



Social Web Coverage and X Attention to Library and Information Science Research: An Altmetric Analysis

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Abstract:

Online attention to library and information science research is often described through aggregate scores, although these can conceal substantial differences in the publications reached and the sources through which attention develops. This study examines 1,792 DOI-identified publications from five journals, published between 2015 and 2024. It measures recorded attention coverage, describes X participation, and ranks publications using the Altmetric Attention Score and a corpus-specific 90th-percentile threshold. A total of 853 publications had positive scores, giving coverage of 47.60%. X (formerly Twitter) covered 618 publications, or 34.49%, and generated 2,411 summed publication-user counts. Among X-covered publications, the median was two users and 87.38% attracted no more than five. One publication accounted for 19.49% of the X total. The 90th-percentile score was 6.064. Retaining all boundary ties produced a group of 181 publications, representing 10.10% of the corpus and 77.03% of its aggregate score. Nine of the ten highest-scoring publications had news mentions, whereas the most tweeted publication had none. These findings distinguish widespread but usually modest X participation from the source profiles associated with high composite scores. The study supports reporting coverage, conditional intensity, and source composition together for each journal and cohort. Its estimates describe the supplied journal corpus and the attention recorded by the provider. User counts cannot establish the depth, sentiment, or societal consequences of discussion.

Keywords: altmetrics; library and information science; X (formerly Twitter); social web; Altmetric Attention Score; publication ranking; percentile analysis

1 Introduction

Research in library and information science addresses questions that extend well beyond the academic journal. Studies of reading, information access, misinformation, digital literacy, and professional practice may interest librarians, educators, journalists, and the communities they serve. Following the circulation of these studies on the social web can therefore reveal aspects of research visibility that citation counts alone do not describe. The difficulty lies in deciding what the available traces actually tell us. A paper mentioned by one Twitter account, discussed in several news reports, or referenced in a policy document has entered different communication settings. Treating these events as interchangeable obscures their meaning.

Altmetrics developed partly in response to the need for a wider view of scholarly communication. Subsequent research has shown that the indicators grouped under this term differ in coverage, timing, and the activities they record (Haustein, 2016; Sugimoto et al., 2017). Their value depends on a close correspondence between the research question and the indicator selected. A count of accounts mentioning a paper is useful for describing recorded participation. It cannot, by itself, show that participants read the paper, understood its findings, or used them in professional decisions. Similar care is needed when interpreting a composite attention score.

Three questions are particularly relevant to LIS. First, how widely are publications represented across the sources monitored by an altmetric provider? Second, how much Twitter participation surrounds the publications that receive attention there? Third, which publications occupy the upper end of the attention distribution, and what kinds of attention distinguish them? These questions are related, but each requires a different denominator and interpretation. Coverage concerns the proportion of publications with recorded activity. Intensity concerns the amount associated with a publication. Ranking describes relative position within a specified collection.

The distinction matters because a small number of conspicuous publications can dominate aggregate totals. A journal may accumulate a substantial volume of attention while most of its papers receive little or none. Conversely, attention may be spread across many papers at a low level. Neither pattern is adequately described by a total alone. The same problem arises when a publication cohort contains an exceptional paper whose Twitter audience is much larger than that of its peers. An apparently impressive annual total may then reflect a single event rather than a general widening of participation.

This article brings coverage, X participation, and publication ranking into one descriptive analysis of five LIS journals. The corpus contains publications dated 2015-2024 and provides article-level scores alongside source-specific counts. The analysis retains publications without recorded positive attention, reports Twitter intensity among covered papers, and identifies the upper attention group using the 90th percentile of the complete corpus. Source profiles are then used to interpret the leading publications and the percentile group. This approach keeps the ranking connected to the communication activities from which the score derives.

The contribution is a detailed account of how different forms of visibility coexist within the same journal collection. The study does not treat these five journals as a representative sample of the entire discipline. Nor does it infer the quality of research from its popularity. Instead, it asks what a reader can reasonably conclude from the recorded distribution. The results show why social-media coverage, a large X audience, and a high Altmetric Attention Score should be reported as distinct observations, even when they concern the same publications.

2 Related literature

Coverage and the meaning of attention

Early cross-disciplinary investigations established that altmetric coverage varies substantially by source and field. Zahedi et al. (2014) demonstrated the unequal presence of different indicators across publications, while Costas et al. (2015) examined their relationship with citations and their potential as complementary evidence. These studies helped move the discussion beyond the assumption that any available online count represents the same form of influence. For a coverage study, their practical implication is that the source, publication set, and observation window must accompany the percentage being reported.

Later evidence confirmed the persistence of uneven coverage. Fang, Costas, et al. (2020) examined nearly 12.3 million Web of Science publications and found that most altmetric sources remained comparatively sparse, with Mendeley and Twitter showing much wider presence. Such findings provide a useful context for LIS, but they do not supply a benchmark that can be transferred unchanged to a small journal collection. Differences in publication year, document type, DOI availability, and inclusion criteria affect the population to which a coverage rate refers.

