 A limitation of traditional citation indexes is they do not offer information on whether
22 the citing authors agree or disagree with the publication they cited. *scite*, a new citation
23 index, uses artificial intelligence (AI) tools to analyze text and provide ‘Smart Citations’
24 that reveal contextual information on how a publication is being cited [33]. This
25 includes whether the citing publication provides supporting or contrasting evidence, or
26 only mentions it. Smart Citations include the text surrounding a citation, the location of
27 a citation within the article (introduction, materials and methods, etc.) and information
28 from Crossref and PubMed such as retractions and corrections (**Figure 6**). Smart
29 Citations are produced via an automated extraction and classification of citations from
30 scientific texts openly available from repositories such as PubMed Central, publishers’
31 websites, and subscription articles have also been included via indexing agreements
32 with numerous publishers. *scite* can also produce similar data aggregated for a specific
33 journal.
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52 *scite* can offer authors and other publication stakeholders insights into how and where
53 their publications are cited, including whether other researchers’ data agrees or contrasts
54 with particular findings. Editorial mentions of publications can be identified and highly-
55 cited authors within specific fields can be identified, including if their work is supported
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3 or disputed by other researchers.
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9 ***Publication Extender Metrics***

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11 The use of publication extenders to broaden the reach and increase the engagement of
12 publications involves content delivered through an omnichannel approach. Publication
13 extender metrics are in their infancy but are technically simple to implement when
14 extenders are hosted on an appropriate HCP education platform. Reach and engagement
15 of extenders can be measured by leveraging already established content performance
16 metrics for online content. These quantitative metrics may include overall views,
17 organic search traffic, time spent on page, scroll depth, click-through rate, video play
18 rate and watch time, and podcast consumption rates. Metrics can also assess the
19 pathways taken by audience members towards and away from the extender. As the use
20 of publication extenders becomes more common, their metrics may become more
21 standardized and may be incorporated into other ALMs.
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40 **Discussion**

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42 Traditional publication metrics preceded the availability of modern digital tools and
43 channels that have profoundly changed the dissemination of peer-reviewed publications.
44 Furthermore, they are unsuitable for evaluating the impact of individual articles, and do
45 not provide information about the context in which a publication is cited. The rise of
46 ALMs has created a diverse set of metrics that complement traditional bibliometrics and
47 can evaluate the impact of an individual article both within academia and in society.
48 Despite these options, there is a lack of broad awareness and uptake of newer ALMs.
49 Educational efforts aimed at multiple stakeholders to raise awareness of the limitations
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3 of traditional metrics and potential alternatives may help correct this situation. The San
4
5 Francisco Declaration on Research Assessment (DORA) is a welcome example of
6
7 education and advocacy to promote change in this field [34]. Education on the
8
9 importance of ALMs should be directed to thought-leaders in academia, among policy-
10
11 makers and in the life-sciences industry. The many different types of ALMs complicates
12
13 efforts to explain their meaning and utility to non-publication professionals.
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18 Another area where education of stakeholders may be warranted is the need to choose
19
20 ALMs that are appropriate to an article's objectives. Studies comparing ALMs across
21
22 different publication types have already shown that different publication types receive
23
24 different levels and sources of online attention, with guideline publications, editorials,
25
26 and systematic reviews, receiving higher attention than original publications [35,36].
27
28 Therefore, institutions, life-science companies and other stakeholders should be
29
30 informed of the importance of setting a specific communication objective for a peer-
31
32 reviewed publication and monitoring ALMs that align with that objective.
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37 The incorporation of social media activity into the assessment of research impact is a
38
39 timely step, especially considering the rise in online scientific communication during
40
41 the COVID-19 pandemic. Research institutions, professional societies, publishers and
42
43 life sciences companies are increasingly using social media for research
44
45 communication, with many open-access journals actively promoting commenting and
46
47 online engagement [15]. Social media activity must be interpreted with caution; a tweet
48
49 or comment may only indicate brief engagement, not thorough understanding. Some
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51 companies impose strict restrictions on social media engagement, which will limit the
52
53 representativeness of social media activity. The continuous changes in popularity of
54
55 social media platforms over time may make trends in these metrics difficult to analyze.
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3 However, social media will remain an important channel for researchers to engage in
4 communication with their peers, and for society to engage with the scientific
5 community. Initial studies suggest the latter interaction is under-developed but may be
6 addressed by institutions and policy makers [15]. Furthermore, social media
7 commentary can give researchers and other stakeholders a unique insight into a
8 patient's experience of a drug or disease, and when combined with clinical trial tools
9 may assist with clinical trial enrolment [37].

10
11
12 The diverse nature of ALMs means they have a variety of potential uses. Authors and
13 research funders can use them to identify research topics that are attracting high levels
14 of attention and that are likely to have a higher impact. Another potential use is to
15 identify 'key opinion leaders' (KOLs) and their online equivalent 'digital opinion
16 leaders' (DOLs) – respected individuals with expertise and influence in a particular
17 field – to form collaborations that ensure publications can achieve a wide audience.
18 While traditional metrics may be helpful for identifying KOLs, the online nature of
19 DOLs are best identified using ALMs, and both scite and the Altmetric Attention Score
20 have noted this potential use [38,39].

