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DETECTING FAKE PUBLICATIONS AND STRENGTHENING AUTHENTIC RESEARCHAN ANALYTICAL STUDY OF SCHOLARLY CREDIBILITY, PUBLICATION ETHICS, AND PREVENTIVE SAFEGUARDS

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Abstract

Background: The academic communication is being attacked by paper mills, altered peer review, fake data, plagiarised content, hijacked journals, citation engineering, and undisclosed machine-generated content. However, the retractation data should be taken with a pinch of salt, as it contains both misconduct and honest error. As a result, it does not measure the prevalence of fake science. The study's objective was to analyse recent patterns of retraction, and develop a layered preventive framework for detecting unreliable publications while preserving due process and legitimate correction. According to Retraction Watch Database, methods used are retrospective cross-sectional bibliometric analysis done. The retraction records was filtered for 2020-2025, duplicate revisions were removed, and records were de-duplicated based on valid original-paper DOI or record identifier. Different reasons were explained, and a unique family hierarchy was useful for testing associations. We used Chi-square tests, Mann–Whitney U testing, and multivariable logistic regression to study whether the retraction patterns within 2 years of publication.
Results: The final dataset included 37,344 records. The top reason for core family publication-manipulation, while peer-review concerns, paper-mill signals, computer-aided or generated-content tags increased sharply in some years. The time to retraction (TTR) was 593 days median. Although the statistical associations were significant, many effect sizes were small, suggesting that statistical significance should not be treated as practical significance. To produce authentic research, coordinating author, journal, institution, database, funder and regulator verification systems. While automated screening play a role in triage, transparent human adjudication, metadata validation, data availability, reviewer authentication and proportionate correction are still essential.

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Introduction:-

Scholarly publishing is a venue in which it made cumulative knowledge rather than a market for documents. To the OECD and Brookings: Making the Next Economy Work for Everyone

Clinical guidelines, public policy, industrial design, educational practice, funding decisions and subsequent experiments rely on the assumption that published claims can be traced to genuine authors, authentic data, legitimate peer review and verifiable sources. The scale and speed with which knowledge is published today have opened up opportunities for increased access to knowledge, but have also created space for organized deception. There are many ways in which the integrity of academic publishing can be compromised, including document factories producing papers or selling authorship; hijacked journals that masquerade as legitimate journals; citation brokers who create references; fabricating reviewers; and recycling or manipulating images, methods, data, and text. The generative artificial intelligence has useful features such as language and coding support but can also produce credible-sounding passages and references when claimed unverified or undisclosed use (Flanagin et al. 2023; Lund et al. 2023; Thorp 2023).

The term "fake publication" should not be used lightly. Honest Mistake, Irreproducibility, Questionable Practice and Deliberate Fraud exist at different levels of wrongdoing. A retraction alerts us that the findings or processes in a publication are unreliable. A retraction does not mean that every element was fabricated and absence of a retraction does not mean that nothing was. Damaging authors and dissuading correction, crude labelling. According to COPE (2023) and ICMJE (2025), transparent notices of artificial intelligence usage must be made and authors must be accountable.

Latest evidence suggests that organized fraud is not limited to marginal scholarly journals. Following Christopher (2021) and Wittau and Seifert (2024), we can affirm that paper-mill manuscripts can pass through established publication systems and look like legitimate articles at the level of metadata and prose. Incentives favouring publication volume over reliability, publication pressure, special-issue workflows, weak reviewer authentication, and fragmented institutional oversight allfacilitate paper mill production. According to Candal-Pedreira et al. (2022), the number of papers that get retracted by profession paper mills is on the rise. Parker et al. 2024 detail a system-wide response. It has been reported that retracted articles can still be embedded in review and derivative claims (Bolland et al., 2022).

Detection is a social problem. Text-similarity and image-forensics tools can flag instances of overlap or duplication. They require a contextual review for verification or authentication. Metadata anomalies may indicate manipulation or innocuous variation. AI detectors are not appropriate as sole arbiters because their mistakes and limited explain ability can entail false positives. A dependable evaluation connects the identity of the journal, DOI metadata, authorship, provenance of data and image, peer-review record, statistical coherence, references, and whether retraction (Bordewijk et al., 2021; Byrne et al., 2022).

This study addresses the demand for an integrated, evidence-based framework through an analysis of the official public Retraction Watch dataset maintained by Crossref. This study on fake wash to address some human aspect of retraction was limited to the period 2020–2025. The goal of this paper is to identify the dominant integrity signals, analyse how such reason profiles evolved over time, to assess what is associated with comparatively rapid preventive action, and how the findings can be applied to construct preventive safeguards. The core of the research problem is that credibility screening is highly fragmented; they do checks on plagiarism and journal metrics and sometimes on ad hoc suspicion. But any authentic research requires layered verifications. These should be done before submission of the research, during editorial assessment, after publication of the research, and across all institutional governance.

2. Evaluation of Prior Studies and Unexplored Areas

Predatory publishing and organised paper production are distinct but related. Two main categories of entities engaged in the unethical publishing of scientific research are predatory journals and paper mills. Predatory journals typically misrepresent editorial services, peer review, indexing, or governance for financial profit. In contrast, paper mills manufacture or broker manuscripts and authorship, including submissions to legitimate journals. The working definition agreed upon by Grudniewicz et al. (2019) is still useful because it focuses on deceptive behaviour rather than low prestige. Elmore and Weston (2020) turned the issue into actionable warning signs such as implausible editorial boards, false claims of indexing, opaque fees and aggressive solicitation. Nonetheless, if checklists are used mechanically they are untrustworthy; legitimate new journals will have no proven track record, while sophisticated deceptive operations can reproduce credible-looking sites and metadata.

Research on paper mills shifted the debate from isolated wrongdoing to organized production. Christopher 2021 demonstrated how systematic faking can be detected, including through the identification of template-style writing, insufficiently credible experimental patterns and through use of repeated images. Christopher and Byrne 2020 also documented digital and textual cues that could indicate hoaxed manuscripts. Pérez-Neri et al. (2022) mapped the threats during the research process while Byrne et al. (2022) showed how misidentification of nucleotide sequences can unveil compromised human-gene research. According to Candal-Pedreira et al. (2022), they quantified the published retracted paper-mill articles and later surveyed their continuing citation footprint (Candal-Pedreira et al., 2024). The studies show that individual red flags are more informative when combining across text, images, methods, metadata, and citation networks.

