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ORIGINAL RESEARCH ARTICLE

To Tweet or Not to Tweet: A Longitudinal Analysis of Social Media Use by Global Diabetes Researchers

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Abstract

Background Engaging influential stakeholders in meaningful exchange is essential for pharmaceutical companies aiming to improve care. At a time where opportunities for face-to-face engagement are limited, the ability to interact, learn and generate actionable insights through digital channels such as Twitter, is of considerable value.

Aim The aim of this study was to evaluate digital engagement among global diabetes mellitus researchers.

Materials and Methods We identified every global tweet (20,614,515) and scientific publication (44,135) regarding diabetes mellitus from 1 August 2018 to 1 August 2020. Through author matching we combined datasets, resulting in a list of digitally active scientific authors. Generalised linear modelling identified factors predicting their digital engagement.

Findings Globally, 2686 diabetes researchers used Twitter to discuss the management of diabetes mellitus, posting 110,346 diabetes-related tweets. As Twitter followers increased, so did tweet frequency ($p < 0.001$), retweets ($p < 0.001$) and replies ($p < 0.001$) to their content. Publication count (overall/per month) and proportion of first/last authorships were unrelated to tweet frequency and the likelihood of being retweeted or replied to ($p > 0.05$). Those with the most academic co-authors were significantly less likely to tweet than those with smaller networks (< 50; $p = 0.001$). Finally, those publishing most frequently on specific themes, including insulin ($p = 0.041$) and paediatrics ($p < 0.001$), were significantly more likely to tweet about these themes.

Conclusion Academic expertise and seniority cannot be assumed as proxies for digital influence. Those aiming to promote science and obtain digital insights regarding condition management should consider looking beyond well-known 'key opinion leaders' to perhaps lesser known 'digital opinion leaders' with smaller academic networks, who are likely to specialise in the delivery of highly specific content to captive audiences.

Plain Language Summary

Traditionally, research scientists and clinical experts in any field make their opinions and expertise known by writing academic journal papers. After successful peer review, they are accepted and made publicly available. However, during the coronavirus disease 2019 (COVID-19) pandemic, more scientific information has been shared and discussed using digital

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platforms such as Twitter than ever before, setting the stage for their greater role in scientific discussions in the future. It is important that the pharmaceutical industry is aware of this shift as it may offer up new insights and opportunities. Using diabetes as a test case, we compared researchers' publishing activity with their Twitter activity over a 2-year period. We found that less established researchers who are less well-known in their fields, and with less publications to their name, are far more likely to be active in sharing valuable scientific content to large Twitter audiences. This makes them 'opinion leaders' even if they would not be thought of as such in a traditional, academic sense, suggesting that those who look only to high-ranking academic journals, and those who publish within them, may be missing an important and ever-increasing part of the conversation. This is the first ever study to compare digital and traditional publishing activities and highlights the potential of this approach to gain novel and valuable knowledge about specific topics.

Key Points

The dissemination of scientific information has seen a move towards the use of digital platforms such as Twitter to reach wider and more varied audiences.

As such, there is a growing need to analyse both social content as well as academic content from key opinion leaders (KOLs) for a rounded view of the field, as is required by pharmaceutical Medical Science Liaisons (MSLs).

'Digital opinion leaders' (those most active and reaching the highest audiences on Twitter) were typically less well-established in the publishing sphere within their individual fields. They are critical to the scientific discourse and are important to consider alongside traditional 'key opinion leaders'.

1 Introduction

As the scientific face of a pharmaceutical organisation, Medical Affairs is uniquely positioned to develop and maintain external relationships, building credibility with key healthcare decision makers. In recent times, the role of medical affairs has evolved significantly, from origins as a support function to now representing a strategic pillar within organisational business units [1]. Because of their scientific expertise, Medical Science Liaisons (MSLs) have the unique opportunity to engage the most critical decision makers in meaningful peer exchange, to highlight unmet needs, identify practice gaps, support patient-centric endeavours, and bring the voices of stakeholders back to their organisations.

With increasing movement towards more complex pipelines, previously unknown modes of action, and the multidisciplinary management of disease [2, 3], there is now a need to interact with time-poor healthcare professionals (HCPs) in far greater clinical depth. Coupled with the greater accessibility of medical information by patients and the rise of the 'connected patient' and 'citizen science', this means HCPs require greater support from their MSLs than ever before. Recent restrictions on travel and face-to-face engagement during the coronavirus disease 2019 (COVID-19) pandemic, which are likely to persist into the foreseeable future, have undoubtedly hindered this process, but in doing so have also accelerated the movement towards a new era of patient-centric and digitally augmented processes [4, 5].

