

Scientific ghosts: Life after retraction – A case of Nature Index journals

Journal of Information Science
1–23
© The Author(s) 2026
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/01655515261424867
journals.sagepub.com/home/jis



Müge Akbulut 

Department of Information Management, Faculty of Humanities and Social Sciences, Ankara Yıldırım Beyazıt University, Türkiye

Abstract

Scientific paper retractions do not terminate their academic impact; rather, they create a ghost-like existence in the scientific literature. This study examines the ‘afterlife’ of retracted articles in high-prestige journals. Accordingly, it analyses the citation patterns after retraction of 994 retracted articles from Nature Index journals and their 21,047 citations. The findings indicate that 93.9% of these articles continued receiving citations post-retraction, with 47.86% of citations being neutral and 39.79% carrying a positive tone. In descriptive comparisons, categories involving ethical or misconduct-related issues showed a larger reduction in citations after retraction, whereas categories dominated by scientific errors exhibited a more moderate decrease. These patterns should be interpreted as associations rather than as definitive causal differences, particularly because retraction notices may include multiple overlapping reasons and vary in the level of detail they provide. Citation persistence also varied by section: introduction citations remained stable, while citations in the ‘Methods’ and ‘Results’ sections declined significantly. These results highlight the complex and lasting impact of retracted articles on scientific discourse, emphasising the need for enhanced retraction visibility and improved citation tracking mechanisms.

Keywords

Nature Index journals; post-retraction citations; publication ethics; scientific communication; scientific misconduct; scientific retraction research integrity

1. Introduction

The global rise in the number of universities, academic promotions, Funding mechanisms, and rankings has led to a surge in scientific output. This increase has brought new challenges to scholarly communication, emphasising the need for transparency and adherence to ethical standards throughout the research process. The acceleration of scientific publishing has led to concerns that some peer review practices may become rapid or superficial, posing potential risks to both authors and journals. Pressures such as ‘publish or perish’ for authors and impact factor considerations for journals have accelerated publication rates, often at the expense of rigorous evaluation. Furthermore, some large publishers misuse open access models for profit, and their leniency in publication selection has resulted in the proliferation of inadequately reviewed articles.

Retracted articles have risen significantly due to compromised research integrity, poor evaluation and the drive to publish rapidly [1,2]. While the highest retraction rates are found in biomedical, medical [3–5], life sciences and chemistry journals [6], the reasons vary, including methodological errors, flawed data analysis, plagiarism and other ethical violations [7]. Retraction Watch reports that most retractions are for content correction, with a 90% increase over the past decade [8,9].

Given the cumulative nature of science, retracted publications – still accessible or poorly marked in metadata – continue to be cited, perpetuating misinformation and undermining scientific rigour. A notorious case is the retracted Lancet paper by Wakefield et al. [10], which falsely linked the MMR vaccine to autism. Despite its retraction, it contributed to declining vaccination rates in the United Kingdom and the United States [7]. A case study on this article revealed a

Corresponding author:

Müge Akbulut, Department of Information Management, Faculty of Humanities and Social Sciences, Ankara Yıldırım Beyazıt University, 06760 Ankara, Türkiye.
Email: mugeakbulut@aybu.edu.tr

steady rise in negative citations over two decades [11]. Retraction Watch [12] found that seven of the ten most cited retracted papers received the majority of citations before retraction, though post-retraction citations remain substantial.

This study investigates the citation impact of retracted articles from journals listed in the Nature Index. Since Nature Index journals are selected by independent experts for their high quality, articles published there are presumed to undergo stricter evaluation. Accordingly, this study analyses retraction cases in these journals, examining their citation characteristics and continued influence on the literature – not only whether they are cited post-retraction, but also how they are cited.

While existing literature provides a foundational understanding of post-retraction citations, several critical gaps remain. Prior studies have often relied on smaller, more heterogeneous samples, making it difficult to generalise findings. Furthermore, most analyses have focused on whether a retracted article is cited, rather than the more nuanced question of how it is cited, often lacking large-scale sentiment or contextual analysis. This study addresses these limitations directly through three key innovations. First, it focuses on a large, curated corpus of 994 retracted articles from the prestigious Nature Index journals, providing a robust case study of citation dynamics at the highest tier of scientific publishing. Second, it moves beyond simple citation counts by employing a two-level design that includes a large-scale, BERT-based sentiment analysis of more than 21,000 citations to understand the qualitative nature of these ‘scientific ghosts’. Finally, by systematically linking retraction reasons to post-retraction citation trajectories, this study offers one of the most comprehensive views to date on how the scientific community differentially responds to misconduct versus honest error. In doing so, this research provides a more complete and nuanced picture of life after retraction in science.

2. Research objectives

This study aims to examine the afterlife of retracted articles in high-impact journals by analysing citation patterns and their contextual usage. The objective is to understand how retracted studies continue to shape scientific discourse despite their withdrawal from the literature. Focusing on retracted articles in Nature Index journals, the study addresses the following research questions:

- How do citation patterns of these articles change after retraction? (Research Question 1 (RQ1))
- What is the relationship between the reasons for retraction and post-retraction citation patterns? (Research Question 2 (RQ2))
- How are citations to retracted articles characterised in academic texts? (Research Question 3 (RQ3))
- By answering these questions, this study contributes to the broader discussion on research integrity, the persistence of retracted work in scholarly communication and the need for improved retraction visibility in citation databases.

The first and second research questions were formulated and tested *a priori*, while the RQ3 involved exploratory analysis of citation contexts to complement the main findings.