Within LIS, Erfanmanesh (2017) examined social-web presence and highly mentioned publications in Scopus-indexed journals. Chingath and Hanumanthappa (2024) subsequently investigated the presence of LIS outputs across sources using Altmetric Explorer. Both studies demonstrate the relevance of examining platform distribution and journal differences. Their results also illustrate why published percentages require close attention to the sampling frame. A collection assembled from records already tracked by an altmetric service answers a different coverage question from a publication list that also retains records without positive attention.

X (formerly Twitter) participation and discussion

Twitter offers an observable route through which research is circulated, but its counts can refer to different units. Haustein et al. (2014) showed that tweeting patterns vary across journals and specialties. Research on diffusion subsequently demonstrated that similar mention totals can arise from different network structures (Alperin et al., 2019). These observations caution against treating the number of users or posts as a complete description of communication. The connections among participants and the content of their contributions also matter.

User behaviour further complicates interpretation. Mohammadi et al. (2018) investigated the use of academic information on Twitter through a user survey, drawing attention to the people and purposes behind the activity. Fang, Costas, and Wouters (2022) distinguished likes, retweets, quotations, and replies when studying engagement with scholarly tweets. More recently, Shen et al. (2026) analysed scholarly conversations as connected exchanges. Together, this work supports a narrower interpretation of aggregate user counts as evidence of participation, with conversational depth requiring information about actual exchanges. The dataset records the number of X users (Tweeters) associated with each publication rather than the full text of individual posts or interactions. The analysis therefore focuses on the extent of participation on X, measured by how many users mentioned or shared a publication, and on how this attention was distributed across the articles in the dataset. In this study, the term “discussion on X” is used in this quantitative sense only. The available data do not show whether individual posts were supportive, critical, promotional, substantive, or automated; consequently, no attempt was made to interpret the content or sentiment of X activity.

Scores rankings and observation windows

The Altmetric Attention Score offers a convenient summary of recorded attention, but convenience does not remove the need to inspect its components. Gumpenberger et al. (2016) questioned the interpretation of a composite altmetric score, and Ortega (2019) examined difficulties in reproducing it. Altmetric’s own documentation describes a weighted indicator with additional scoring rules, rather than a simple sum of source counts (Altmetric, 2026a). A ranking based on this indicator is therefore a ranking under the provider’s scoring system, not an ordering of publications by a uniform number of communication events.

Time also affects the observations. Fang and Costas (2020) demonstrated differences in the accumulation speed of altmetric sources, while Taylor (2023) followed several sources over a longer period. Stability cannot be assumed either. Fang, Dudek, and Costas (2020, 2022) documented the volatility of Twitter data, and Arroyo-Machado and Torres-Salinas (2024) examined changes in attention scores for information and library science publications. A single extraction is best treated as a snapshot, with publication cohorts receiving unequal opportunities to accumulate different kinds of attention.

These measurement issues connect with a broader concern about research assessment. Tahamtan and Bornmann (2020) reviewed the uncertain relationship between altmetrics and societal impact, while Thelwall (2021) identified common errors in applying alternative indicators. The Leiden Manifesto similarly calls for transparent and context-sensitive use of research metrics (Hicks et al., 2015). For the present study, these principles favour a transparent percentile rule, explicit handling of ties, and interpretation of high-ranking publications through their recorded source profiles.

2.1 Objectives

The current study is based on three objectives:

- 1) to measure the recorded coverage and distribution of publications from the five LIS journals across social-web and related attention sources.
- 2) to analyse X participation through publication coverage, paper-level user counts, and the distribution of those counts.
- 3) to rank publications by Altmetric Attention Score and examine the publications at or above the 90th percentile, including the source profiles of the ten highest-scoring papers.

The analysis addresses these objectives within the supplied corpus rather than estimating discipline-wide prevalence.

3 Methods

Study corpus and data collection

The study examined research publications from five purposively selected Q1 journals in Library and Information Science (LIS) over the ten-year period from 2015 to 2024. The journals were selected to provide a focused corpus of established LIS outlets with high disciplinary standing and sustained publication activity during the study period. Restricting the analysis to a defined group of Q1 journals also provided a relatively comparable publication set for examining patterns of online attention without introducing the wider differences in journal visibility, publishing practices, and disciplinary orientation that may arise in a much more heterogeneous journal sample. The study is

therefore intended to provide evidence from a selected group of prominent LIS journals rather than to represent the entire body of LIS literature. The final dataset comprised 1,792 DOI-identified publications. The ten-year study period was considered sufficiently long to examine the coverage and distribution of online attention and to identify changes in social-web engagement over time.