It is estimated that 29.1% of healthcare workers now use social media at least once a day to exchange medical knowledge with their peers, with 24.6% engaging multiple times a day [6]. In fact, stakeholder expectations are now for ever-greater digital engagement, as evidenced by the increasing utilisation of digital platforms for the purpose of peer-to-peer exchange and content sharing during scientific congresses [7–9]. This use of social media allows conference attendees to interact with one another and with their greater social networks with minimal barriers to conversation, facilitating the sharing of information and ideas. This was observed at the annual meeting of the American Society of Clinical Oncology (ASCO), which has seen an increase in tweets from 10,475 in 2012 [8] to 83,078 in 2019 (data from Twitter).

Publication history, guideline authorship, and symposia presentations have historically been the mainstay of understanding how engaged, interested or influential HCPs may be in a given therapeutic universe; however, digital media has provided a much-needed third dimension to augment our understanding of HCP interests and unmet needs. A survey in 2017 demonstrated that 87.9% of HCPs are now estimated to be using social media [10], up from 41% in 2010 [11], with estimates also suggesting that between 54 and 59% [10] of healthcare institutions surveyed also had a social networking policy.

Therefore, channel insights, and the ability to strategically plan, engage and deliver information via multiple channels (including Twitter, webinars, publications and symposia), is essential for medical departments. Understanding the engagement and impact of science on the various channels enables MSLs to deepen their understanding of real-world condition management. With HCPs frequently using Twitter for personal development and exchange of knowledge [12], scientific relationship management and the ability to proactively analyse HCPs' consumption of evidence across channels and over time may give medical affairs new opportunities. This will include deepening relationships, leveraging of novel information to create new avenues for collaboration and supporting better healthcare engagement and understanding of both patient and HCP needs.

While multichannel fluency is undoubtedly a critical step towards the future of pharmaceutical engagement, it is yet to be empirically explored in practice. This study examines the link between traditional (publications) and novel (digital) content dissemination and consumption among a group of diabetes researchers, including key opinion leaders (KOLs). Our main aim was to determine factors associated with digital engagement among diabetes HCPs. To address this, we asked the following questions: (1) can digital media be utilised as a means of both engagement and a source of customer insights; (2) are diabetes KOLs currently engaging with digital media; (3) can we identify predictors of digital engagement, and factors associated with increased sharing and commenting on digital content among diabetes HCPs?

2 Materials and Methods

2.1 Data Collection

A literature review was conducted in PubMed to identify all diabetes mellitus-related publications during the period 1 August 2018 to 1 August 2020. The search string used for this search is provided in Online Resource 1 Box S1. Using personal information, including author names (first, last and middle), previous and current institutions, and both city and country data, a list of unique academic contributors was created. This consisted of any individual who had been a contributing author to at least one diabetes mellitus-related publication during the study period.

Second, we identified all global tweets from the Twitter social media platform (San Francisco, CA, USA) regarding the subject of diabetes mellitus over the same period (1 August 2018–1 August 2020). Data were collected using the Brandwatch consumer research platform (Brighton, UK) with direct access to the Twitter application program interface (API). We collected data on all retweets and comments/replies related to diabetes Twitter content over this period, as proxies for content resonance and engagement, respectively. A combination of generic free-text terms (diabetes, diabetic, blood sugar, hypoglycaemia), in addition to product-specific terms (Novorapid®, Metformin®, Sitagliptin®) and class-specific terms (sodium glucose co-transporter 2 [SGLT-2] inhibitor, glucagon-like peptide-1 [GLP-1] inhibitor, thiazolidinediones), were used to identify tweets related to the management of diabetes. In total, three reviewers contributed and cross-checked the search strings used for both the literature review and the Twitter search. A complete list of all terms used for the Twitter search can be found in Box S2 in Online Resource 1. The Twitter search was supplemented by adding all tweets that included hashtags specific to diabetes scientific conferences and symposia. Relevant conferences were identified following a 2-year retrospective analysis where hashtags retrieved from the primary Twitter search were summed by frequency. They were then filtered to include only those mentioned within 50 words of the terms 'symposia', 'congress', 'conference' or 'scientific events'. Following this process, any tweet containing hashtags related to the following diabetes conferences were included: (1) European Association for the Study of Diabetes (EASD); (2) International Society of Paediatric and Adolescent Diabetes (ISPAD); and (3) American Diabetes Association (ADA). Once all tweets regarding diabetes mellitus were obtained, a list of unique identifiers (Twitter handles) was extracted in order to identify all unique contributors of diabetes-related social media content over the study period.

2.2 Linking Bibliometric and Social Media Data

Once the Twitter data and publication data were combined, we subsequently refined the list of all diabetes mellitus-related tweets to only include those published by individuals with at least two diabetes mellitus-related scientific publications. This ensured the analysis only captured those who were both digitally and academically active with regard to the management of diabetes mellitus. At this point, we used the Brandwatch API to obtain data regarding the following: (1) total number of diabetes tweets; (2) number of Twitter followers; (3) number of retweets; and (4) number of comments and replies, and Twitter biography. Finally, the textual content of both tweets and scientific publications (titles and abstracts) were segmented using rapid automatic keyword extraction. These corresponded to either clinical, outcome-based or treatment-related areas of interest within diabetes, including insulin, glycosylated haemoglobin A1c (HbA1c), self-management of blood glucose (SMBG), and type 1 versus type 2 (diabetes). A full list of all search strings utilised is provided in Box S2 in Online Resource 1.