The issue is adaptable. Fake papers could be batch-generated, authorship slots sold, references inserted to appease brokers, and peer review routed through controlled identities. According to Sabel and Seifert the activity can be framed as an attack on knowledge production while Heck et al. describe a journal's response to fake data and paper-mill authors. According to Wittau and Seifert (2024), fake papers that have been retracted can still appear ordinary on many metadata measures, limiting the utility of simple country, email, or affiliation heuristics. Evidence collected on network scale indicates that entities thought to enable fraud are resilient and growing (Richardson et al., 2025). It re-affirms an important ethical principle of screening for evidence in the manuscript and process, rather than demographic profiling.

Due to language and reference manipulations detection becomes more difficult. According to Cabanac et al. (2021), mechanical rephrasing of technical phrases gave rise to "tortured phrases", that is, such a signal may reveal a compromise but is not conclusive by itself. According to Besançon et al. (2024), fabricated reference metadata can distort citation counts, while Ibrahim et al. (2025) show that organized citation mills and preprint infrastructures forced citation manipulation. Abalkina (2024) indicated a high textual similarity in hijacked-journal content. These findings support DOI resolution, references and text checks and citation network review.

Apprehensive of over-simple interpretations of its findings The causes of retraction are misconduct, unreliable results, authorship disputes, noncompliance with ethical norms and error. Bolland et al. (2022) highlighted the continued citation of retracted articles as a reality which demonstrated the knowledge lag. The solution will not just be retraction, but full reproducibility and transparency. Correction is needed, but prevention goes further than that: whenever possible preregistration, accessible data and code, robust methods, more use of incentives to verify rather than to simply publish. Retractieaantallen kunnen omhooggaan omdat de fraude toeneemt, omdat detectie verbetert, omdat uitgevers grote onderzoeken doen of omdat databases completer worden. Accordingly, bursts in time should be read as signs of corrective rather than rate incident.

Generative AI expands the frontier of opportunity but also poses risks. Salvagno et al (2023) noted that it is beneficial for scientific writing but must be verified. The risk to academic integrity in relation to assessment and authorship was highlighted by Perkins (2023) and Lund et al. (2023) described a changed scholarly environment whereby fluent text can be produced without understanding. Flanagin et al. (2023), COPE (2023), WAME (2023), and ICMJE (2025) share important beliefs. first, AI tools cannot be authors. second, human authors are responsible. third, material use should be disclosed. finally, generated references or claims must be checked. The living guidelines of the European Commission also encourage responsible and transparent use versus an outright ban.

Integrity is becoming a research-culture issue in institutional and policy frameworks. The Enhanced European Code of Conduct focuses on being dependable, trustworthy, respectful, and responsible (ALLEA, 2023). The open-science recommendation of UNESCO connects transparency and accessibility with public trust. (UNESCO, 2021). The report on Paper Mills by COPE and STM requests collaboration among publishers, institutions and infrastructure providers (COPE & STM, 20222). The release of the Retraction Watch dataset by Crossref helps enhance machine-readable correction signals (Crossref, 2025). Often, policy guidance is divorced from empirical patterns of retraction, and technical detection studies are divorced from studies of education, incentives, and due process.

The research gap, therefore, is integrative. The existing literature identifies many individual threats – paper mills, plagiarism, image manipulation, hijacking, fake peer review, citation schemes, or AI misuse – but fewer studies connect observed patterns of retraction to a workable architecture for prevention. That prevention architecture would span researchers, journals, institutions, databases, funders, and regulators. There exists a methodological divide between extremely specific detection tools and proportionate, explainable decision-making to the complexity of the case at hand. By merging an open, reproducible investigation of recent retraction records with a safeguarded multi-level model, this study contributes. It identifies where verification and governance should be focused, using patterns of reasoning and timing of correction to obviate fraud diagnosis from metadata.

3. The goals, research queries and analytical hypotheses.

The research had four empirical objectives: to describe the volume, timing, and reason tags of retractions by 2020–2025; to identify systems of records into transparent primary reason families; to test correlations between metadata or integrity tags and timing of retraction; and to derive safeguards against retraction from the empirical and normative literatures. The research questions asked which integrity concerns were recorded most frequently, how did the profile change between 2020–2022 and 2023–2025, which characteristics were associated with having a retraction within two years, and how the patterns ought to inform layered prevention. It was not possible to test the proposed awareness and training hypotheses without fabricating data since there was no respondent-level survey. Accordingly, we prespecified four hypotheses appropriate for the datasets, specifically: Reason-family distribution does not differ by period (H01); Paper-mill-tagged and other records share the same lag distribution (H02); DOI validity independent of rapid retraction (H03); and Multi-country authorship is independent of publication-process manipulation (H04). A multivariable model was used to estimate associations adjusted for retraction in 2 years.

4. Conceptual framework

The conceptual framework treats academic credibility not as a binary property inferred from a single signal but as an outcome of layered controls. Institutional support and editorial capacity; up-stream publication ethics knowledge, metadata literacy, responsible AI use. Through five mechanisms, these inputs work - identity verification, evidence provenance, methodological scrutiny, process authentication, and transparent correction. The pressure to publish weakens each mechanism by supplying rewards for speed and quantity whereas peer-review experience and supportive research culture strengthen them. The better detection of suspicious submissions, lower false accusations, clearer notices of retraction or correction and more rapid communication of status changes to databases. A research record in which claims are traceable, uncertainty is explicit and corrections are visible is the long-term outcome. The framework provides that automated triage is separate from adjudication: while an algorithm may rank risk, only accountable human review examines context, and permits author response.

Table A:- Editable conceptual framework for scholarly credibility.

Upstream inputs	→	Verification mechanisms	→	Credibility outcomes
Ethics knowledge and responsible AI		Identity and role verification		Authentic authorship and accountability
Metadata and database literacy		DOI, journal, reference, and retraction checks		Traceable and current evidence
Editorial and peer-review capacity		Reviewer authentication and risk-based screening		Fewer compromised submissions
Institutional support and data stewardship		Data, code, image, and consent provenance		Reproducible and auditable claims
Transparent correction culture		Corrections, expressions of concern, and retractions		Visible, proportionate record repair

Note. Author-developed framework synthesising ALLEA (2023), COPE & STM (2022), ICMJE (2025), UNESCO (2021), and the present analysis. All text is editable.