21
22 For pharmaceutical and medical device companies, ALMs can inform several important
23 activities. By providing timely feedback on audience attention, ALMs may help
24 companies evaluate their communication activities and identify opportunities to
25 improve communications or correct misperceptions. Publication professionals can
26 identify communication channels that are more effective for specific audiences, and
27 impact can be compared with publications from competitors, or among similar
28 publications where different communication strategies were used. An example of the
29 latter is an analysis comparing two potentially practice-changing studies published in
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3 the same therapy area in the *New England Journal of Medicine*, one of which was
4 published simultaneously with a congress presentation, the other published
5 asynchronously (6 months after a congress presentation) [32]. Simultaneous
6 presentation was associated with more article views and associated Twitter activity than
7 asynchronous presentation [32]. Publication extenders can provide diverse options for
8 the adaptation of communication strategies to increase reach and engagement of focused
9 content, and provide key data from peer-reviewed publications in easily-digestible
10 formats tailored to specific audiences.
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25 ***Current limitations and future directions***

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28 A limitation for ALMs is that sharing of information across online platforms is
29 inconsistent, leading to some platforms being excluded from inclusion in ALMs. For
30 example, LinkedIn, and The National Comprehensive Cancer Network (NCCN, a
31 guideline provider) do not provide machine access to their content for automated
32 analysis, and among reference managers, only one (Mendeley) provides anonymized
33 usage data. Another source of inconsistency is the audience and volume of usage of a
34 particular platform, which may wax and wane over time [40]. Some metrics – e.g. the
35 EMPIRE index – are based on a limited subset of studies that may limit applicability to
36 other study types or disease areas [29]. As with traditional metrics, ALMs are open to
37 manipulation by authors and existing tools may be subject to inaccurate classifications
38 of text or citations [33,41]. However, some of these limitations will diminish as ALMs
39 and the technologies that underpin them are further refined. In particular, the further
40 development of AI-based text analysis, already incorporated into BEAM and scite, is
41 likely to lead to wider adoption. Large language models will increasingly be trained on
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3 scientific materials and refined to be human oversight, leading to more efficient topic
4 categorization and the development of further ALMs that offer both qualitative and
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6 quantitative evaluations of online attention.
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11 An encouraging observation is the evolution that is occurring within the field of ALMs,
12 and this has started to slowly offer more appropriate options beyond Journal Impact
13 Factors. While PlumX provides a wide range of very generic metrics, among which the
14 user must select, AAS consolidates various forms of attention into one score. However,
15 in general ALMs may have a tendency to be heavily driven by metrics from a few
16 specific channels, such as attention from news media and social media, and may not
17 appropriately weight the importance of mentions in policy documents or guidelines
18 [40,42]. This attribute can affect the relevance and utility of such scores for a diverse set
19 of users, who may have different perspectives on relative scoring and are keen to have
20 more input on the types of channels and the importance assigned to them in the overall
21 score. The EMPIRE Index and BEAM represent industry-led initiatives attempting to
22 address this gap, and a key consideration being transparency, control and balance in
23 relation to the importance of different attention types. Metrics for publication extenders
24 are of increasing interest, particularly among publications professionals in the
25 pharmaceutical industry, due to a strong preference among HCPs for short form content.
26
27 Appropriate content performance metrics that can identify factors within the control of
28 the publications team can be used to refine and optimize communication efforts within a
29 short period of time. More broadly, important future steps in the field of ALMs include
30 identifying uniform criteria for defining impact, and identifying appropriate benchmarks
31 for an impactful publication, across diverse disease areas and study types. These steps
32 can lead to metrics that can help answer the core questions underlying the impact of a
33 peer-reviewed publication – if the publication has been read, if so by whom, has it been
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3 understood, and if anything changed as a result.
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8 9 **Conclusions**

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11 The development of ALMs has created a suite of tools that complement traditional
12 metrics and provide a more timely evaluation of the impact of a peer-reviewed
13 publication across a wider variety of audiences than journal- or author-level metrics.
14
15 Due to the wide variety of ALMs available, it is important that users carefully consider
16 the specific communication objectives and audiences for a publication and choose
17 ALMs that match. If used appropriately, ALMs can offer authors, research sponsors,
18 and various other stakeholders a more holistic view of the impact of a peer-reviewed
19 publication. However, current ALMs lack the ability to provide a clear and concise
20 measurement of a publication's impact and an explanation of its value, especially to
21 non-publication professionals. Therefore, we look forward to further refinement and
22 innovation in this field.
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41 **Data availability**

42 No data are associated with this article.
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48 **Competing interests**