3. Hypotheses

The study is guided by the following hypotheses:

H1: Citation patterns of retracted articles vary based on their reasons for retraction. This hypothesis is based on prior research showing that the academic community reacts differently to various forms of scientific misconduct (Mongeon & Larivière, 2016; Azoulay et al., 2017). It assumes that deliberate misconduct is perceived as a more serious breach of scientific norms than honest errors.

H2: Articles retracted due to serious errors or academic misconduct experience a significantly greater citation loss post-retraction, while articles retracted for minor errors experience a less drastic citation loss. This hypothesis aligns with studies demonstrating that citation behaviour is influenced by the severity of research violations (Bar-Ilan & Halevi, 2017; Schneider et al., 2020). It also reflects the broader theory that perceived research reliability impacts citation practices.

Hypothesis 3 (H3): In-text characterisation of citations to retracted articles differs based on the nature of the retraction: serious violations are referenced with critical language, whereas technical errors receive neutral citations. This

hypothesis is rooted in citation context analysis studies (Teixeira da Silva & Bornemann-Cimenti, 2017), suggesting that the way researchers discuss retracted studies mirrors their assessment of the cited work's credibility.

RQ1 and RQ2 were formulated and tested a priori, while RQ3 involved exploratory analysis of citation contexts to complement the main findings.

4. Literature review

4.1. Trends and patterns in scientific retractions

Studies on retracted articles provide essential insights into the impact of scientific errors and ethical violations. While some research addresses general reasons and characteristics of retractions [9,13], others focus on smaller samples [14–20]. According to Shuai et al. [7], more than 25% of retractions are due to plagiarism (including duplicates), about 24% from unintentional author errors and 23% from falsification or fabrication. The retraction reason affects outcomes: papers retracted for fraud receive fewer citations and suffer greater damage to scientific literature and authors' careers compared with honest errors [21]. Papers retracted for errors may still offer valid insights, whereas fraud-retracted works tend to be discredited.

Many studies have shown that retracted articles continue to be cited for some time [22–25]. For example, 17 retracted articles by Jan Hendrik Schön continued to receive roughly 50 citations per year even after exposure of data manipulation [26]. Most citations were neutral (90.9%), with few mentioning the retraction (4.2%). Similarly, Kochan and Budd [18] found 85% of post-retraction citations were positive without noting retraction. Bar-Ilan and Halevi [14] reported 83% positive, 12% neutral and 5% negative post-retraction citations, while Bornemann-Cimenti et al. [15] observed only 25% of citations mentioned retraction. Cor and Sood [27] noted more than 30% of citations occurred at least a year post-retraction.

Despite continued citations, a decline in citation counts post-retraction has been documented. Azoulay et al. [28] demonstrated negative effects on articles' and authors' citations. Dinh et al. [29] reported an average 86.5% citation loss. Lu et al. [4] found faster citation decline for retracted papers and their authors' prior work, with reduced self-citations after retraction [2,30].

However, some studies reveal persistent or even increased citation rates post-retraction [19]. High-impact journals' retracted articles often retain high citations [31], especially those highly cited before retraction [31,32]. For instance, Scott S. Reuben's 21 retracted articles remained popular 5 years post-retraction [15].

Citing retracted articles undermines research integrity even pre-retraction [33]. Examining 113 osteoporosis-related retractions due to integrity concerns, 94% of citations occurred before the concern was publicised. The authors argue that citing studies should also be retracted to prevent literature distortion [33,34]. Avenell et al. [35] reviewed 68 citations (reviews, guidelines, clinical trials) and found 19% would probably change conclusions if retracted references were removed, with 12% uncertain.

4.2. Persistence of retracted articles in literature

Retracted articles persist in the literature for several reasons. About 10% of retraction reports lack a stated reason, complicating assessment of the issue's scope or severity [36–40]. Delays or failures in notifying databases about concerns or retractions further limit awareness [33,41]. The main cause for ongoing citations is authors' unawareness of retraction, driven by insufficient retraction statements, incomplete metadata [5,42] and continued access to the articles via multiple sources [14]. Local saving of articles before retraction is also critical [43].

Publishers often do not adequately alert readers. Major databases and search engines (WoS, Google Scholar, Scopus) rarely flag retracted articles in search results [20,44]. For example, 22% of MEDLINE-indexed articles retracted in 2008 were not marked as retracted 3 years later on publisher sites or PDFs [45]. Reference management tools lack systematic retraction notifications, though tools like ReTracker [46] and Zotero's Retraction Watch integration [47] improve author awareness. Crossref's Crossmark service also helps track article updates, displaying retraction status even on local copies [48].

Beyond technical issues, Schmidt [49] highlights that rhetorical framing and perceived credibility can sustain retracted articles' influence, even when retractions are documented. The principal reason for ongoing citations remains author unawareness, with 94% of authors unaware of retractions of sources they cited [50]. Thus, retraction notices must be clear, accessible and distinguish misconduct from honest errors, linking to the original article [51]. However, the relationship between retraction visibility and post-retraction citations remains unclear [52,53].