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5. Methodology:-

As supported by the critical review of publication-ethics literature, a quantitative retrospective cross-sectional bibliometric design was adopted. The Retraction Watch database, made public via the GitLab repository of Crossref, is the source of data. According to Crossref, it obtained and has made openly available the dataset to support correction metadata and other research uses; the user guide that comes with this dataset defines the fields and warns users to interpret reasons in context of notices (Crossref, 2025; Retraction Watch, 2024). The CSV file was downloaded on July 23rd, 2026. Only records coded as “Retraction” with retraction dates from January 1st 2020 through December 31st 2025 were analysed. Records coded as revisions were excluded. The DOI of the original paper was normalized by removing resolver prefixes, converting it to lower case, and testing against a standard DOI pattern. Duplicates were removed with valid original DOI; where no valid DOI available, database record identifier was retained as the deduplication key. The duplicate keys were assigned the earliest retraction date. Cases missing publication-to-retraction intervals or with negative intervals were excluded. A total of 37344 unique retraction records were found This refers to a count of qualifying database records, not a probability sample of all scholarly publications or an estimate of the prevalence of misconduct.

Reasons for retraction are multi-label types. We then calculated frequencies for each recorded tag, with percentages allowed to exceed 100% across tags. A disclosed hierarchy assigns each test type to a primary family: publication process; data/image result; plagiarism/duplication/citation; authorship/research ethics; error/ reproducibility; or other/administrative. The order of importance assigned by the hierarchy to the paper-mill, peer-review, third-party investigation, rogue-editor, computer-generated-content terms; data/image terms; plagiarism/citation terms; authorship/ethical terms; and error/reproducibility terms. This coding simplifies the analysis but is not a replacement of the original reason field.

The descriptive statistics consider counts, percentages, medians, interquartile ranges and annual trends. Many categorical associations were examined through chi-square tests. As lag was right skewed, the MannWhitney U test and rankbiserial correlation were used for paper mill tagged and other records. The logistic regression approximated the relationships with retraction within 730 days using period, DOI validity, multi-country listing, and five integrity-tag groups. The study included odds ratios, confidence intervals, model fit, ROC area and variance-inflation factors. The level of statistical significance was set at $p < .05$, although interpretation prioritised level of effect. As the study utilized administrative records rather than a scale for surveys, a check was inapplicable.

We made use of scikit-learn statsmodels, SciPy, and pandas in Python for analyses. No intervention or private respondent data with personal contact. The public dataset contains bibliographic and notice-derived information; nevertheless, users should consult their institutional policy regarding ethical review of public secondary data. The study does not claim people or countries act with intent and only reports aggregates. The reproducibility is attained by the careful inclusion, deduplication, coding and modelling rules; all table and figure values derive from the same filtered dataset.

Table 1:- Dataset selection and characteristics.

Measure	Value	Operational definition
Raw CSV records	71,269	All records in downloaded Crossref-hosted file
Retraction nature; 2020–2025	37,502	Date and nature filter
Revision records excluded	4	ArticleType contained “Revision”
Final deduplicated analytic records	37,344	Valid DOI or record-ID key; earliest retraction retained
Valid original-paper DOI	36,533 (97.8%)	DOI syntax check after normalisation
Multi-country listing	6,893 (18.5%)	Country field contained multiple entries
Retracted within 730 days	22,577 (60.5%)	Binary model outcome
Median lag (IQR)	593 days (366–1121)	Original publication to retraction date

Note. Calculated from the Crossref-hosted Retraction Watch CSV downloaded 23 July 2026. The final sample is a census of qualifying records, not a sample of all publications.

6. Results:-

The last dataset was composed of 37,344 deduplicated retractions dated 2020–2025. The proportion of valid original-paper DOIs for the records was 97.8%, as 36,533 were found to possess one of these. Since 6,893 records (18.5%) had more than one country listed as the origin, that's a huge number. Moreover, 22,577 records (60.5%) were retracted within two years. The median time taken for retraction was 593 days. The annual volume rises to 13,060 in 2023 from 3,071 records in 2020, before falling to 6,137 in 2024 and 5,619 in 2025. This information reflects corrective actions captured by the database, quite possibly involving publisher investigations, bulk retractions, change in detection capacity, and the like rather than a direct change in the underlying misconduct.

The multi-label reason analysis revealed that the most common tag was "investigated by the journal / publisher", with 24,993 tagged (66.9%). The most frequent code was unreliable results or conclusions, which appeared in 19,767 (52.9%) of reports. It was followed by third-party investigation in 16,562 (44.3%) reports. Referencing or attribution concerns were noted in 13,858 (37.1%), and data concerns in 12,987 (34.8%) reports. 11,695 records (31.3%) noted tags at paper mills. A broad match yielded 19,714 records containing terms related to peer review. These included 11,129 with a general peer review concern and 9,590 with compromised peer review. The terms computer-aided or generated-content appeared in 9,085 records (24.3%). A record can be registered for more than one reason. So, the percentages reported refer to overlapping signals.

The manipulation of the publication process accounted for 24,534 (65.7%) of the exclusive hierarchy, followed by the integrity of the data/image/other results, which amounted to 7107 (19.0%) issues, while plagiarism/duplication/citation counted for 3251 (8.7%). The reasons relating to other or administrative 1090 (2.9%), authorship/research ethics 715 (1.9%), error/reproducibility 647 (1.7%). The family to period association was significant, $\chi^2(5) = 4808.47$, $p < .001$, Cramer's $V = 0.359$, evidence of a moderate change, 2020-2022 to 2023-2025. The null hypothesis was rejected

Records tagged as from a paper mill had a median lag of 1.60 years versus 1.65 years for other records. The Mann–Whitney test was statistically significant, $U = 153{,}612{,}155$, $p < .001$ but the rank biserial effect was merely 0.024 and thus although H02 was rejected statistically, the difference is practically negligible. The study found that DOI validity was linked with retraction within two years, $\chi^2(1) = 79.51$, $p < .001$, phi = 0.046. The multi-country listing was connected with the process-manipulation family, $\chi^2(1) = 256.51$, $p < .001$, phi = 0.083. H03 and H04 were rejected because both effects were small and unsuitable for individual-level screening.