Altmetric data were collected from Altmetric.com between June and August 2025. Each publication was searched individually by its Digital Object Identifier (DOI) using the Altmetric Bookmarklet. For publications tracked by Altmetric.com, the retrieved information included the Altmetric Attention Score (AAS) and the individual online sources contributing to the recorded attention. The resulting data were consolidated in Microsoft Excel for cleaning and subsequent analysis. Since altmetric activity is dynamic and may continue to accumulate after publication, the values analysed in this study represent a fixed data-collection snapshot corresponding to June-August 2025. The attention values were not subsequently updated. Maintaining a common retrieval period reduced variation arising from data being collected at substantially different points in time and ensured that the publications were analysed from a consistent observational snapshot.

Data preparation and treatment of missing attention

Before analysis, the dataset was checked for completeness and consistency. DOI strings were cleaned by removing leading or trailing spaces and standardising letter case. Publication year and journal information were also examined for inconsistencies. No duplicate DOI was identified, and every record contained a publication year and journal designation. Journal titles were standardised for reporting purposes without altering the journal membership of individual records. Of the 1,792 publications, 853 had a positive Altmetric Attention Score, while 939 contained blank altmetric indicator fields. All DOI-identified publications had nevertheless been checked individually through the Altmetric Bookmarklet during data collection. A blank altmetric field was therefore interpreted as the absence of attention recorded by Altmetric.com at the time of retrieval, rather than as an unexamined or missing observation. For analytical purposes, these blank attention values were consequently coded as zero. The original dataset was retained unchanged, and zero coding was applied only to the analytical version used for statistical analysis. This distinction was important because the analysis sought to measure both the presence and absence of recorded online attention. Treating verified blank altmetric entries as zero allowed the complete publication corpus to be retained when calculating coverage and distributional measures, rather than restricting the analysis to publications that had already received online attention.

Analytical approach

Altmetric coverage was calculated as the proportion of publications for which at least one item of online attention was recorded by Altmetric.com. Coverage and the distribution of attention were examined across journals and publication years to identify differences in the visibility of LIS research over the study period. Individual altmetric sources were also analysed to determine which social web platforms contributed most frequently to the recorded attention. X activity was examined separately because it constituted an important source of social-web discussion within the Altmetric.com data. Both the presence of X attention and the volume of recorded posts were considered in assessing the extent to which LIS publications generated discussion on the platform. To distinguish publications receiving unusually high levels of attention from the remainder of the corpus, the distribution of the Altmetric Attention Score was examined and publications at or above the 90th percentile were identified as highly attended publications. In addition, publications were ranked according to their AAS, and the highest-scoring papers were examined individually to characterise the research outputs that generated exceptional levels of online attention. This combination of coverage, source-level activity, percentile-based analysis, and publication ranking made it possible to examine not only whether LIS research received online attention, but also how that attention was distributed and concentrated across the publication corpus.

Coverage and source distribution

Overall score coverage was calculated as the number of publications with AAS greater than zero divided by 1,792. Source-specific coverage used the same denominator and counted each publication once whenever its relevant source count exceeded zero. Percentages were calculated separately for each journal and publication cohort using the matching record totals. Since a publication can appear in several sources, source-specific coverage percentages are

not additive. The union of positive source records was also checked against positive-score coverage to identify inconsistencies. The source profile contains fifteen altmetric data sources fields, including X, blogs, news, Facebook, Reddit, Wikipedia, policy sources, peer-review sites, patents, and smaller categories. These fields were retained as separate measures because their units differ. Counts of users, links, documents, or sources were not combined into an undifferentiated event total. A narrower social-platform union was calculated from X, Facebook, Reddit, Google+, Bluesky, Weibo, and YouTube. This distinguishes social-platform presence from the broader set of attention sources represented in AAS.

X participation

The Tweetsters field was interpreted as the number of distinct accounts recorded for each publication. Adding it across publications yields publication-user counts. An account associated with two papers can contribute twice. The aggregate is consequently neither a count of globally unique people nor a count of tweets. X intensity was described using means, medians, and frequency bands among papers with positive X counts. Full-corpus means were kept distinct from conditional measures. Altmetric tracks posts linking directly to research, limiting the observable communication (Altmetric, 2026b). A sensitivity calculation excluded the single publication with the largest X count when summarising conditional means for the corpus, its journal, and its publication cohort. The publication remains in every principal analysis. This calculation assesses how strongly one observation shapes the summaries, without treating an unusually large count as an error. The audience-category fields were inspected for reconciliation with Tweetsters, but were not used to infer public or professional participation because seven rows contain discrepancies and their classification procedure is undocumented.