2.3 Statistical Analysis

Generalised linear regression modelling, with a gamma error distribution and log-link, was used to explore whether the healthcare stakeholders' information (scientific activity, social media activity or geographical, as explained below) significantly predicted digital engagement. The primary outcome and dependent variable was the total number of diabetes mellitus-related original tweets, with secondary outcomes including engagement in diabetes mellitus-related conversations on Twitter (i.e., number of replies) and information propagation (i.e., retweets). Covariates included within the regression model included academic and social indicators. Academic indicators were (1) number of first or last authorships; (2) number of co-authors over the study period; (3) total diabetes-related publications; (4) publications per month; (5) proportion of first/last authorships as a percentage of overall publication count; and (6) publication impact factor. Impact factors are often used within research to denote average annual citations of scientific articles published in given journals, however increasing attention is being paid to ranking the research outputs of individuals, in order to provide estimations of impact or influence, within a given scientific research environment. The impact factor used in this analysis was a weighted sum of all publications since 2010 and therefore reflected the overall research impact of each author. We calculated individual-level impact factors by summing all publications in the period and providing a point for each publication, with first or last authorships receiving additional points. We additionally applied a logarithmic time penalty such that points awarded for publications from 5 years ago were discounted compared with those published 3 years ago, and those discounted from those published today. Totals were calculated for each author and normalised between 0 (lowest collective research output over the past 10 years) to 100 (highest research output).

Social media indicators were (1) number of Twitter followers and (2) number of tweets to date and geographical data to the country level. Because several prior studies have demonstrated that the gamma family with a log error link is not only robust but also the most applied approach for datasets in which non-negative and skewed data are guaranteed [13, 14], such as in the case with tweet data, our analysis also assumed a gamma error distribution with log link. Subgroup analyses explored the relationship between scientific and digital content dissemination, and whether those with a prior history of publishing on specific themes, including SMBG, type 1 versus type 2, etc., are also more likely to post digital content on these themes compared with those who do not specialise in publishing research related to these themes.

3 Results

3.1 Characteristics of the Study Population

Figure 1 shows a schematic of the study design. In total, 44,135 publications focusing on diabetes mellitus were identified during the study period, authored by 141,032 unique authors globally. Over the same period, data were collected on 20,614,515 diabetes mellitus-related tweets. These constituted 4,869,492 original tweets, 12,347,321 retweets and 3,397,702 replies and comments. Tweets were published by a total of unique authors, consisting of but not limited to diabetologists and endocrinologists, general practitioners, patients, medical organisations and medical journals. Following author matching of tweets and publication data, a total of 2686 unique global HCPs were identified who had published both at least one diabetes-related scientific manuscript and at least one diabetes-related tweet during the 2-year study period, details of which are provided in Table 1. Those included published a mean of 13 diabetes-related manuscripts over the 2-year study period (range 2–469), with an average of five first or last authorships (range 0–192) and 157 co-authors (range

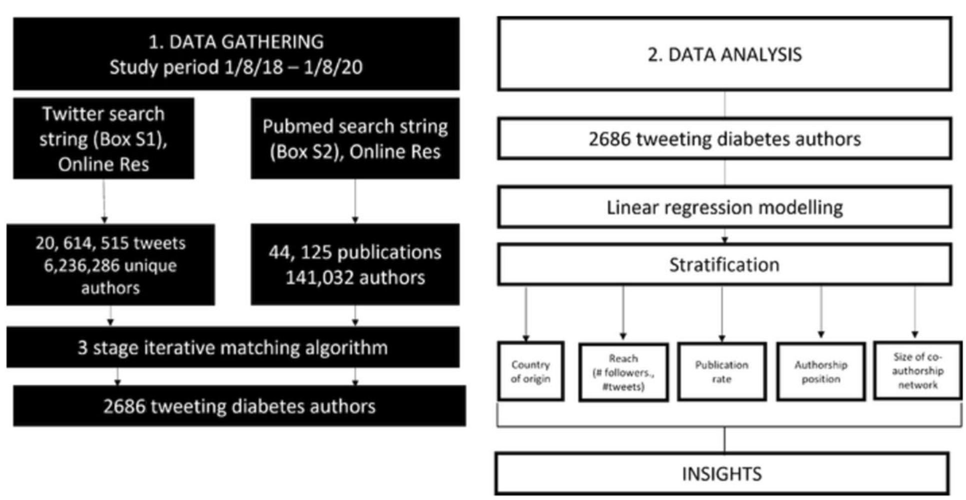

Fig. 1 Schematic of the study design

Table 1 Characteristics of the study cohort

	Mean	SD	Minimum	Maximum
Twitter indicators				
Length of Twitter account activity (months)	84.5	38.1	0.3	164
Total diabetes-related tweets	41.1	189.8	1	5876
Retweets	23.3	82.4	0	1533
Original posts	14.0	79.5	0	2457
Comments and replies	6.8	63.5	0	2858
Number of times author has been retweeted by others	4.6	51.4	0	1592
Number of times author has been replied to by others	1.6	16.1	0	626
Total number of Twitter followers	1931	10,331	0	359,752
Bibliometric indicators				
Total scientific publications	13	27	2	469
Publications/month	1	1	0.1	20
First/last authorships	5	11	0	192
Diabetes co-authors	157	686	0	6271