There was a significant result of the adjusted logistic model overall with an achievable area under the curve of 0.724. The value of McFadden's pseudo-R^2 was 0.122 and maximum variance-inflation factor was 1.77. Retraction within two years was most strongly positively associated with peer-review concern (OR = 4.53, 95% CI 4.29–4.80) and with computer-aided or computer-generated content (OR = 2.02, 95% CI 1.87–2.18). Having a valid DOI was associated with higher odds of rapid correction (OR = 1.48, 95% CI 1.27–1.71). Individuals with data/image/result concerns had lower odds (OR = 0.40, 95% CI 0.38-0.42), reflecting possibly longer investigations. After adjusting for overlapping signals, the paper-mill tags also showed lower odds (OR = 0.77, 95% CI 0.73-0.82). Associative estimates do not imply causes of events.

Table 2:- Annual retractions, timing, and selected integrity tags.

Year	n	Median lag (years)	Paper mill (%)	Peer review (%)	Computer content (%)
2020	3,071	1.47	8.0	2.5	1.3
2021	3,893	1.65	20.9	15.3	12.4
2022	5,564	1.76	16.8	50.4	6.9
2023	13,060	1.41	51.9	79.7	42.2
2024	6,137	2.25	29.4	55.2	23.1
2025	5,619	1.84	19.8	43.3	22.3

Note. Percentages are based on broad text matching of multi-label reason fields. Multiple tags may apply to one record.

Table 3:- Ten most frequent recorded reason tags.

Reason tag	Count	Records (%)
Investigation by Journal/Publisher	24,993	66.9

Reason tag	Count	Records (%)
Unreliable Results and/or Conclusions	19,767	52.9
Investigation by Third Party	16,562	44.3
Concerns/Issues about Referencing/Attributions	13,858	37.1
Concerns/Issues about Data	12,987	34.8
Paper Mill	11,695	31.3
Concerns/Issues about Peer Review	11,129	29.8
Compromised Peer Review	9,590	25.7
Computer-Aided Content or Computer-Generated Content	9,085	24.3
Concerns/Issues about Results and/or Conclusions	8,682	23.2

Note. Reason tags are multi-label; percentages do not sum to 100%. Wording follows the database field.

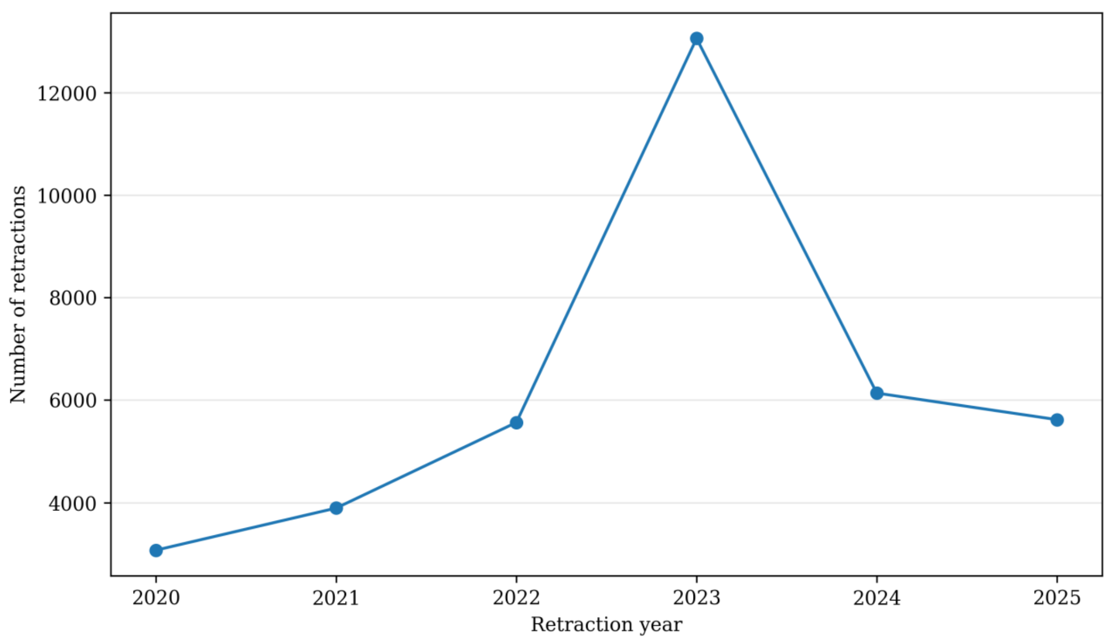

Figure 1:- Annual number of qualifying retractions, 2020–2025.
Source: Crossref-hosted Retraction Watch data; values reproduced in Table 2.