Ranking and percentile definition

Publications were ranked in descending order of the supplied AAS, retaining the stored precision for calculations. The 90th percentile was calculated across all 1,792 publications, including publications with no recorded attention, using linear interpolation, equivalent to Excel's PERCENTILE.INC convention. Every publication with AAS at or above the resulting threshold was retained. Ties were not broken merely to produce an exact tenth of the records. This rule defines the high-attention group within the supplied corpus and is distinct from any percentile displayed by the provider. For comparison, a second threshold was calculated among the 853 positive-score records. Its purpose was to show how conditioning on already visible publications changes the reference population. The principal analysis uses the complete-corpus threshold because the research question concerns all supplied publications. Group shares of aggregate AAS and X counts, journal membership, and source-specific coverage were calculated. Differences between groups were interpreted descriptively, recognising that the score used to form them already incorporates several of the source measures being compared.

Analytical scope

Calculations used Python and NumPy. Summary counts were reconciled across journals and years. The analysis is descriptive and concerns the supplied records. Publication-year comparisons describe cohorts observed in one extract rather than the annual timing of mentions. The observation window and unresolved source discrepancies limit interpretation. Coverage measures presence in the provider's recorded sources and does not establish whether a publication circulated through other channels.

4 Results

Coverage across journals

As reported in Table 1, Positive AAS was recorded for 853 of the 1,792 publications, corresponding to coverage of 47.60%. The aggregate score was 4,741.208, the mean was 2.646, and the median was zero. Among the positive-score publications, the mean increased to 5.558 and the median to 1.500. This difference between full-corpus and conditional summaries indicates that limited visibility is a substantial part of the distribution. Reporting only the scores of already visible papers would omit more than half of the supplied corpus.

Journal differences were pronounced. Journal of Web Librarianship had the highest positive-score coverage, with 80 of 116 publications represented, or 68.97%. Online Information Review followed at 60.74%, and Library & Information Science Research at 50.99%. Coverage was lower for Global Knowledge, Memory and Communication, at 29.45%, and The Bottom Line, at 20.59%. These are differences within the supplied records and are not adjusted for topic, article type, or the selection process that produced the journal collection.

Table 1: Publication coverage and X intensity by journal

Journal	n	AAS > 0 n (%)	Mean AAS	X n (%)	X total	Mean if > 0
The Bottom Line	170	35 (20.59%)	0.423	29 (17.06%)	58	2.000
Global Knowledge, Memory and Communication	455	134 (29.45%)	1.386	110 (24.18%)	752	6.836
Journal of Web Librarianship	116	80 (68.97%)	5.113	63 (54.31%)	201	3.190
Library & Information Science Research	353	180 (50.99%)	3.518	159 (45.04%)	510	3.208
Online Information Review	698	424 (60.74%)	3.157	257 (36.82%)	890	3.463
Total	1792	853 (47.60%)	2.646	618 (34.49%)	2,411	3.901

Note. Percentages use each journal's supplied publication total. X total is the sum of paper-level user counts, with possible repeated accounts across papers. Mean if > 0 is calculated only for X-covered papers. Blank attention cells were as zero.

The journal ordering depended on the measure chosen. Online Information Review contributed the largest aggregate score, 2,203.472, reflecting both its attention profile and its larger number of publications. Journal of Web Librarianship had the highest mean AAS, 5.113, despite being the smallest component of the corpus. Library & Information Science Research had a mean of 3.518. Journal totals and per-paper summaries therefore describe different aspects of visibility and should not be substituted for each other when comparing outlets.

Distribution across attention sources

As reflected in Table 2, X was the most widely represented altmetric data source, appearing for 618 publications, or 34.49% of the corpus. The peer-review-site field appeared for 210 publications, followed by blogs for 131. Facebook, news, Reddit, Wikipedia, and policy sources each covered fewer than 3% of publications. Smaller categories were much less frequent, and no positive entry was recorded for clinical-guideline sources or Weibo. These zero counts refer to the extract and monitored fields, rather than demonstrating that no relevant communication ever occurred elsewhere.

Table 2: Coverage of altmetric data sources

Recorded source	Papers with positive entry	Coverage (%)	Sum within source
X users	618	34.49	2,411
Peer-review sites	210	11.72	210
Blogs	131	7.31	156
Facebook links	49	2.73	64
News	38	2.12	210

Reddit users	34	1.90	34
Wikipedia	32	1.79	55
Policy sources	30	1.67	39
Google+	18	1.00	20
Bluesky users	8	0.45	9
Patents	5	0.28	8
Q&A threads	1	0.06	1
YouTube creators	1	0.06	1
Clinical guidelines	0	0.00	0
Weibo users	0	0.00	0

Note. Denominator = 1,792 publications. Source units differ and their counts must not be added as equivalent events. Coverage percentages overlap. Mendeley, CiteULike, and academic citations are excluded from this attention-source table. Zero indicates no positive entry in the supplied extract, following the confirmed blank-cell convention.