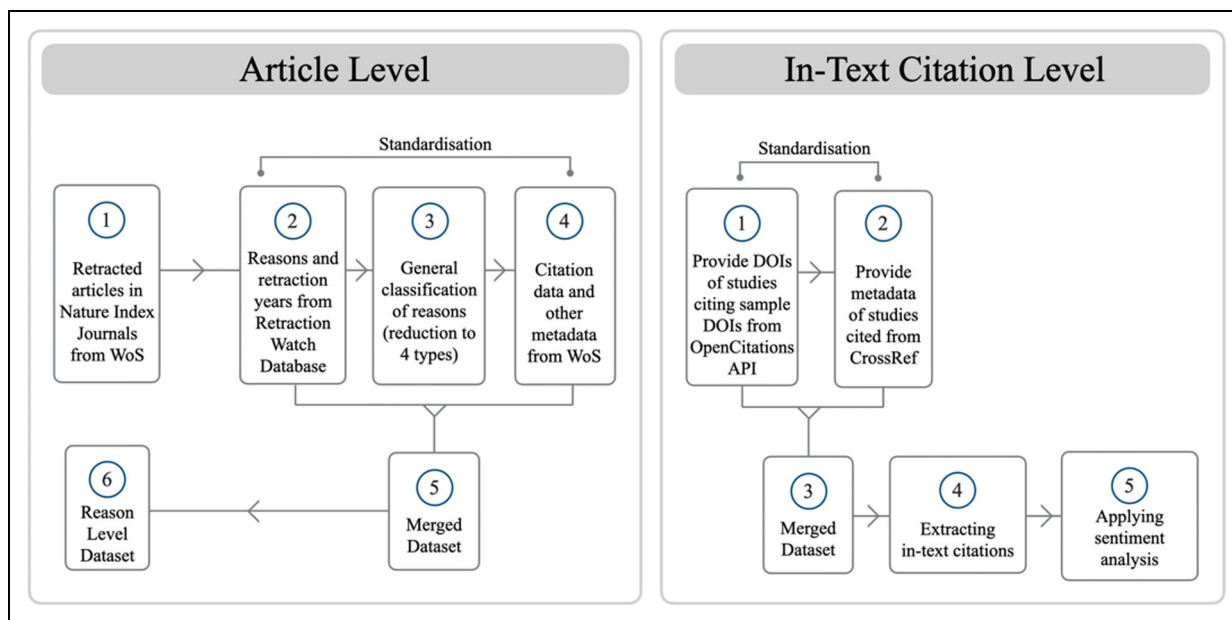


Figure 1. Workflow for preparing research data sets, showing data flow, applied exclusions and reproducible processing criteria.

The impact of retracted articles is complex. Their persistence threatens scientific integrity [14,44]. Fanelli et al. [54] identify lack of integrity policies, profit-driven publishing and career pressure as key drivers of misconduct. Aligning with Fanelli [55], the rising number of retractions observed in recent years may be interpreted as a sign of improved detection and scientific self-correction rather than solely an increase in misconduct rates.

5. Methods

This study focuses on retracted articles from Nature Index journals, a set of 145 natural and health sciences journals selected by an independent panel of active scientists based on their reputation and quality [56]. These journals are known for rigorous peer review standards, ensuring high scientific validity and reliability. To enhance methodological transparency, all stages of data identification, classification, and analysis were explicitly documented in the subsequent subsections, following reproducible and auditable procedures. Their selection allows for a deeper examination of the retraction process and its underlying causes. The typically high citation rates of these journals offer a valuable data set for analysing citation behaviours pre- and post-retraction. Despite stringent review processes, retractions in these journals reveal critical insights into research integrity and quality control. While their impact factors vary, Nature Index journals form a coherent group for assessing retraction dynamics due to their consistently high publishing standards.

5.1. Data collection process and analysis

The research involved analysis at two levels. The first level focused on analyses of retracted articles (article level), while the second level examined in-text citations using a 20% sample of these retracted articles (in-text citation level). Different data collection and analysis processes were followed for each level, as illustrated in Figure 1.

5.2. Preparation and analysis of article-level data set

As shown in the left panel of Figure 1, the article-level data set (The data sets have been uploaded to Zenodo. This citation has been removed for the peer review process to ensure anonymity; the data will be provided upon request.) was prepared in six stages. The process of identifying retracted articles involved a two-step procedure to enhance coverage and precision. Initially, a comprehensive search was conducted in the WoS to identify candidate articles from Nature Index journals marked with titles such as ‘retracted article’. To validate this initial list, reduce false negatives and enrich the data, a systematic cross-referencing was performed against the Retraction Watch Database. This database is a