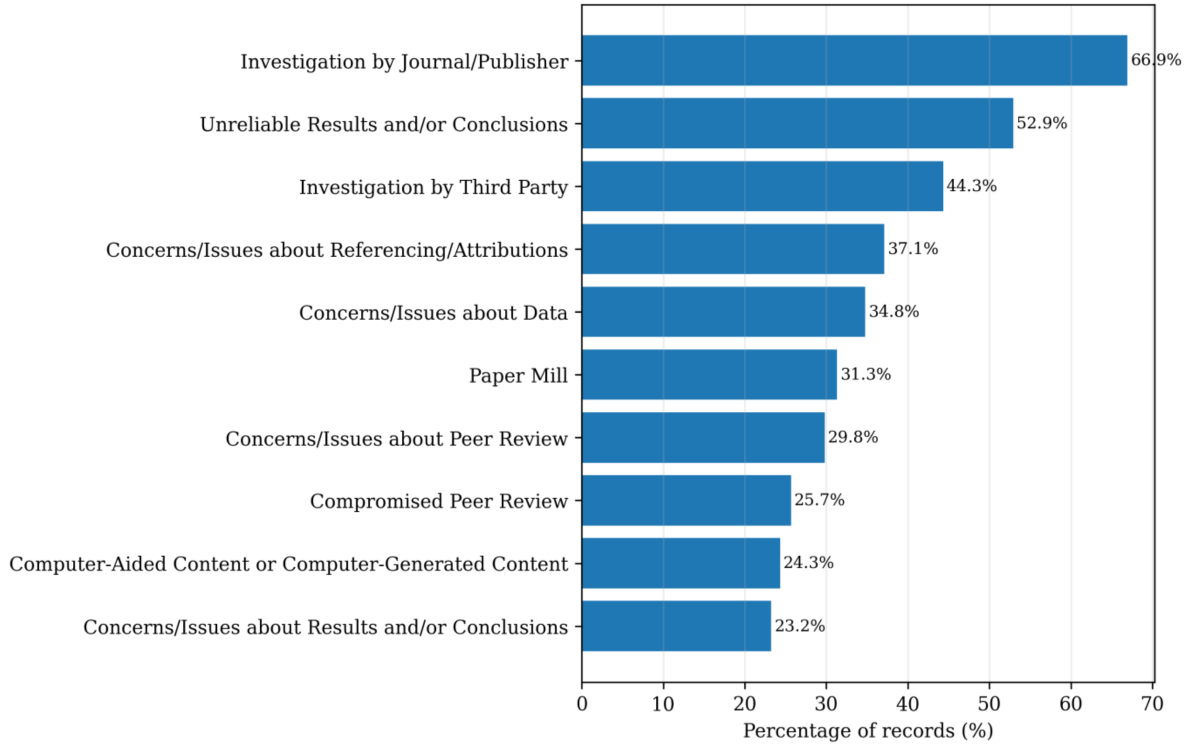

Figure 2:- Most frequent Retraction Watch reason tags

Source: Crossref-hosted Retraction Watch data; multi-label counts.

Table 4:- Exclusive primary reason families.

Primary family	Count	Percent
Publication-process manipulation	24,534	65.7
Data/image/result integrity	7,107	19.0
Plagiarism/duplication/citation	3,251	8.7
Other/administrative	1,090	2.9
Authorship/research ethics	715	1.9
Error/reproducibility	647	1.7

Note. Author-defined hierarchy described in Methodology. This mutually exclusive classification is secondary to the original multi-label reason field.

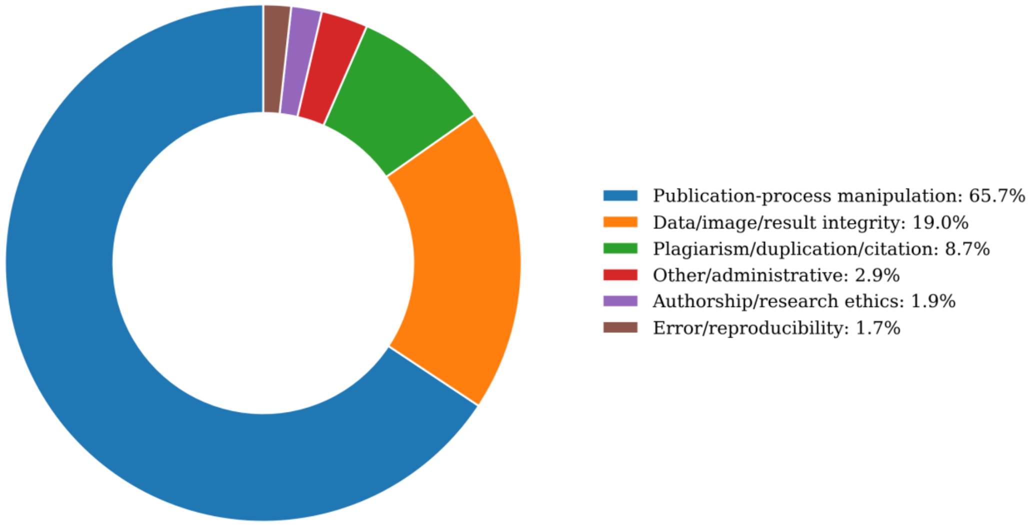

Figure 3:- Distribution of exclusive primary reason families.
Source: Author classification of Crossref-hosted Retraction Watch reason fields.

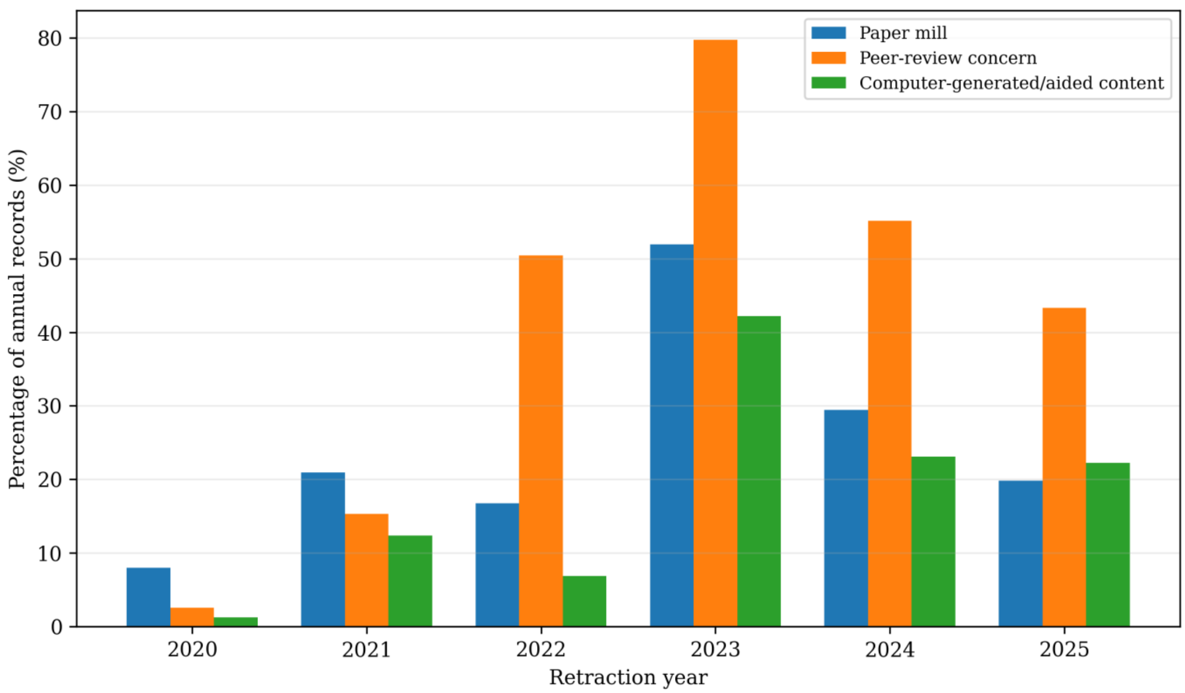

Figure 4:- Selected integrity tags by retraction year.
Source: Crossref-hosted Retraction Watch data; broad multi-label matching.