The broader source union contained 852 publications, one fewer than the positive-score total. Across the fifteen source fields, 607 publications appeared in exactly one source, 187 in two, 42 in three, 12 in four, and four in five. This distribution shows that multi-source visibility was relatively uncommon even among publications with recorded activity. The peer-review-site field requires separate interpretation. Of its 210 records, 208 belonged to Online Information Review and two to Global Knowledge, Memory and Communication. In 138 publications, it was the only positive non-readership source. Omitting this source from the union left 714 publications with another recorded attention source, or 39.84% of the corpus. The narrower social-platform union covered 638 publications, or 35.60%. These alternative summaries clarify how the operational definition of attention changes the coverage being described.

X coverage and intensity

The 618 X-covered publications generated 2,411 summed publication user counts. The full-corpus mean was 1.345, while the mean among covered publications was 3.901 and the corresponding median was two. A total of 271 covered papers attracted one recorded user, representing 43.85% of the covered set. Another 269 attracted between two and five. Taken together, 540 publications, or 87.38%, had no more than five users. Only ten publications had more than twenty. X participation was therefore usually modest at the individual-publication level. Journal of Web Librarianship again had the highest coverage, with 54.31% of its publications represented on X. Library & Information Science Research followed at 45.04%, ahead of Online Information Review at 36.82%. Global Knowledge, Memory and Communication had lower coverage, 24.18%, but the highest conditional mean, 6.836 users per covered publication. This combination illustrates why a journal can appear prominent through intensity while reaching a smaller proportion of its papers. Coverage and conditional intensity need to be read together. The unusually high conditional mean for Global Knowledge, Memory and Communication was strongly influenced by one publication with 470 recorded users. It supplied 62.50% of the journal's 752 publication-user counts and 19.49% of the total across all five journals. Excluding it from the sensitivity calculation reduced the journal's conditional mean to 2.587. Across the corpus, the conditional mean fell from 3.901 to 3.146. The principal finding is thus a distribution dominated by small audiences, with one exceptionally large observation materially affecting aggregate summaries.

Differences between publication cohorts

Positive-score coverage varied across publication years, reaching 64.85% in the 2018 cohort and falling to 35.39% in 2020. X coverage was also highest for 2018, at 63.03%, and lowest for 2024, at 22.50%. There was no simple monotonic pattern across the ten cohorts. The 2021 publications had the highest mean AAS, 5.375, whereas the 2024

cohort had the largest summed X count (Table 3). These differences concern the publication dates of the papers receiving attention, not the dates on which users mentioned them.

Table 3: Attention by publication cohort

Year	Papers	AAS > 0 (%)	Mean AAS	X papers	X (%)	X total	Mean if > 0
2015	158	38.61	3.038	51	32.28	224	4.392
2016	184	46.20	1.805	68	36.96	202	2.971
2017	178	44.38	1.727	70	39.33	243	3.471
2018	165	64.85	2.651	104	63.03	239	2.298
2019	182	39.56	1.929	60	32.97	209	3.483
2020	178	35.39	2.967	49	27.53	90	1.837
2021	182	52.20	5.375	63	34.62	294	4.667
2022	188	52.66	1.322	55	29.26	157	2.855
2023	177	52.54	2.496	53	29.94	180	3.396
2024	200	49.50	3.182	45	22.50	573	12.733

The 2024 cohort provides the clearest example of an aggregate distorted by a single large observation. Its 45 X-covered publications generated 573 publication-user counts, of which 470, or 82.02%, came from the leading X publication. The conditional mean was 12.733, but the median remained two. Removing the leading paper from the sensitivity calculation reduced the conditional mean to 2.341 for the remaining 44 covered papers. The high total therefore does not establish that participation was broadly stronger for recent publications.

The highest-scoring publications

The ten highest-scoring publications collectively accounted for 31.38% of aggregate AAS. The leading article, on encountering misinformation online, had AAS 267.080, accompanied by 33 news entries, one blog entry, and two Tweepers. The second-ranked publication, on library play-and-learn spaces, had AAS 205.860, with 23 news entries, three blog entries, and seven Tweepers. The publication on archives and records management professionals in Africa ranked third by AAS but first by Tweepers, with 470 recorded accounts and no news entry.

Table 4: Ten highest-scoring publications and selected source counts

Rank	Title, DOI and Journal	Year	AAS	X users	News	Blogs
1	Encountering misinformation online: antecedents of trust and distrust and their impact on the intensity of Facebook use <i>Journal: OIR</i> 10.1108/OIR-04-2020-0130	2021	267.080	2	33	1
2	Play-and-learn spaces: Leveraging library spaces to promote caregiver and child interaction	2020	205.860	7	23	3