meticulously curated resource that often provides more detailed retraction notices and more consistent notice-based timing information than indexing services. The final corpus of 994 articles was established based on confirmed matches between these two sources. The data search in Web of Science was conducted on 6 March 2024, at which point these 994 articles were identified across 108 journals (mean: 9.2; median: 3), with a total of 81,658 citations (mean: 82 per article). In the second stage, retraction reasons were gathered. Since WoS often lacks detailed explanations, the Retraction Watch Database was used. DOIs were employed to match records, and for unmatched cases, titles were normalised (e.g. for DOI 10.1016/j.annemergmed.2004.09.036). The retraction year for each article was established based on the date provided in the Retraction Watch Database, as it is generally more aligned with the publisher's official notice date than the record update date in WoS. At the same time, it is acknowledged that this two-source integration functions as a single measurement system with inherent coverage and timing constraints. In practice, multiple 'retraction dates' may coexist, including the publisher's notice date, the date an indexing database updates its record and the date on which the retraction signal becomes visible through downstream platforms. Such discrepancies can introduce boundary noise around the event year and may contribute to apparent post-retraction citations that were, in practical terms, written before the retraction notice became widely visible due to editorial workflows and indexing delays. To address this limitation transparently, comparative pre-post analyses were anchored to the Retraction Watch retraction year as the event year, and the dependence of key descriptive pre-post counts on event-boundary timing is acknowledged as a measurement sensitivity, and pre-post comparisons are interpreted conservatively in light of stricter event-year handling assumptions. Retraction Watch identified at least one, and often multiple, reasons per article, totalling 83 unique reasons. Because retraction notices may list more than one reason, two analytical units were defined and used consistently throughout the article. Article-level analyses treat each retracted paper as a single observation ($N = 994$). Reason-level analyses treat each assigned reason as a separate classification instance, meaning that the same article can contribute to more than one reason category. Therefore, whenever results are reported at the reason level, totals and percentages may exceed the number of unique articles by design, and this distinction is explicitly indicated to avoid overinterpretation. All exclusion steps and decision criteria used in the data preparation process are summarised in Figure 1. To further strengthen reproducibility and auditability, the article, in addition, documents the main operational rules used during data set construction. First, deduplication was performed at the DOI level whenever available, and title-based normalisation was used only when DOI metadata was missing or inconsistent. Second, cross-source matching between Web of Science and Retraction Watch was primarily conducted using DOIs, and in unmatched cases, records were resolved using normalised titles to minimise false exclusions. Third, because retraction metadata can contain timing discrepancies across platforms, the retraction year was consistently defined using the Retraction Watch notice date, and the interpretation of event-boundary patterns is presented with this constraint in mind. Finally, for reason classification and citation labelling, borderline cases were handled using explicit decision rules. When a retraction notice listed multiple reasons, multi-label assignment was retained rather than forcing a single dominant label. When citation sentences contained mixed signals (e.g. descriptive mention combined with mild caution), the tone label was treated as a model-based estimate and interpreted conservatively at the aggregate level. These rules provide an auditable trace of how key variables were derived and how ambiguous cases were treated, and they are intended to support replication and verification of the reported results. To support computational reproducibility, the analysis scripts and an environment specification documenting the software and library versions used for data preparation and modelling are provided alongside the data set in the repository.

Given the overlap among retraction reasons, the analysis was challenging. About 73% of articles had multiple reasons (average: 2.8). Frequent co-occurrences included 'investigation by company/institution' with 'concerns about data' (62%), 'duplication of image' with 'image manipulation' (58%) and 'falsification/fabrication' with 'author misconduct' (51%). To manage this complexity, reasons were grouped using Feng et al.'s [57] four-category framework based on two dimensions: evidence of misconduct and impact on research validity. Articles were classified as involving *academic misconduct* (deliberate violations) or *scientific error* (issues compromising conclusions), regardless of intent. The categories are as follows:

- Type 1 (Academic misconduct, scientific errors): Cases where deliberate misconduct led to demonstrable errors in the research, such as data fabrication or image manipulation.
- Type 2 (Academic misconduct, no scientific errors): Cases involving ethical violations that do not necessarily invalidate research findings, including unauthorised data use, authorship disputes or duplicate publication of valid results.
- Type 3 (No academic misconduct, no scientific errors): Cases involving technical or administrative issues without questioning research validity, like accidental duplicate publication or publisher errors.
- Type 4 (No academic misconduct, scientific errors): Cases where honest mistakes or unintentional errors affected research findings, such as incorrect statistical analyses or equipment calibration errors.

It is important to clarify that this study employed a multi-label classification approach. If a single article was retracted for multiple reasons that fell into different categories (e.g. both plagiarism and an honest statistical error), it was included in the analyses for each of its corresponding categories. This method was chosen over a single-priority rule to allow for a more nuanced examination of how different types of issues are associated with post-retraction citation patterns.

In the fourth stage, citation data and metadata were collected from WoS. The fifth stage involved standardising and merging all data sets, and in the sixth, a final data set was constructed at the retraction reason level.

Descriptive statistics were used to analyse the 994 retracted articles, focusing on annual trends, retraction age and citation patterns. Annual citation counts were computed using the citing year recorded in WoS. To operationalise the comparison periods consistently at the variable level, the retraction year (as defined by Retraction Watch) was treated as the event year (Year 0). Citations occurring in calendar years strictly before the retraction year were counted as pre-retraction (Year -1 , -2 , ...), whereas citations occurring in calendar years strictly after the retraction year were counted as post-retraction (Year $+1$, $+2$, ...). Citations in the retraction year itself (Year 0) were treated as a transitional period and were not pooled into either side for pre-post comparisons, as they can reflect timing effects related to editorial workflows and indexing visibility. Accordingly, early post-retraction citations were interpreted with the understanding that some may have been written before the retraction notice becoming widely visible due to publication and indexing delays. Comparative analyses explored shifts in citation behaviour across the defined pre- and post-retraction periods, including differences across retraction age groups and WoS indices.

This study also differentiated citation types (mentioning, supporting, contradicting, unclassified) and sentiments (positive, negative, neutral). Sentiment analysis was conducted using a BERT-based model to identify the model-predicted evaluative tone expressed in citation contexts. Because academic prose often conveys epistemic evaluation in subtle and discipline-dependent ways, the sentiment results are reported and interpreted as exploratory model-based estimates rather than as human-verified ground truth. Accordingly, the conclusions drawn from sentiment distributions are presented cautiously, and the need for corpus-specific manual validation is acknowledged as an important limitation.