49
50 Avishek Pal is an employee of Novartis (co-developer of the EMPIRE Index). Tomas
51 Rees is an employee of OxfordPharmagenesis, co-developer of the EMPIRE Index and
52 Ipsen-adapted EMPIRE index). Michael Taylor is an employee of Digital Science
53 (owner of Altmetric and Dimensions). Sarah Thomas is an employee of Ipsen
54 (developer of the Ipsen-adapted EMPIRE Index). Gareth Morrell and Kim Brown are
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3 employees of Madano and Novo Nordisk, respectively (co-developers of BEAM). Josh
4
5 Nicholson is an employee of scite.ai. Avishek Pal, Renu Juneja, Brian Falcone, Wesley
6
7 Portegies, and Jennifer Schwinn are members of the Medical Affairs Professional
8
9 Society (MAPS) Medical Communications Focus Area Working Group (provided
10
11 funding for medical writing assistance for this manuscript).
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16 **Grant information**

17
18 Medical writing support for this manuscript funded by the Medical Affairs Professional
19
20 Society (MAPS).
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23

24 **Author contributions**

25
26 This manuscript was conceived and designed by Avishek Pal, Wesley Portegies,
27
28 Jennifer Schwinn, Brian Falcone, and Renu Juneja. All authors contributed to the
29
30 writing of the manuscript and critical revisions for intellectual content. All authors
31
32 approved the final version and are accountable for all aspects of this work.
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38 **Acknowledgements**

39
40 Medical writing assistance was provided by Alister Smith of MedComms Experts, Inc.
41
42 NY, USA, and funded by the Medical Affairs Professional Society. The authors would
43
44 like to thank all other members of the Medical Affairs Professional Society (MAPS)
45
46 Medical Communications Focus Area Working Group for discussions and feedback that
47
48 assisted in the writing of this manuscript.
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Tables

Table 1. Traditional bibliometric indicators article-level metrics: pros and cons.

Traditional bibliometric indicators		Article-level metrics	
Pros	Cons	Pros	Cons
Proxy indicator in the absence of validated and objective alternatives to measure impact	Not a true indicator and is not intended to be a measure of impact of individual articles	Allow measurement of reach, engagement and impact of individual articles	Does not necessarily measure quality of individual articles
Measure of individual researcher's publication output	Require a long time to accrue	Avoid category errors common with traditional metrics	Could be subjective, differing by individual, organization and context
Measure of impact at the journal level based on citation rate	Measured at a journal level, so often skewed by a small number of highly cited articles	Allow transparency in parameters considered to define impact and their relative weighting	Influenced by the speed of accrual of individual metrics contribute to the overall score
	Does not consider publication extender tactics and diversity of dissemination channels including social media	Considers publication extender tactics and diversity of dissemination channels including social media	Variable by trial design, disease area, publication type and stage in life cycle
	Biased by self-citations, honorary authorship, etc.	Allow monitoring of multiple publications from a chosen portfolio and teases out articles by relative impact	Susceptible to manipulation by authors
	Does not offer insights on sentiment of the context of citations, reach among intended audience or engagement	Could have predictive components to forecast metrics over a period of time and shape tactics for publication extenders	Inter-article comparability is a challenge
	Variable by trial design, disease area, publication type and stage in life cycle	Can integrate sentiment analysis	Require access to proprietary scoring systems
	Inter-article comparability is a challenge		

Table 2. Examples of data sources for use as article-level metrics.

Sources: Adapted from Haustein, 2016 and Taylor, 2023 [9,16].

Attention source	Examples
Social networks	Facebook, ResearchGate
Journal websites	<i>F1000, PLoS One</i>
Reference management software	Mendeley
Social data sharing	Figshare, MedShr, Kudos
Blogging	Wordpress, ResearchBlogging
Microblogging	Twitter, Weibo
Wikis	Wikipedia
Recommendations and reviews	F1000Prime, Reddit, Stack Exchange
Academic publications	Citations logged by CrossRef, Web of Science, Scopus, or Google Scholar
Collaboration platforms	hypothes.is
News sources	BBC News, CNN
Article views	-
Article downloads	-
Policy citations	-
Patent citations	-

Table 3. Overview of metrics sets and typical metrics by medium.

Medium	Level of focus	Metric set	Typical metrics
Journals	Comprehensive (e.g., therapy area)	Journal-level metrics	Journal Impact Factor, Eigenfactor Score, Immediacy Index
Publications	Focused (e.g., safety and efficacy)	Article-level metrics	Citations, downloads, article-level attention scores
Extenders	Detailed (e.g., primary efficacy and safety only)	Content performance metrics	Number of visitors, time on page, downloads, traffic sources, organic search traffic

Table 4. Default weightings of attention sources used to calculate the Altmetric Attention Score.

Source: Altmetric.com; reproduced with permission [25].

Attention source	Default weight	Attention source	Default weight
News	8	LinkedIn (not trackable since 2014, but historical data kept)	0.5
Blog	5	Twitter (tweets and retweets)	0.25
Policy document (per source)	3	Facebook (only a curated list of public Pages)	0.25
Patent	3	Reddit	0.25
Wikipedia	3	Pinterest (not trackable since 2013, but historical data kept)	0.25
Peer review (Publons, Pubpeer)	1	Q&A (Stack Exchange)	0.25
Weibo (not trackable since 2015, but historical data kept)	1	Youtube	0.25
Google+ (not trackable since 2019, but historical data kept)	1	Number of Mendeley readers	0
F1000	1	Number of Dimensions and Web of Science citations	0
Syllabi (Open Syllabus)	1		