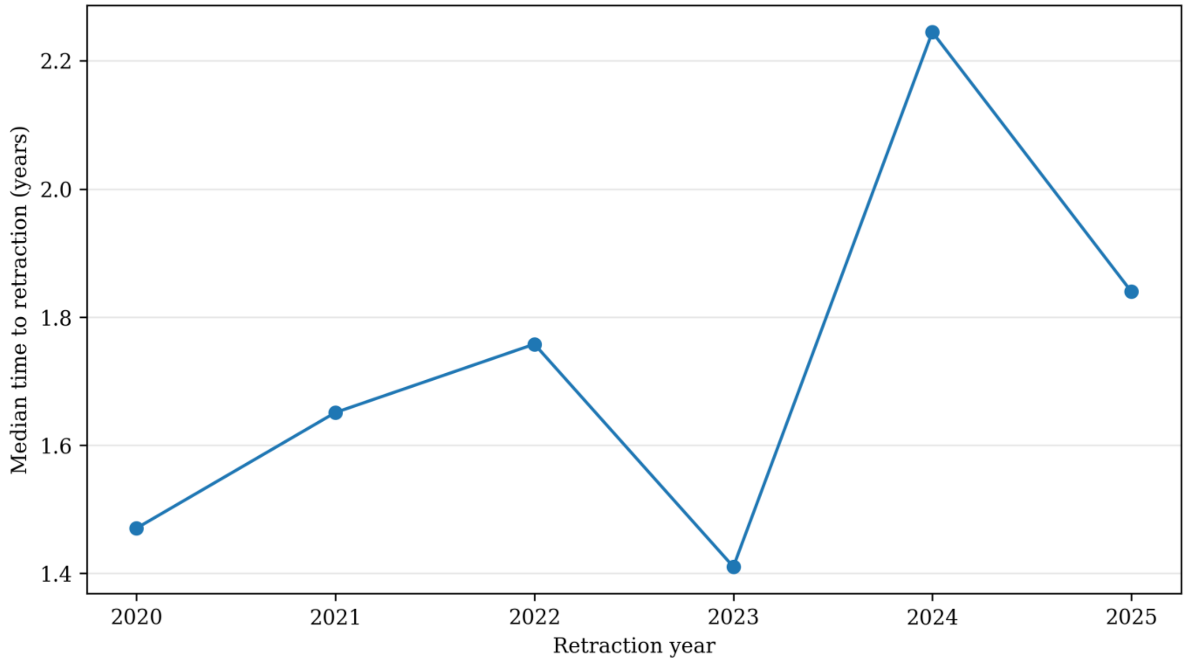

Figure 5:- Median publication-to-retraction lag by year.
Source: Crossref-hosted Retraction Watch data.

Table 5:- Hypothesis-testing results.

Hypothesis/test	Statistic	p	Effect size	Decision
H01: Period × reason family	$\chi^2(5) = 4{,}808.47$	< .001	Cramer's V = 0.359	Reject H01; moderate association
H02: Paper-mill tag × lag	U = 153,612,155	< .001	Rank-biserial r = 0.024	Reject H02; trivial effect
H03: Valid DOI × rapid retraction	$\chi^2(1) = 79.51$	< .001	Phi = 0.046	Reject H03; very small effect
H04: Multi-country × process family	$\chi^2(1) = 256.51$	< .001	Phi = 0.083	Reject H04; small effect

Note. Two-sided tests. Statistical significance was evaluated at .05; practical interpretation is based on effect size.

Table 6:- Logistic regression predicting retraction within two years.

Predictor	B	SE	OR	95% CI for OR	p
Retraction in 2023–2025	-0.116	0.029	0.891	0.842–0.942	< .001
Valid original-paper DOI	0.390	0.075	1.477	1.275–1.712	< .001
Multiple countries listed	0.073	0.030	1.075	1.014–1.140	0.015
Paper-mill tag	-0.259	0.031	0.772	0.726–0.821	< .001
Peer-review concern tag	1.512	0.029	4.534	4.287–4.795	< .001
Computer-aided/generated-content tag	0.703	0.038	2.020	1.874–2.177	< .001
Plagiarism/duplication/reference tag	-0.101	0.026	0.904	0.859–0.951	< .001
Data/image/result concern tag	-0.917	0.029	0.400	0.378–0.423	< .001
Authorship/ethics concern tag	-0.084	0.034	0.919	0.860–0.983	0.014

Note. N = 37,344; AIC = 44,049.59; McFadden R^2 = 0.122; ROC AUC = 0.724; maximum VIF = 1.77. Outcome coded 1 for lag ≤730 days. OR >1 indicates higher adjusted odds.