5.3. Preparation and analysis of in-text citation-level data set

A five-stage process was followed for in-text citation analysis (The data sets have been uploaded to Zenodo. This citation has been removed for the peer review process to ensure anonymity; the data will be provided upon request.), as shown in the right panel of Figure 1. In the first stage, a representative 20% sample ($n = 199$) was drawn from the full population of 994 retracted articles. To ensure the sample accurately reflected the diversity of the population, a probability-based stratified sampling method was employed. The population was stratified based on three key characteristics known to influence citation patterns: publication year (strata: 1980–1999, 2000–2009, 2010–2023), retraction reason (strata: the four main categories of misconduct and error) and journal index (strata: SCI-EXPANDED, SSCI, etc.). Articles were then randomly sampled from within each stratum in proportion to their representation in the full population. Stratification was based on publication years (1980–2023), retraction reasons (four main categories) and journal indices (SCI-EXPANDED, SSCI, CPCI-S, CCR-EXPANDED, IC). DOIs and citation counts for sampled articles (totalling 36,365 citations, mean: 183 per article) were retrieved via OpenCitations.

To empirically verify the representativeness of this sample, a balance analysis was conducted comparing the sample to the non-sampled articles from the population. As shown in Table 1, the distributions of publication year, retraction age, pre-retraction citations and retraction reason categories are highly similar between the two groups, with no

Table 1. Balance analysis of sampled versus non-sampled retracted articles.

Variable	Sampled ($n = 199$)	Non-sampled ($n = 795$)	p
Mean publication year	2008.5 (SD = 6.2)	2009.1 (SD = 5.8)	0.281
Mean retraction age (years)	5.1 (SD = 4.8)	5.0 (SD = 4.5)	0.754
Mean pre-retraction citations	85.3 (SD = 150.1)	81.2 (SD = 142.5)	0.693
Retraction reason (%)			
Type 1: Misconduct, errors	14.1%	14.3%	0.935
Type 2: Misconduct, no errors	21.1%	20.5%	0.850
Type 3: No Misconduct, no errors	10.6%	10.8%	0.941
Type 4: No Misconduct, errors	46.2%	45.7%	0.902

Note. Percentages for retraction reason do not sum to 100% as a small subset of articles could not be classified into any of the four categories due to insufficient information in the retraction notice.

statistically significant differences observed. This confirms that the findings from our in-text citation analysis can be reliably generalised to the entire corpus of retracted articles.

In the second stage, citing articles' metadata (title, authors, year, abstract, etc.) was collected using CrossRef's API, which hosts metadata for more than 150 million records. Python was used to automate data collection and preprocessing – removing errors, duplicates and normalising fields.

In the third stage, all data sets were merged and standardised.

The fourth stage involved collecting in-text citation sentences from the citing articles. Overall, 16,136 citations to the retracted articles were identified; however, in-text citation contexts could be extracted for 15,923 citations, because full-text access and parsable citation locations were available for these cases, while the remaining 213 citations were excluded due to missing or non-retrievable full-text citation context. This process faced two sequential challenges. First, full-text access was not available for 5124 of the 21,047 potential citations (24.4%). For the remaining 15,923 accessible citations, a second challenge emerged: many articles did not follow a standard IMRAD format (e.g. reviews, editorials and letters), making programmatic section mapping impossible. Due to this second issue, an additional 5897 citations could not be mapped. In total, section location could not be determined for 11,021 citations (52.4%), which were subsequently labelled 'N/A' in the sectional analysis.

Citation types (mentioning, supporting, contradicting, unclassified) capture the functional role of citations, while *sentiments* (positive, negative, neutral) reflect evaluative tone. Sentiments were analysed using a BERT-based model [58] and trained to interpret complex academic texts through bidirectional context understanding [59]. For example, a citation might be 'mentioning' in type but express a negative sentiment.

Despite its strengths, BERT had limitations. Citations in non-English languages (Greek, Russian, Ukrainian, Chinese, Japanese, Korean; $n = 59$) were excluded. In addition, the model sometimes struggled with domain-specific terms and neutral academic phrasing [60–62]. To improve reliability: (1) articles without full-text access were excluded, (2) non-IMRAD structures were manually reviewed and (3) ambiguous citation types were labelled 'unclassified'.

5.4. Incorporating BERT for citation sentiment analysis

To operationalise the tone of in-text citations, an automated sentiment analysis was performed. The unit of analysis was the full sentence in which a citation to a retracted article appeared. For this classification task, a BERT-based sentiment analysis model was employed, specifically the pre-trained framework provided by Sandacian [58], which is fine-tuned for interpreting nuanced academic texts. This approach leverages a transformer-based neural network that analyses the contextual relationships between words in a sentence to classify its overall sentiment as positive, negative or neutral.

However, it is important to note that while this study utilises a well-established pre-trained academic sentiment model, a separate manual validation on a subsample drawn from the present corpus was not performed. Therefore, the reported sentiment labels should be interpreted as model-based predictions rather than as human-verified ground truth. This limitation is especially relevant because the target construct is not everyday 'sentiment', but epistemic evaluation expressed in scholarly writing, which can be euphemistic and discipline-dependent. Accordingly, the sentiment findings are presented as exploratory evidence, and future work would benefit from a human-coded validation protocol on a modest random subsample (e.g. double-coding with adjudication) to estimate classification error, particularly between neutral and positive labels. Each observation in the data set corresponds to a distinct retracted article, and sentiment variables were aggregated at the article level using the distribution of sentence-level sentiment predictions linked to that retracted work. Because multiple citation sentences can originate from the same citing article and because individual sentences may contain multiple references and rhetorical functions, the sentiment labels should be understood as descriptive, model-based summaries of citation contexts rather than as independent observations. The analyses did not involve formal hypothesis testing with uncertainty estimation (e.g. confidence intervals or p) for the sentiment outcomes. Accordingly, no inferential claims are made that would require independence assumptions or clustering corrections, and results are interpreted as descriptive patterns subject to within-document dependence and contextual ambiguity. To enhance the transparency of the classification process, the following table provides annotated examples of sentences assigned to each sentiment category by the model. In addition, it is acknowledged that sentence-level tone may not fully capture all rhetorical functions of a citation, and that the same retracted work may be characterised differently across multiple sentences within the same citing paper. No separate error analysis was performed, as the focus of this study was on describing discourse-level sentiment patterns rather than on quantitatively evaluating model performance; therefore, sentiment findings are presented conservatively as aggregate descriptive evidence rather than as definitive article-level judgements.