SD standard deviation

0–6271). Similarly, those included had been active using Twitter for a mean 84.5 months (range 0.3–164), posting 41.1 tweets (range 0–5876) to 1931 Twitter followers each (range 0–359,752).

3.2 Who is Most Likely to Publish Original Tweets Regarding Diabetes Management?

Those with a greater number of Twitter followers demonstrated a greater likelihood of publishing diabetes-related Twitter content. Compared with those with fewer than

Table 2 Factors associated with the likelihood of publishing original Twitter content

	Exp (b)	Std error	Z score	*p*-Value	95% CI (low)	95% CI (high)
Twitter characteristics						
Age of Twitter account (months)	0.994	0.001	−4.420	0.000	0.992	0.997
Followers						
251–500	2.012	0.347	4.060	0.000	1.435	2.820
501–2000	4.187	0.616	9.730	0.000	3.137	5.587
2001–5000	6.894	1.696	7.850	0.000	4.257	11.166
5001–10,000	14.130	4.079	9.170	0.000	8.024	24.882
10,000+	12.495	8.299	3.800	0.000	3.399	45.926
Bibliometric characteristics						
Publication impact factor	1.024	0.007	3.280	0.001	1.010	1.039
Total publications	1.010	0.007	1.410	0.159	0.996	1.024
Publications/month						
1–3	0.778	0.190	− 1.030	0.302	0.482	1.254
4–6	0.420	0.290	− 1.260	0.209	0.109	1.626
7+	0.450	0.688	− 0.520	0.601	0.022	8.998
First/last authorships per month						
1–2	1.490	0.404	1.470	0.141	0.877	2.534
2–3	3.379	2.614	1.570	0.116	0.742	15.388
4+	0.789	0.642	−0.290	0.771	0.160	3.889
Publication co-authors						
50–100	0.520	0.090	− 3.760	0.000	0.370	0.731
101–200	0.577	0.163	− 1.950	0.049	0.332	1.003
201+	0.477	0.103	− 3.430	0.001	0.313	0.728

CI confidence interval, *Exp (b)* exponentiated GLM co-efficient, *Std* standard

250 Twitter followers, those with 501–2000 followers were fourfold more likely to publish original content, while those with more than 5001 followers were between 14.1 and 12.5-fold more likely to publish diabetes-related content via Twitter (Table 2). Those publishing a greater number of diabetes-related publications were no more likely to post diabetes content via Twitter than those with fewer publications ($p = 0.159$). Interestingly, those publishing more than seven publications per month, who may be considered 'KOLs', were significantly less likely to publish content via Twitter than those publishing at a rate of fewer than one per month ($p = 0.022$).

A typical indicator of academic responsibility and experience are the primary and final (lead) positions on the author list. In line with the previous results, we found that first/last authorship position had no statistically significant relationship with the likelihood of posting diabetes-related Twitter content. Those with 1–2 ($p = 0.141$), 2–3 ($p = 0.116$) and 4+ ($p = 0.771$) first/last authorships per month were equally as likely to post Twitter content as those with fewer than one first/last author publications per month. Finally, publication co-authors, an indicator of how well-known and well-networked a researcher is, demonstrated a significant negative association with the posting of Twitter content. Those with 50–100, 101–200 and 201+ co-authors were 48% ($p < 0.001$), 42.3% ($p = 0.049$), and 52.3% ($p = 0.001$) less likely to publish diabetes-related Twitter content, respectively, than those with fewer than 50 research co-authors.

3.3 Who is Most Likely to Retweet Content or Have Their Content Retweeted by Others?

Again, those with greater numbers of Twitter followers were significantly more likely to both retweet others' content (Table S1, Online Resource 1) and have their own content retweeted by others. Even those with 250–500 followers were 4.2-fold more likely to have their content retweeted than those with fewer than 250 followers, reaching a maximum of a 36.9-fold increase for those with 5001–10,000 Twitter followers (Table 3). Conversely, those with a greater number of first and last authorships and co-authors were no more likely to have their diabetes-related Twitter content shared than those with fewer co-authors or first and last authorships (Table 3).