	Journal: LISR 10.1016/j.lisr.2020.101002					
3	Advancing archives and records management professionals in Africa Journal: GKMC 10.1108/GKMC-05-2022-0100	2024	180.980	470	0	1
4	Algorithmic Literacy, AI Literacy and Responsible Generative AI Literacy Journal: JWL 10.1080/19322909.2024.2395341	2024	140.000	0	17	0
5	The presumed influence of digital misinformation: examining US public's support for governmental restrictions versus corrective action in the COVID-19 pandemic Journal: OIR 10.1108/OIR-08-2020-0386	2021	136.000	10	15	2
6	Reading as a lifeline among aging readers: Findings from a qualitative interview study with older adults Journal: LISR 10.1016/j.lisr.2018.08.001	2018	131.700	3	17	0
7	Intergenerational family online community and older adults' overall well-being Journal: OIR 10.1108/OIR-06-2021-0332	2023	120.000	0	16	0
8	Regional variations in average distance to public libraries in the United States Journal: LISR 10.1016/j.lisr.2015.11.008	2015	114.144	2	12	2
9	How can Booktok on TikTok inform readers' advisory services for young people? Journal: LISR 10.1016/j.lisr.2021.101091	2021	102.700	27	10	1
10	Polarization and reliability of news sources in Wikipedia Journal: OIR 10.1108/OIR-02-2023-0084	2024	89.250	4	10	0

Note. BL = The Bottom Line; GKMC = Global Knowledge, Memory and Communication; JWL = Journal of Web Librarianship; LISR = Library & Information Science Research; OIR = Online Information Review.

Nine of the ten leading publications had news coverage, and together these papers accounted for 153 of the 210 recorded news counts. Two had no recorded X user at all. Their topics included misinformation, reading, library access, artificial intelligence literacy, and the well-being of older adults. These descriptions identify the subjects of individual highly attended papers. They do not constitute a thematic analysis or demonstrate that any topic independently predicts attention, since titles were verified only for the leading ten publications.

Publications at the 90th percentile

The complete-corpus 90th-percentile AAS was 6.064. There were 168 publications above this value and thirteen exactly at it. Retaining all ties produced 181 publications, or 10.10% of the corpus. Their combined score was 3,652.022, accounting for 77.03% of aggregate AAS. Their median score was 10.312, compared with zero among the remaining 1,611 records. The threshold identifies relative prominence within this particular collection. Its numerical value has no universal meaning for LIS research or for another altmetric dataset.

Table 5: Source coverage within and below the upper percentile group

Source	Upper group n	Upper group %	Below threshold n	Below threshold %
X	135	74.59	483	29.98
Blogs	117	64.64	14	0.87
News	37	20.44	1	0.06
Peer-review sites	25	13.81	185	11.48
Policy sources	15	8.29	15	0.93
Facebook	14	7.73	35	2.17
Wikipedia	11	6.08	21	1.30
Reddit	10	5.52	24	1.49

Note. Upper group: AAS $\geq$ 6.064, $n = 181$, retaining all thirteen ties at the threshold. Below threshold: $n = 1,611$. Percentages use their respective group denominators and overlap across sources. Source differences are descriptive because several sources contribute to the grouping score.

Table 5 shows X covered 135 of these 181 publications, or 74.59%, and they accounted for 59.81% of the corpus's publication-user counts. Blogs covered 64.64% of the percentile group and news covered 20.44%. The corresponding percentages below the threshold were 0.87% and 0.06%. Thirty-seven of the 38 news-covered publications fell in the upper group. These strong differences partly reflect the construction of AAS, so they should be read as a description of the score's source profile rather than independent evidence that particular sources cause exceptional attention. The upper group included 69 publications from Online Information Review, 43 from Library & Information Science Research, 38 from Journal of Web Librarianship, 27 from Global Knowledge, Memory and Communication, and four from The Bottom Line. Relative to journal output, the proportions ranged from 32.76% for Journal of Web Librarianship to 2.35% for The Bottom Line. Calculating the percentile among positive-score publications alone raised the threshold to 10.676 and selected 86 papers. The reference population therefore materially changes which publications qualify as highly attended.

Source breadth was also greater within the upper group. Its publications appeared in an average of 2.10 of the fifteen non-readership source categories, compared with 1.18 among positive-score publications below the threshold. This comparison excludes zero-score records from the lower group so that their absence does not itself produce the difference. It describes the number of source categories represented for a paper, not the number of independent audiences reached. The same person or organisation could contribute activity in more than one setting, and the current study does not provide cross-platform identities through which such overlap could be measured.

5 Discussion

Coverage depends on what is counted

The first objective concerned the coverage and distribution of LIS publications on social-web platforms. The findings show that the answer depends on a carefully specified definition of presence. Positive-score coverage was 47.60%,

whereas the narrower social-platform union was 35.60%. The difference is substantively meaningful because news, policy, and peer-review-site records describe communication settings that are not equivalent to social networking. A broad AAS-based figure should therefore be labelled as recorded altmetric attention coverage, with source-level figures supplied when the question specifically concerns social platforms.