By integrating BERT for citation sentiment analysis, our study presents a scalable, interpretable and domain-specific approach that mitigates key limitations of existing methods while balancing computational efficiency. All model

architectures, hyperparameter choices, preprocessing routines and library versions are documented in the respective subsections to ensure methodological transparency and reproducibility.

A significant challenge in this analysis was that the section containing the in-text citation could not be determined for a substantial portion of cases (52.4%) due to full-text access restrictions or non-standard article formats (e.g. editorials and letters). To assess the potential for systematic bias from this missing data, as recommended by our reviewers, we analysed its pattern. The analysis revealed that missingness was slightly more prevalent in citations from articles published before 2010, probably due to less standardised digital formats, but it was not significantly correlated with the journal's index (e.g. SCI-E vs SSCI) or the retraction reason of the cited paper. While this mitigates concerns of systematic bias related to the study's core variables, the high proportion of missing data necessitates caution in interpreting the section-based findings. This issue is further addressed as a limitation of the study.

6. Results

The findings are presented at two main levels. First, at the article-level analysis, we examine retraction patterns and trends, citation dynamics of retracted articles and retraction reasons along with their effects. Second, under in-text citation-level analysis, we provide detailed examination of the distribution of citations across sections, citation types and sentiment analysis results.

6.1. Article-level analyses

6.1.1. Basic statistics. The retraction dynamics of scientific articles published in Nature Index journals reveal significant findings. As shown in Figure 2, while the total number of publications in Nature Index journals showed continuous growth from 1980 to 2023, retraction rates followed a fluctuating pattern. The fact that these rates generally remained below 0.07% (minimum: 0.02%, maximum: 0.068%, median: 0.021%) indicates that quality control mechanisms in journals functioned consistently and research ethics awareness persisted. The notable increase in retraction rates during the 2000s can be attributed to the transition of scientific communication to electronic media. This transformation and initiatives like Retraction Watch, established in 2010, led to both diversification and more effective detection of ethical violations [6]. In addition, increased oversight by research Funding agencies and academic institutions has strengthened accountability pressure on researchers [63].

Figure 3 shows the time between publication and retraction. About half of the articles (52.4%, $n = 521$) were retracted within 5 years of publication, with 21% ($n = 209$) retracted within the first year. However, some articles were retracted 10 to 25 years later. The apparent decline in retractions after 2010 (Figure 2) may be misleading, as the retraction process for recent articles is likely ongoing and rates may rise. This highlights the dynamic, long-term nature of retraction processes.

Using the detailed retraction reasons from the Retraction Watch Database, this study applied Feng et al. [57] four-category classification. Figure 4 displays the distribution of retraction reasons from 1980 to 2020. Notably, retractions due to scientific errors without misconduct (Type 4) increased significantly after 2010, with fluctuating peaks between 2015 and 2020, reaching up to 50 articles at times.

Articles containing academic misconduct (Types 1 and 2) showed a low-level increase from the early 2000s, experienced fluctuations between 2010 and 2020 and remained at levels of approximately 15–20 articles. Articles retracted for technical or administrative reasons, categorised as 'no academic misconduct, no scientific errors' (Type 3), exhibited a relatively low and stable pattern compared with other categories, generally remaining below 10 articles per year throughout the entire period.

The increasing trend observed across all categories since the 2010s can be attributed to several interrelated factors. First, the development of digital technologies has enabled more detailed and systematic examination of scientific content. In addition, increased awareness of academic integrity has encouraged the establishment of stricter monitoring mechanisms. The rise in transparency and accountability standards in scientific publishing has also supported this process.

Overall, Figure 4 demonstrates that efforts to maintain the reliability of scientific literature have increased, and researchers have adopted a proactive approach to preventing problems before they emerge. In particular, the increase in detecting scientific errors indicates that published works are being more carefully evaluated by the scientific community, and problematic studies are increasingly being identified.

6.1.2. Post-retraction citations. Retraction does not end an article's scientific impact. Our analysis shows that 93.9% of 994 retracted Nature Index articles continued to be cited post-retraction, persisting like a ghost in the literature. Figure 5

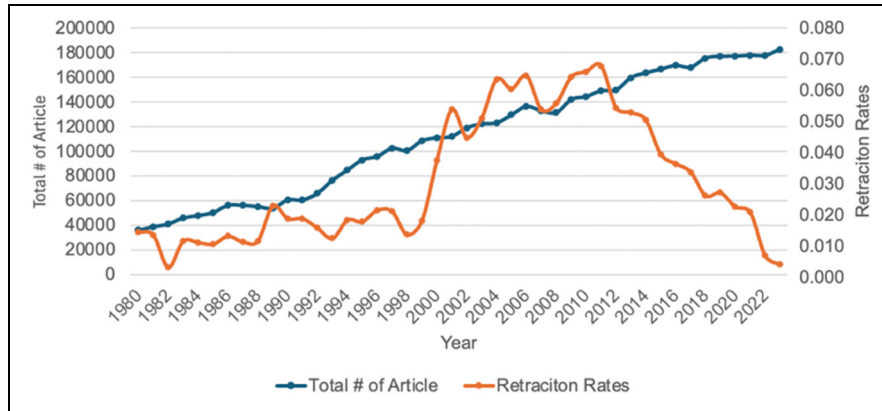


Figure 2. Retraction rates of articles in Nature Index journals (interactive graph: <https://mugeakbulut.com/nature/graphs/fig2/>).