Table 3 Factors associated with the likelihood of being retweeted by others

	Exp (b)	Std error	Z score	*p*-Value	95% CI (low)	95% CI (high)
Twitter characteristics						
Age of Twitter account (months)	1.000	0.002	0.230	0.817	0.997	1.004
Followers						
250–500	4.197	1.215	4.950	0.000	2.380	7.403
501–2000	6.075	1.043	10.510	0.000	4.339	8.505
2001–5000	16.250	4.087	11.090	0.000	9.926	26.602
5001–10,000	36.876	12.416	10.710	0.000	19.062	71.340
Followers (10,000+)	34.987	26.087	4.770	0.000	8.114	150.860
Bibliometric characteristics						
Publication impact factor	1.048	0.009	5.540	0.000	1.031	1.065
Total publications	1.004	0.006	0.730	0.468	0.993	1.015
Publications/month						
1–3	0.780	0.243	− 0.800	0.425	0.424	1.436
4–6	0.129	0.075	− 3.52	0.000	0.041	0.403
7+	0.174	0.209	− 1.46	0.145	0.016	1.829
First/last authorships per month						
1–2	0.780	0.243	− 0.800	0.425	0.424	1.436
2–3	0.129	0.075	− 3.520	0.000	0.041	0.403
4+	0.174	0.209	− 1.460	0.145	0.017	1.829
Publication co-authors						
50–100	0.567	0.152	− 2.120	0.034	0.335	0.958
101–200	0.861	0.320	− 0.400	0.687	0.416	1.783
201+	1.451	0.522	1.030	0.301	0.717	2.937

CI confidence interval, *Exp (b)* exponentiated GLM co-efficient, *Std* standard error

3.4 Who is Most Likely to Comment on Content or Have Their Content Commented on by Others?

Those publishing the most scientific content were significantly less likely to have their diabetes-related Twitter content commented on and replied to by others, with those publishing 1–3 and 4–6 publications per month experiencing a 69.8% and 91.8% reduction in comments and replies, respectively, versus those publishing fewer than one scientific publication per month (Table 4). Similarly, the most academically active individuals were also significantly less likely to interact with others' content and offer opinions and commentary, as demonstrated in Table 5. Those publishing 1–3, 4–6 and 7+ scientific research publications per month were 57.8% ($p = 0.015$), 86.7% ($p = 0.011$) and 90.4% ($p = 0.051$) less likely to provide opinions on others diabetes-related Twitter content than those publishing fewer than one publication per month.

3.5 Are Those Who Publish Most Often on Specific Themes Most Likely to Tweet About Them Also?

Those publishing research on the topic of insulin were significantly more likely to tweet about insulin also ($p = 0.049$), with each additional insulin publication resulting in 1.192 additional insulin-related tweets. The effect in paediatrics was far greater, with each additional paediatric publication resulting in an additional 1.796 paediatric tweets ($p = 0.031$), with a first or last authorship resulting in an additional 0.641 tweets ($p = 0.083$). As demonstrated in Table 6, a similar relationship was also observed with respect to type 1 diabetes, with each additional type 1 diabetes publication resulting in an additional 1.253 type 1 diabetes tweets ($p = 0.045$). Finally, total publications, first and last authorship, publications per month and total number of academic co-authors an HCP has were all unrelated to digital engagement at conferences, suggesting that high impact 'KOLs' are no more likely to promote and respond to content at conferences than lesser known HCPs.

4 Discussion

4.1 Summary of Principal Findings

This first-of-its-kind study reports on the largest and most comprehensive analysis to date to assess the factors associated with social media engagement among global

Table 4 Factors associated with the likelihood of being replied to or commented on by others

	Exp (b)	Std error	Z score	*p*-Value	95% CI (low)	95% CI (high)
Twitter characteristics						
Age of Twitter account (months)	1.004	0.002	1.980	0.047	1.000	1.009
Followers						
250–500	6.610	2.438	5.120	0.000	3.208	13.619
501–2000	9.252	2.383	8.640	0.000	5.585	15.328
2001–5000	20.607	5.446	11.450	0.000	12.276	34.592
5001–10,000	90.426	31.938	12.750	0.000	45.254	180.688
10,000+	22.994	14.257	5.060	0.000	6.821	77.512
Bibliometric characteristics						
Publication impact factor	1.045	0.011	4.340	0.000	1.025	1.066
Total publications	1.000	0.006	0.070	0.947	0.989	1.012
Publications/month						
1–3	0.302	0.117	− 3.100	0.002	0.142	0.643
4–6	0.082	0.067	− 3.040	0.002	0.016	0.410
7+	0.090	0.137	− 1.590	0.112	0.005	1.759
First/last authorships per month						
1–2	2.600	1.048	2.370	0.018	1.181	5.727
2–3	2.069	1.616	0.930	0.352	0.448	9.561
4+	1.113	1.063	0.110	0.911	0.171	7.235
Publication co-authors						
50–100	0.846	0.242	− 0.580	0.559	0.483	1.483
101–200	1.191	0.485	0.430	0.668	0.536	2.646
201+	1.102	0.545	0.200	0.844	0.419	2.903