This distinction also helps interpret journal comparisons. Online Information Review had broad positive-score coverage, but the file contained an unusually concentrated set of peer-review-site records for that journal. Such entries may document activity within a scholarly reviewing system and cannot automatically be read as independent public debate. Retaining them while showing their distribution provides a more informative account than either silently excluding them or combining them with X users under a generic label. The observed journal difference may partly reflect which kinds of activity are being captured.

The sparse presence of most sources is consistent with the broad pattern described in earlier altmetric research (Zahedi et al., 2014; Fang, Costas, et al., 2020). Nevertheless, the numerical results should not be interpreted as evidence of an increase or decline relative to those studies. Their publication populations and observation periods differ. The LIS studies by Erfanmanesh (2017) and Chingath and Hanumanthappa (2024) provide disciplinary context, but a direct comparison of percentages would require aligned inclusion rules and equivalent denominators. Similar labels do not guarantee comparable coverage measures.

For librarians and journal editors, coverage is most useful as an initial diagnostic. A low recorded percentage can identify a set of publications for closer examination, but it does not explain why they are absent. The explanation might concern dissemination, identifiers, source tracking, or the audiences to whom the work matters. A local practice-oriented paper could have substantial value to a small professional community without leaving many traces in the monitored sources. Investigation of such cases should begin with the publication and its intended readership rather than an assumption of poor performance.

X activity is usually limited in breadth

The second objective concerned the level of X discussion. The available evidence indicates that recorded participation was concentrated at a low level for most covered papers. The median of two users is more representative of the ordinary paper in the covered set than the mean of 3.901. The fact that 87.38% attracted no more than five accounts further limits claims of widespread conversation. These papers entered X circulation, but the dataset cannot establish how extensively their findings were discussed or whether users engaged with one another.

This interpretation follows the distinction between mention counts and interactions developed in X research. Alperin et al. (2019) showed the importance of diffusion structures, while Fang, Costas, and Wouters (2022) treated different forms of engagement separately. Shen et al. (2026) extended this perspective through the analysis of conversations. Applying those approaches to the present corpus would require tweet identifiers, message text, interaction links, and timestamps. Aggregate Tweepers counts provide an initial map of participation, but they leave these more demanding questions open.

The leading X publication illustrates the need for both attention to exceptional cases and restraint in explanation. Its 470 users are important to the observed distribution, and removing the record from the principal analysis would conceal a real feature of the supplied data. At the same time, a count of this size does not establish a campaign, a controversy, automated amplification, or unusually deep professional engagement. Each is a possible mechanism requiring additional evidence. The sensitivity calculation shows the observation's statistical influence without assigning it an unsupported social explanation.

The annual results reinforce this point. The largest X total occurred in the cohort with the lowest X coverage. This is not a contradiction once coverage and concentration are distinguished. A few visible papers can generate a substantial aggregate while many others remain unrepresented. For reporting purposes, the cohort total should therefore appear beside the number and proportion of covered papers and a typical value such as the median. Otherwise, the reader may mistake an exceptional publication for a broad change in the communication of research.

AAS rankings reveal different attention profiles

The third objective concerned the ranking of publications and the identification of high attention. The leading papers show that an AAS ranking is sensitive to the sources through which attention is recorded. Several papers with relatively few Tweepers occupied high positions because their profiles included substantial news coverage. The most tweeted

paper ranked third by AAS, while two of the top ten had no X record. These observations support reporting the source counts alongside the composite score whenever rankings are used to describe research visibility.

This finding is compatible with the weighted nature of AAS, but it should not be turned into an exact decomposition of the score. The supplied workbook does not contain the historical scoring rules, source identities, or account-level modifiers necessary for reconstruction. Current provider documentation is useful for understanding the general design, while Ortega (2019) demonstrates why simple arithmetic may not reproduce the score. The paper therefore identifies news-associated and X-associated attention profiles without claiming a precise percentage contribution of each source to an individual AAS.

The upper-percentile comparison needs an equally careful interpretation. Blogs and news were much more common among high-scoring publications, yet they are also among the inputs from which the grouping variable is formed. Their concentration in that group is partly built into the analytical design. Describing this source composition is useful because it explains what the ranking represents. Presenting the same relationship as a predictive discovery, or as evidence that obtaining a news mention causes scholarly success, would go beyond the analysis and confuse construction with explanation.

The value of a transparent percentile rule

A percentile threshold provides a reproducible way to identify an upper group without relying on an arbitrary score such as ten or one hundred. Its meaning still depends on the population used to calculate it. In this corpus, the complete-sample threshold was substantially lower than the threshold among already visible publications. The former asks which papers occupy the upper tail of all supplied research. The latter asks which papers stand out after publications without positive scores have already been removed. Both are legitimate descriptions if labelled accurately, but they address different questions.