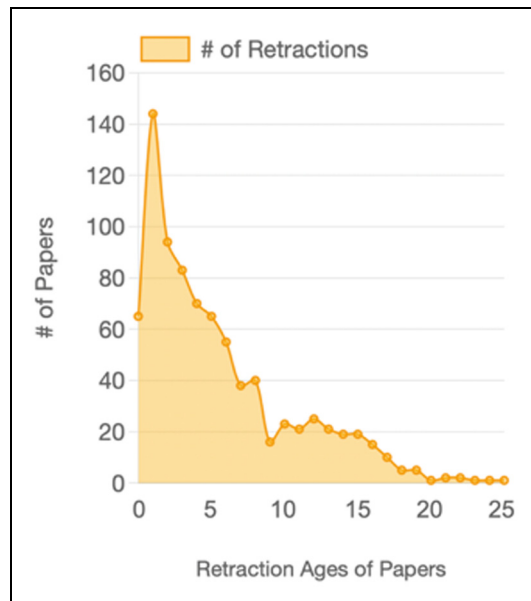


Figure 3. Retraction ages of articles (interactive graph: <https://mugeakbulut.com/nature/graphs/fig3/>).

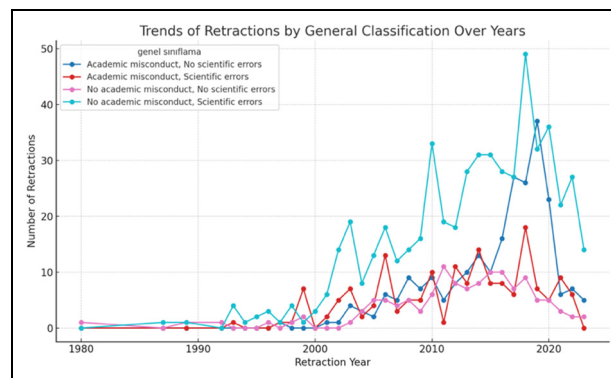


Figure 4. Distribution of retraction reasons by years according to the four-category classification.

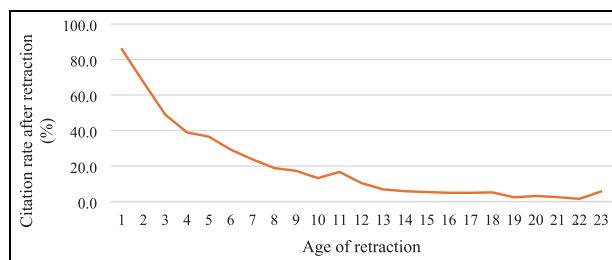


Figure 5. Retraction ages of articles and the ratio of post-retraction citations to total citations¹ (interactive graph: <https://mugeakbulut.com/nature/graphs/fig5/>).

shows these citations decline over time: 86% of total citations occur in the first year after retraction, dropping to 67% in the second year and 39% in the third and then gradually decreasing further. This pattern reveals that while retraction does not immediately stop influence, it significantly reduces citations over time, directly answering our RQ1. It is also important to acknowledge the potential for citation lag; citations appearing in articles published shortly after a retraction may have been included in the article before the retraction notice was widely visible due to publication and indexing delays.

Considering factors such as scientific evaluation process and indexing time of studies, it is normal to observe a pattern similar to pre-retraction citation rates immediately after retraction. This ratio gradually decreases after retraction. The temporal decline in citation rates of retracted articles shows a trend similar to the citation pattern of normal articles.

6.1.3. Citation analysis based on age of retraction. Citation patterns of retracted articles vary notably by their age at retraction. Figure 6 shows that articles retracted early (0–4 years) have similar citation rates before and after retraction, possibly because the retraction went unnoticed. For example, due to citation indexing delays averaging 2 years [64], an article published in 2022 might cite a paper retracted in 2020, creating the illusion of post-retraction citations.

An inverse relationship exists between age at retraction and post-retraction citation decline: the older the article at retraction, the greater the citation decrease. Mann–Whitney U tests confirm no significant difference for articles retracted within 0–4 years ($U = 8245$, $p = 0.382$), but significant declines for articles retracted after 5 years (5–9 years: $U = 3421$, $p < 0.001$; 10–14 years: $U = 1876$, $p < 0.001$; 15+ years: $U = 942$, $p < 0.001$). This pattern reflects literature obsolescence, where scientific publications naturally see decreased impact over time, varying by field and journal [65,66].

Citation patterns of articles based on their age at retraction have been examined in detail. The graph on the right side of Figure 7 shows the post-retraction citation distributions for all retracted articles. Articles typically receive their highest number of citations in the year they are retracted (averaging 12 citations), but this rate decreases over time. It is important to note that post-retraction citations are not always negative; some citations may be negative citations that discuss or

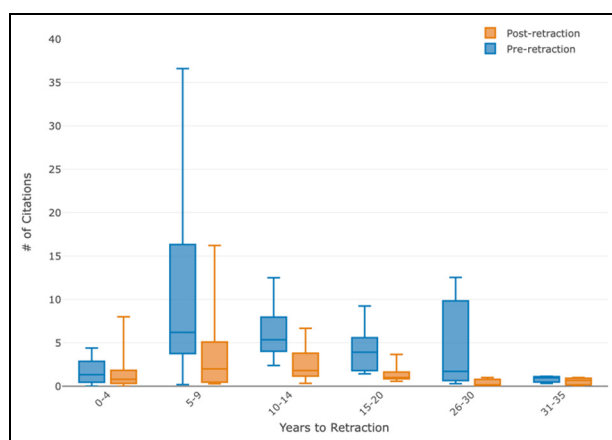


Figure 6. Citation rates pre- and post-retraction based on years to retraction (interactive graph: <https://mugeakbulut.com/nature/graphs/fig6/>).