CI confidence interval, *Exp (b)* exponentiated GLM co-efficient, *Std* standard

Table 5 Factors associated with the likelihood of replying to or commenting on others' content

	Exp (b)	Std error	Z score	*p*-Value		95% CI (low)	95% CI (high)
Twitter characteristics							
Age of Twitter account (months)	1.004	0.002	2.470	0.013		1.001	1.007
Followers							
250–500	1.532	0.558	1.170	0.242		0.750	3.127
501–2000	3.732	1.371	3.580	0.000		1.816	7.668
2001–5000	7.190	2.656	5.340	0.000		3.486	14.832
5001–10,000	28.349	12.315	7.700	0.000		12.099	66.423
10,000+	17.208	13.329	3.670	0.000		3.771	78.528
Bibliometric characteristics							
Publication impact factor	1.011	0.012	0.940	0.349		0.988	1.034
Total publications	1.011	0.008	1.380	0.166	0.996		1.026
Publications/month							
1–3	0.422	0.150	– 2.430	0.015	0.211		0.846
4–6	0.133	0.105	– 2.550	0.011		0.028	0.625
7+	0.096	0.134	– 1.680	0.050		0.006	1.475
First/last authorships per month							
1–2	2.247	0.846	2.150	0.032		1.074	4.702
2–3	1.075	0.545	0.140	0.887		0.397	2.906
4+	0.486	0.448	– 0.780	0.434		0.080	2.959
Publication co-authors							
50–100	0.681	0.168	– 1.550	0.120		0.419	1.106
101–200	0.862	0.266	– 0.480	0.629		0.470	1.578
201+	0.827	0.312	– 0.500	0.615		0.394	1.734

CI confidence interval, *Exp (b)* exponentiated GLM co-efficient, *Std* standard

diabetes researchers. The dataset included 20,614,515 tweets and 44,125 scientific publications, authored by 2686 unique global diabetes researchers over a 2-year period. We demonstrated that among digitally activated diabetes researchers, diabetes-related tweet rates were over three times greater than diabetes-related publication volumes. While researchers on average benefited from 157 academic co-authors, they also had an average of 1931 Twitter followers, suggesting digital media may improve the reach of their research. Those with the most followers had a significantly greater likelihood of publishing diabetes-related Twitter content and having this content shared and commented on by others in the diabetes scientific community. Furthermore, those who published the most academic publications regarding specific topics, including type 1 versus type 2 diabetes, insulin, and paediatrics, were also significantly more likely to tweet about these subjects compared with others with lower publication volumes. Interestingly, those with the greatest number of academic co-authors, those with the most first and last authorships, and those publishing the most research (all proxies for research experience and authority) were no more likely to post diabetes content via Twitter (both during and outside of conferences) or have their content commented on or shared than those with fewer publications, first or last authorships or co-authors, respectively. Finally, those most likely to be classed as 'KOLs', with the most publications per month, were significantly less likely to use social media, and when they did, they were significantly less likely to have their content commented on and shared.

4.2 Strengths and Limitations of the Study

The strengths of this study include the vast and novel dataset that was compiled and used for the analysis, which included the identification of over 20 million tweets and 44,000 diabetes-related publications, which were then mapped to 2686 specific global diabetes researchers. To date, no prior study has compared the bibliometric and social media use patterns at an individual level by linking bibliometric and social media records, especially so within a healthcare setting. This study therefore provides previously unreported findings from a novel research methodology, examining the factors predicting digital engagement among those publishing research in the therapeutic area of diabetes.

Table 6 Link between academic interests and Twitter interests

	Insulin tweets	Paediatric tweets	Type-1 tweets	Type-2 tweets	Outcomes tweets	Conference tweets
Twitter characteristics						
Age of Twitter account (months)	1.001	1.001	1.001	1.000	1.000	1.006
Followers (250–500)	0.962	1.526**	1.086	1.832*	1.481*	0.970
Followers (501–2000)	2.322*	2.249*	1.800*	3.209*	3.342*	2.168*
Followers (2001–5000)	2.957*	2.513*	1.494	4.207*	4.602*	7.093*
Followers (5001–10,000)	9.343*	5.223*	5.607*	9.932*	8.654*	15.154*
Followers (10,000 +)	4.149*	2.443*	1.338	1.955*	1.810*	1.181
Bibliometric characteristics						
Publication Impact Factor	1.009	1.025*	1.036*	1.029*	1.021*	1.035
Total publications	1.011	0.996	1.014	0.997	1.006	1.013
Publications/month (1–3)	0.522**	0.664	0.312*	0.527*	0.535*	0.583
Publications/month (4–6)	0.176*	0.066*	0.039*	0.415	0.129*	0.080
Publications/month (7+)	0.095	0.080	0.057	0.778	0.156	0.057
First/last authorships per month (1–2)	2.631*	2.466*	1.433	1.472	2.095*	1.551
First/last authorships per month (2–3)	6.757*	102.423*	8.021*	1.795	8.329*	9.258
First/last authorships per month (4+)	1.110	21.867*	0.357	1.326	1.335	0.372
Publication co-authors (50–100)	0.744	0.524*	0.426*	0.864	0.814	0.695c
Publication co-authors (101–200)	0.952	1.104	1.062	1.377	1.502	0.863
Publication co-authors (201 +)	0.629	0.836	1.075	1.707	1.318	1.071
Bibliometric interests						
Total T1DM publications	1.028	0.868	1.253*	0.950	1.050	0.881
T1DM first/last authorships	1.046	1.361	1.192	1.020	0.902	1.619*
Total T2DM publications	1.102	1.079	0.998	1.044	0.886*	0.945
T2DM first/last authorships	0.896	1.059	1.142	1.295*	1.144	1.134
Total paediatric publications	0.989	1.796*	0.881	0.995	0.990	0.942
Paediatric first/last authorships	0.616**	0.641**	0.802	0.577*	0.562*	0.611
Total insulin publications	1.192*	1.009	0.947	1.207**	0.971	1.334*