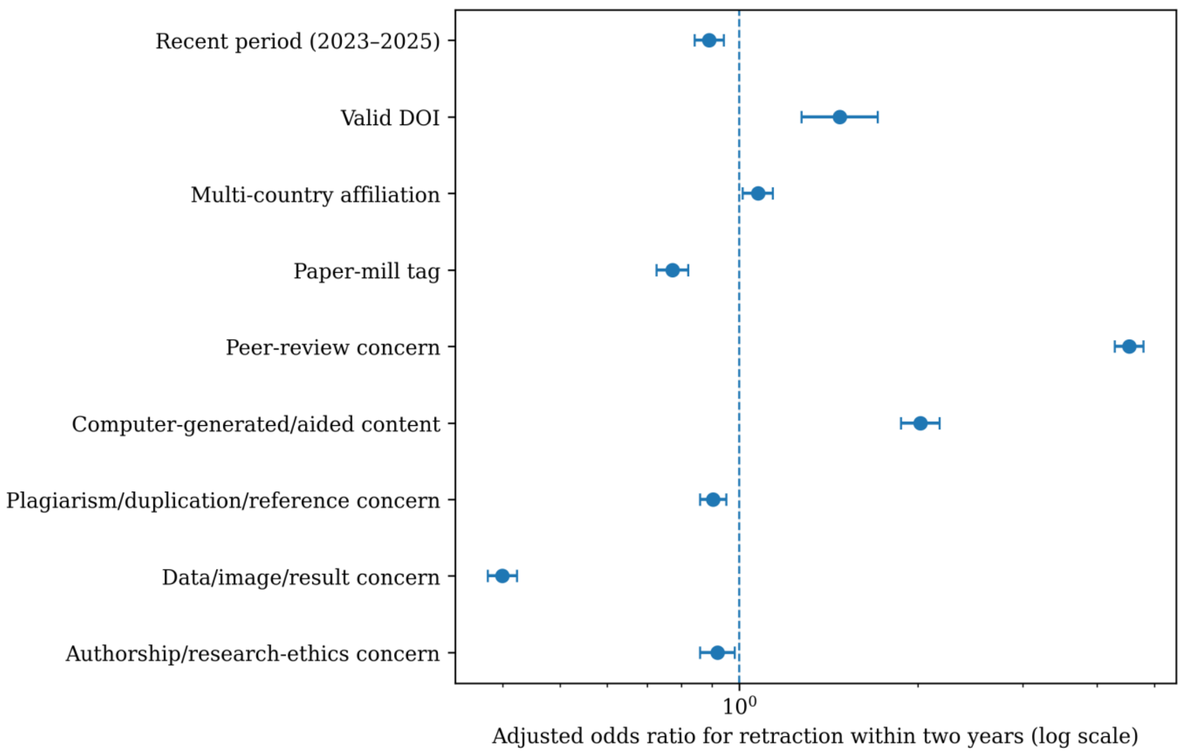

Figure 6:- Adjusted odds ratios for retraction within two years.
Source: Logistic regression in Table 6; horizontal reference line at OR = 1.

7. Discussion:-

Recent retractions are influenced as much by failings in the publication process as defects in the evidence reported. A plethora of investigations involving journals or publishers, peer-review issues, third-party investigations, tagging of paper mills, and signals of generated content suggest that organized misconduct is a systemic problem rather than a problem characteristic of individual authors (COPE & STM, 2022; Parker et al., 2024). Rephrased (12 words):

There were a plethora of investigations and mass corrective measures in 2023. The database records the timing of retraction (not the timing of detection, investigation initiation, or misconduct), so this should not be read as a one-year estimate of fake-paper incidence.

It is easier to detect certain warning signs if they are structurally visible. At a large scale it is possible to screen for things like fake reviewer accounts, repeated domains in emails, impossible timelines to publish … and so on. Problems related to selective reporting require that you have access to the underlying data and actual subject expert knowledge. Many detection methods for misconduct beyond text or image checks were not standardised or validated. Thus, Bordewijk et al. (2021) found. This provides a justification for treating technology as a triage layer, not a verdict. A flag only acquires meaning when it joins with evidence from independent sources.

The steady non-finality of the papers means that process evidence should be sufficiently strong. Otherwise, we will see little adjustment in our approach. It may be easier to adjudicate on e-mail provenance, unusual recommendation patterns and network links than disputes about raw evidence. On the contrary, the lower chances of speedy withdrawal for data/image/result worries may point to the file collection, institution consultation, author engagement, and analysis reproduction required. The investigative burden specified by editors and paper-mill researchers is consistent with this, even though the design cannot definitely demonstrate the mechanism (Christopher, 2021; Heck et al., 2021).

Specific care is required for the generated content association. The Retraction Watch labels represent reasons that have been recorded in notices and the database coding, not a validated detector of AI authorship. Content created with the aid of a computer is defined as anything that uses a computer to create any graphics, words, paraphrasing, text that makes no sense, generation etc. It does not relate to responsible use of grammar, translator, coding, ideation. It is not what they term it (content created anywhere on a computer). The important ethical issue is accountability and transparency. According to COPE (2023), the European Commission (2024), and ICMJE (2025), human authors must verify claims, references, calculations, and permissions, and journals must specify what uses require disclosure. The AI-output classifiers are too unstable and poor in context to support allegations of misconduct.

The amount by which the lag of the paper-mill retraction and other retractions differ is negligible. A difference might have insignificant practical value, but the p-value is still very small. Like DOI validity , multi-country listing were also statistically detectable but weakly associated. There should be a breakdown of how papers were selected. Having a valid DOI may speed up the flow of corrections through Crossref-linked systems, but the presence of a DOI does not guarantee quality. It is common for legitimate authorship to involve many countries, and scientific profiling on demographic or geographic ground would be weak and unethical. Wittau and Seifert (2024) also state that simple metadata features are not very discriminative.

Reference integrity serves as a crucial safeguard as references link the scholarly record. False data, faked citations, hijacked-journal archives and citation mills can generate false authority and inflate metrics (Abalkina, 2024; Besançon et al., 2024; Ibrahim et al., 2025). In cases where it is feasible, editorial systems should resolve every DOI, compare the metadata in the references with the claims made in the text, identify those sources which have been retracted, and review citation clusters that are anomalous. A citation of a retracted article for historical or methodological discussion must be distinguished from uncritical reliance on its results by authors and reviewers. The retraction status should be easy to find in PDFs, metadata feeds, library systems and systematic-review update processes.

Pushing investments could cause publication bias Evaluation criteria based on counts of papers, brands of journals, and short-term metrics can intensify the allure of buying authorship and of suspect outlets. It should give a response which is not just limited to punishment after publication. All institutions need mentoring, statistical support, secure data stewardship, clear roles for contributors, protected channels for raising concerns, and assessment systems that value transparency, correction. The European Code of Conduct and open-science principles from UNESCO locate integrity in research culture, while Richardson et al. show that fragmented enforcement is inadequate against resilient networks.

Finally, retraction ought to be integrated into a complete system of corrections. Readers benefit from the protection provided by transparent retraction notices, expressions of concern, corrections and linked metadata. We should not stigmatise every retraction because it may discourage authors from reporting their honest mistakes which will reduce cooperation. The responsible course of action is proportionate: correct limited errors, withdraw findings incapable of reliable reproduction, investigate evidence of deliberate manipulation, and preserve clear records of what changed and why. The authenticity is robust when the correction is fast, visible, evidence-based, and fair.

8. Implementing Effective Safety Measures.

There should be a practical prevention model at five levels. Researchers must check journal identity and indexing against authoritative sources, resolve DOIs, and check retraction status; keep raw data, code, consent records, and imaging provenance; use contributor-role statements; disclose any material AI assistance. Supervisors must review the data lineage and authorship before submission, not the end score for plagiarism. Plagiarism software should be seen as proof of similarity and not as proof of misconduct.