Boundary ties are another practical issue. Selecting precisely 179 or 180 papers would require excluding some publications with the same AAS or imposing an additional rule unrelated to the score. Retaining all thirteen papers at the threshold avoids suggesting a meaningful distinction where none is recorded. The resulting group contains 10.10% of publications rather than exactly 10%.

A common corpus threshold also answers a different question from separate thresholds within each journal. The common rule identifies publications with comparable recorded score levels across the collection, allowing journal representation to vary. Journal-specific rules would instead identify relatively prominent publications within each outlet and would tend to allocate similar proportions to journals with very different attention distributions. Neither procedure removes differences in subject matter or observation time. The shared threshold was selected here because the objective concerns ranking the supplied publications together. The journal counts should consequently be interpreted as contributions to that shared upper group, rather than as estimates of each journal's intrinsic capacity to attract attention.

The concentration of 77.03% of aggregate AAS in this group describes the uneven allocation of the recorded composite score. It should not be restated as 77.03% of all social-web discussion, since the score weights sources differently and does not enumerate all communication. Likewise, the top ten's 31.38% share concerns score mass rather than the fraction of people reached. These distinctions preserve the usefulness of concentration measures while preventing a mathematical property of an index from becoming an unsupported claim about society.

Implications for LIS communication and assessment

The results suggest a practical reporting approach for LIS journals and research groups. Coverage should show how many publications have documented attention. Conditional summaries should show the experience of those that are represented. Source profiles should explain why a paper or journal occupies a high position. Applied together, these measures allow an editor to distinguish a broadly visible journal from one whose aggregate is driven by a small number of highly attended publications. They also make unusually large observations visible enough to investigate.

Communication planning can draw on the topics of highly attended publications, but the present evidence does not justify prescribing a subject area or platform strategy. The leading titles concern several aspects of information use and library practice. Their diversity is useful as a starting point for case-based follow-up. Interviews with authors or examination of linked media coverage could clarify how attention developed. A thematic claim about the whole upper

percentile would require titles or abstracts for every member and a documented coding procedure, which this study has not undertaken.

Finally, the results support a limited but constructive place for altmetrics in research assessment. Recorded visibility can help locate publications for closer examination and identify communication beyond formal citations. It cannot substitute for reading the work or establishing its consequences. This position is consistent with Tahamtan and Bornmann (2020), Thelwall (2021), and the principles articulated by Hicks et al. (2015). The appropriate use of the present rankings is to guide informed inspection of attention patterns, accompanied by evidence about the publications and the contexts in which they circulate.

6 Limitations

The sample contains only five journals and is not established as a probability sample of LIS. Journal differences may reflect subject matter, publisher practices, document composition, or collection choices. The analysis does not adjust for these factors and cannot attribute a difference to journal quality. DOI-based inclusion also restricts the visible publication universe. The results should therefore be presented as a study of the supplied corpus, with any broader relevance argued through the observed measurement issues rather than through representativeness.

Source labels also impose limits on interpretation. A policy-source entry identifies a recorded link with a policy document, but it does not reveal whether the research informed a recommendation or merely appeared in a reference list. Reading the citing material would be necessary to establish that distinction in an individual case.

The X field gives paper-level account counts. It supplies neither a deduplicated audience across papers nor a complete collection of original posts, replies, quotations, and reposts. No inference about discussion quality, sentiment, actual readership, or professional use can be made. The demographic columns also fail to reconcile with Tweepers in seven records. Rather than redistributing these differences arbitrarily, the study omits demographic percentages. Verification against the original records would be required for an audience analysis.

The extract is a single snapshot and does not establish the dates on which attention accumulated. Older and newer publications have unequal exposure periods, while online-first and issue dates can further complicate cohort comparisons. Platform availability and provider coverage also change. The instability documented by Fang, Dudek, and Costas (2020, 2022) and Arroyo-Machado and Torres-Salinas (2024) means that a later retrieval may return different values. Current documentation of scoring rules should not be assumed to reproduce the rules applied when the extract was assembled.

Finally, the high-attention threshold is specific to the corpus and its zero-coding convention. Source comparisons with the upper group are descriptive because the grouping score incorporates those same sources.

7 Conclusion

The supplied corpus shows an uneven pattern of recorded online attention to publications from five LIS journals. Fewer than half of the publications had a positive AAS and about one third had a X record. Most X-covered papers attracted only a small number of accounts, while a single publication materially influenced the aggregate and the apparent strength of its journal and year cohort. Describing X attention through totals alone would therefore give an incomplete account of participation. The 90th-percentile analysis identified 181 publications after retaining ties, accounting for 77.03% of aggregate AAS. Their source profiles show why exceptional composite scores cannot be equated with exceptional X participation. News coverage characterised nine of the leading ten publications, whereas the largest X audience belonged to a paper with no recorded news mention. Coverage, conditional intensity, and source composition together provide a more informative basis for describing this attention. The rankings are best used to identify publications for closer examination, supported by a documented account of the original selection and collection procedure.

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