Table 6 (continued)

	Insulin tweets	Paediatric tweets	Type-1 tweets	Type-2 tweets	Outcomes tweets	Conference tweets
Insulin first/last authorships	1.053	0.974	1.267	0.866	1.230	0.638
Total outcomes publications	0.823*	0.916	0.912	0.902*	1.142*	1.006
Outcomes first/last authorships	1.059	0.888	0.825**	0.870	0.889	0.867

*Denotes statistical significance ($p < 0.05$), ** denotes numerical significance ($0.05 < p < 0.1$)

T1DM type-1 diabetes mellitus, *T2DM* type-2 diabetes mellitus

There are also several weaknesses of this study that should be considered. First, while every effort was made to ensure that the majority of digitally active diabetes publishers were included, we cannot guarantee this. We used a data collection period of 2 years. It is plausible that otherwise frequent academic publishers may have experienced a lull or a sabbatical over this period, including parental leave or investment in longer-term research, including randomised controlled trials (RCTs), which may have temporarily reduced their publication volume and therefore omitted them from the analysis. Similarly, while retweet and comment rates were considered for digital mentions, no metric for the success of, reach, or interest in academic publications was included. Use of Altmetric or similar measures of publication interest may have added to the analysis by providing another dimension to the academic outputs analysed.

Second, as the purpose of this study was to compare bibliometric and social media use among those using both channels, the study cannot and did not identify factors leading to increased frequency of use among those currently only communicating via social media. These individuals who are disproportionately more likely to be at an earlier point in their careers and who are yet to be named as co-authors on diabetes-related academic manuscripts may have been missed as a result of the prerequisite to have published at least one scientific manuscript. Another limitation resulting from this is the lack of recognition of a potential confounding variable, digital influence. Social network analysis may have highlighted who was most digitally influential and used this as a variable in predicting Tweet, retweet and comment rates. Further research should aim to determine the role of social influence in digital activity.

Finally, while the rapid automatic keyword extraction algorithm used to identify and tag diabetes-related mentions was highly sensitive and was based on approximately 300 search terms in total (Box S1, Online Resource 1), including patient outcomes and brand names (including market variations), we cannot guarantee that all mentions were retrieved and included in the analysis. This is particularly likely where patients and/or HCPs used abbreviations or commonly known shorthand for treatments or outcomes under consideration, or in the event of spelling errors. However, there is no reason to believe that this may have affected any one aspect of the analysis more than any other, therefore making it unlikely to affect the analysis, as, in the event that mentions were omitted, these were likely to be missing at random.

4.3 Contextual Interpretation

The findings of several previous studies not specific to diabetes have suggested that HCPs often use social media to refer to experts or 'KOLs' for better decision processes and outcomes [15–17], enabling access to KOLs and their opinions that may not have otherwise been possible. However, our findings do not agree with this suggestion presented in previous studies. Rather, we learned that all things being equal, not only do the most frequently and influential HCPs use social media less often but when they do they are significantly less likely to have their content shared or interacted with by the diabetes scientific community. The reasons behind this finding may be several. First, the prior studies referred to, although among the most recent examining KOL influence, took place between 2006 and 2012. It is therefore possible that in the time since these publications, scientific communities have improved and matured, and observed that useful scientific information is not solely produced by the most influential and well-published. Second, the lack of engagement with digital content provided by KOLs could be a natural side effect of not wanting to say the 'wrong thing' or provide an opposing opinion to persons of influence. Third, it is likely that given the lower utilisation of digital media by high-publishing HCPs, they have put less effort into cultivating their digital networks. The number of followers a researcher has on Twitter was consistently shown to be predictive of both retweet and comment rates, therefore assisting higher-publishing researchers in growing their digital networks may prove useful in ensuring that their messaging is more widely received.