Journals should confirm the identities of their editors and reviewers, forbidding substitutes for reviewers named in manuscripts, monitoring review speed for suspicious rapidity and recommendations clusters, screening submitted images and reference lists, requiring data-availability statements, and facilitating statistical review for high-risk claims that may not be able to be determined by simple adjustment. Editorial decisions should not trigger on a risk signal but combine them. Authors should be sent targeted queries with a chance to respond. The notice of retraction and correction must state who is retracing, which findings are unreliable for what reason and must not be defamatory if the individual is not aware of supportive evidence.

Institutions must develop mandatory, discipline-sensitive integrity training; publication-support units; secure repositories; data-management plans; auditable research records; and protected whistle-blower procedures.

Investigations need independence, timelines, conflict management, and communication with journals. Funding agencies and assessments bodies should lessen reliance on volume-based incentives and give credit for valuable contributions such as data sharing, replication, negative results, correction, and peer review.

It is recommended that databases and infrastructure suppliers propagate the metadata of retraction and expression-of-concern, validate journal identifiers, expose version history and support citation alert. Automated systems can identify duplicate images, tortured phrases, anomalous citations, or linked reviewer identities, but models should be validated, and monitored for bias, and used only for prioritisation. At the level of policy, publishers, institutions funders and regulators need interoperable reporting protocols shared evidence standards proportionate sanctions for deliberate misconduct and safeguards against misuse of integrity allegations.

Table 7:- Multi-level preventive safeguards and audit evidence.

Level	**Core safeguards**	**Minimum auditable evidence**
Researcher/supervisor	Verify journal identity, indexing, DOI and retraction status; preserve raw data, code and image provenance; use CRediT roles; disclose material AI use.	Submission checklist; repository link; signed contributor statement.
Journal/publisher	Authenticate reviewers and editors; screen references and images; monitor review networks; require data availability; use transparent notices and due process.	Audit logs; resolved-reference report; risk-based integrity review.
Institution	Provide integrity training, statistical support, secure repositories, protected reporting, independent investigations, and incentives for quality and correction.	Training records; data-management plan; investigation protocol.
Database/infrastructure	Propagate retraction and concern metadata; validate identifiers; show version history; flag anomalous citations and duplicate media.	Machine-readable status; alerts; interoperable metadata.
Funder/regulator	Reward transparency and replication; establish evidence-sharing standards; coordinate sanctions for deliberate misconduct; protect fair process.	Assessment policy; cross-organisation referral protocol.

Note. Author-developed framework based on the empirical results and the cited ethics guidance. The table is fully editable.

9. Conclusion:-

The presence of false publications and untrustworthy journals is a threat to scholarly credibility. This is not simply because they feature one or two incorrect papers but rather, because they corrupt citation networks. In addition, they occupy editorial and investigations resources, as well as, generally weaken confidence in genuine work. Between 2020 and 2025, a study analyzed 37,344 public retraction records and found that chances of retraction were strongly influenced by peer-review and generated-content signals, whereas publication-process manipulation was the dominant primary reason family. Numerous relationships were statistically significant but were small or trivial in effect size. It follows from the findings that layered verification is to be encouraged and simplistic profiling based on metadata, country, DOI presence, or a single software score is to be rejected.

Implication is that authenticity cannot be secured through a single detector. To ensure trustworthy research output, the following actions should be taken: enhance institutional integrity culture and conduct fair investigations, ensure journals authenticate peer review and verify evidence provenance, propagate correction metadata, and design funding and regulation incentives towards quality and not quantity. Ensure Generative AI Governance with Disclosure, Verification, Human Accountability, Not Unvalidated Authorship Classifiers.

The proposed framework provides a pragmatic distinction between automated triage and human adjudication. The ability of technology to discover patterns at scale is clear. However, the decisions on how to correct, reject, or determine misconduct call for contextual evidence, due process, and domain knowledge. Retractions should also be seen as corrective signals rather than blanket evidence of fraud. An effective system makes mistakes visible, distinguishes honest errors from deliberate lies, and provides a warning when retracted findings circulate. To ensure authentic research, we need a prevention mechanism before submission, a verification mechanism during review, correction after publication, and coordinated governance.

10. Suggestions for Further Action:-

Scholars submitting articles or data to journals, or PhD thesis designers, are recommended to submit with appropriate check to cover identity of journal; resolution of DOI; screening for retraction; roles of individual contributors; preservation of data and code; provenance of images; and disclosure of AI output. Journals ought to have reviewers verify their identity, validate their references, make data-availability statements, and perform image or statistical screening on a risk-based basis. Universities must set up publication-integrity support cells, regular trainings, protected reporting channels, and independent investigation processes. Librarians ought to instruct database verification and retraction awareness. To reward researchers, funders and promotion committees should reward methodological quality, open materials, replication, and correction, not publication counts. Retraction status should be visible; hijacked identity should be removed. It is important for Regulators and scholarly associations to formulate and apply interoperable evidence-sharing protocols and proportionate sanctions while protecting due process and legitimate whistle-blowing.

11. Constraints and Future Research Directions

There are several important limitations to this study. Retraction Watch is the most complete public retraction resource. Each notice added or revised can change coding and coverage. The causes of retractions depend on the wording and transparency of journal notices and that multi-label coding does not prove legal or ethical intent. The analysis considered only retracted records; there was no denominator of all publications and no estimate of prevalence. The hierarchy of exclusive reasons simplifies overlaps. The publication-to-retraction lag is influenced by publisher processes, institutional investigations and database updates. There can be no causal capability with cross-sectional associations and the rapid-retraction model has moderate, rather than diagnostic, discrimination. Future research ought to connect publication denominators, notice text, citation trajectories, journal workflows and verified case outcomes; prospectively validate machine-learning screening; compare disciplines and publishers; examine propagation to reviews and guidelines; assess whether integrity training and institutional supports improve researcher detection skill, using genuine respondent data.

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Appendix A. Reproducibility Notes

The analysis used the public CSV file retraction_watch.csv. Inclusion required Retraction Nature = Retraction and Retraction Date year 2020–2025. Records whose Article Type contained Revision were excluded. Original-paper DOIs were lower-cased, stripped of resolver prefixes, and checked against a DOI syntax pattern. Valid DOIs served as deduplication keys; otherwise Record ID was used. The earliest retraction was retained for duplicate keys. Lag equalled Retraction Date minus Original Paper Date. Figure values are reproduced in editable Tables 2–6; therefore the visual plots can be regenerated without extracting values from images.