This finding that the most established and highest-publishing HCPs were less likely to utilise social media for the purposes of networking, sharing knowledge and engaging in continued medical education, agrees with the findings of previous studies [18, 19]. A recent survey highlighted that 29.1% of healthcare workers use social media once a day to exchange medical knowledge with their peers, with 24.6% using it multiple times a day [6].Another recent study demonstrated that HCPs typically spend 1 h per day using social media, with those under the age of 40 years far more involved than those above 40 years of age ($p < 0.05$) [10]. The factors driving social media use among HCPs have been extensively researched, and the perceived usefulness of content provided via digital media has previously been shown to be a key predictor of social media use [6]. Among those earlier in their careers, a lot can be learned from social media and from the views of more experienced researchers, which in essence can create a virtual network resembling a living advertisement board. This engaging medium has enormous potential for establishing relationships and disseminating information among physicians, their colleagues, and patients [19]. Previous studies have shown that these 'virtual communities of practice' are a key factor in drawing HCPs into using digital media, with improved knowledge sharing among colleagues just one of the benefits of these groups [20]. One key disadvantage to date has been that many of these online groups are closed and private, confining knowledge to specific users and preventing the dissemination of information within a multidisciplinary environment to help improve performance and outcomes. However, the use of open Twitter virtual communities is likely a significant draw, especially to researchers who still have a lot to learn.

Simplistically assuming age as a proxy for experience, this should be considered when planning digital interactions and performing market landscaping, as it is likely to be the lesser-known HCPs who will provide the greatest volume of insights from a digital listening perspective, and also most likely to consume and share any content provided by industry. Digital media is therefore likely to continue to increase in popularity and relevance, especially as current medical students and early-career HCPs, who are generally more digitally engaged [10, 21], continue their careers into more senior and influential roles. As digital becomes more of a mainstay of scientific communication, engaging with and maintaining awareness of the beliefs of these digitally active HCPs may not only provide a significant medical return on investment but also quantify this return with direct linked metrics. This may be of particular value from a future brand planning and lifecycle management perspective, particularly in identifying and communicating practice gaps, which may provide support to convince government health divisions to take action and update clinical practice guidelines.

As the world transitions from the current COVID-19 landscape, it is apparent that hybrid attendance at conferences is becoming increasingly popular and is unlikely to change any time soon [1]. Digital involvement in these events not only reduces financial costs for those attending but also increases access for those who are looking after children or family, or in fact from more remote locations, who are equally in need of keeping on top of the most up-to-date science. Previous evidence has shown that the use of open online platforms and virtual communities such as Twitter is gaining popularity at health care conferences by allowing attendees to interact with one another and with their greater social networks, facilitating the sharing of information and ideas [7]. The ASCO annual meeting saw an increase in tweets from 10,475 in 2012 to 44,034 in 2014 [8] and 83,078 in 2019 (Twitter data). Our study included tens of thousands of mentions from the ADA and EASD conferences. We found that contrary to 'outside conference', there was no significant difference in digital engagement among researchers of all types. Whereas outside of conferences it was lesser known, and lesser published HCPs who were most likely to be digitally active, during conferences this gap reduced, suggesting that KOLs save their digital media use for these big events but are less likely to engage outside of events. This can be interpreted in one of two ways. First, that medical and commercial teams should acknowledge the different times when HCPs utilise digital media, allowing an evidence-based means of collecting HCP perspectives over time, and second, that industry should consider branching out to lesser-known HCPs for the purposes of symposia and presentations, as they are equally likely as KOLs to promote (and be promoted) at events.

5 Conclusions

The use of digital media by HCPs is significantly increasing year on year and this is the first analysis to explore the link between bibliometric and digital activity on a global medical scale. The findings clearly demonstrate significant digital engagement among publishing diabetes researchers, signifying an opportunity to leverage this communication channel both during and beyond the COVID-19 pandemic. Types of tweets correlated strongly with academic interests, suggesting that segmentation may play a key role in determining who is likely to post and absorb specific 'types' of content. Furthermore, those with the greatest academic expertise (higher publication counts, higher first and last authorships, and larger co-authorship networks) were no more likely to engage with digital content or have their own content shared or commented on than less established researchers. It was these less established researchers who were less well-known in their fields and with fewer publications to their name who were far more likely to be active in sharing valuable scientific content to large Twitter audiences. This makes them 'opinion leaders' even if they would not be thought of as such in a traditional, academic sense. As such, those looking to promote science and monitor or learn from digital scientific content should consider looking beyond the typical 'high-impact' well-known academic experts to perhaps lesser known 'digital opinion leaders' with smaller networks, who are likely to specialise in the delivery of highly specific content to captive audiences.

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Author Contributions SL devised the study and acts as guarantor for the manuscript. He also supervised the collection of data. JI, DW, MN and SL helped collect the data. SL and JI performed data cleaning, and planned and performed all statistical analyses. FP advised on additional analyses. SL and FP wrote the first draft of the manuscript and revised and approved the final manuscript as submitted. All authors helped draft the manuscript and approved the final submitted version.

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