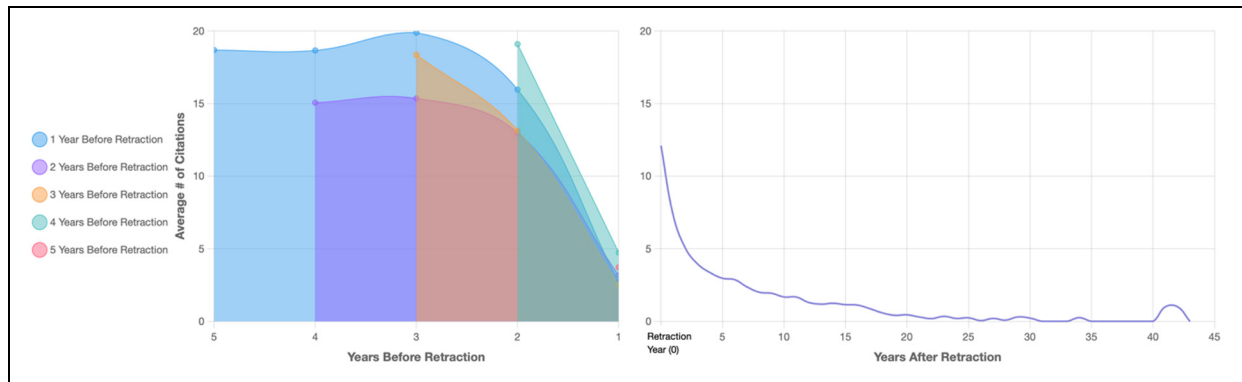


Figure 7. Citation patterns based on articles' age at retraction (interactive graph: <https://mugeakbulut.com/nature/graphs/fig7/>).

critique the reasons for retraction. In addition, authors sometimes citing publications without thorough examination can be considered another explanation for why retracted articles continue to receive citations [67].

The left side of Figure 7 shows pre-retraction citation patterns of articles, separately displayed according to their age at retraction (1–5 years). When examining articles retracted within 5 years, there is an observed increase in citations during the first 3 years, followed by a decline in the 2 years preceding retraction. For articles retracted within 4 years, while the citation trend remains stable during the first 3 years, there is a notable decrease in the final year. However, for articles retracted more quickly, within 1 or 2 years, such long-term patterns cannot be observed. This may be related to both the limited time frame and the rate of literature obsolescence.

6.1.4. Formalising the analysis: interrupted time series. To formally evaluate whether citation trajectories exhibit a discontinuity around the retraction event, an interrupted time series (ITS) regression model was employed. ITS is a quasi-experimental approach that estimates changes in the level and slope of a time-series outcome after a discrete interruption, and it is frequently used to examine whether an event is followed by a detectable shift in longitudinal patterns. In this study, the model analysed the citation trajectory for 5 years before and 10 years after the retraction year, using annual citation counts as the outcome and including a baseline time trend to account for the overall temporal trajectory.

At the same time, the ITS estimates should be interpreted with appropriate caution regarding internal validity. First, citation trajectories are influenced by natural obsolescence, and this process may differ across disciplines and journals. Second, the visibility and salience of retraction notices are heterogeneous and not directly observed in the data set. Third, publication and indexing delays can blur the timing of exposure to retraction signals, especially in the years closest to the event. Therefore, while ITS provides a structured way to quantify level and slope differences around the retraction point, it does not fully eliminate alternative explanations related to underlying ageing dynamics, field-specific citation cultures or unequal retraction visibility. The coefficients are thus interpreted as evidence of a temporal structural break consistent with the timing of retraction, rather than as definitive causal proof.

The ITS model indicates a statistically significant immediate decline in annual citations following retraction (level change: $\beta = -3.15$, $p < .001$). In addition, the post-retraction trend becomes significantly more negative relative to the pre-retraction trend (slope change: $\beta = -1.22$, $p < .001$), suggesting that citation accumulation slows further in subsequent years. Figure 8 presents the observed average citation series together with the fitted ITS regression lines and their 95% confidence bands, illustrating the estimated discontinuity around the retraction event.

6.1.5. Comparative analysis of pre- and post-retraction citations across indices. To address the potential influence of confounding variables, the ITS model was expanded to include interaction terms for scientific field (comparing SCI-EXPANDED vs SSCI indices) and the article's age at retraction. The analysis revealed that the negative impact of retraction was indeed moderated by these factors. Specifically, the post-retraction decline in citations was significantly steeper for articles in the SCI-EXPANDED index compared with those in the SSCI index, where citations tended to persist longer. This finding aligns with the observation that social sciences often engage with retracted literature as a subject of discourse. Furthermore, articles that were older at the time of retraction experienced a less severe immediate drop but a slightly faster rate of subsequent decay compared with articles retracted early in their lifecycle. These results highlight the heterogeneous nature of a retraction's impact across different contexts.

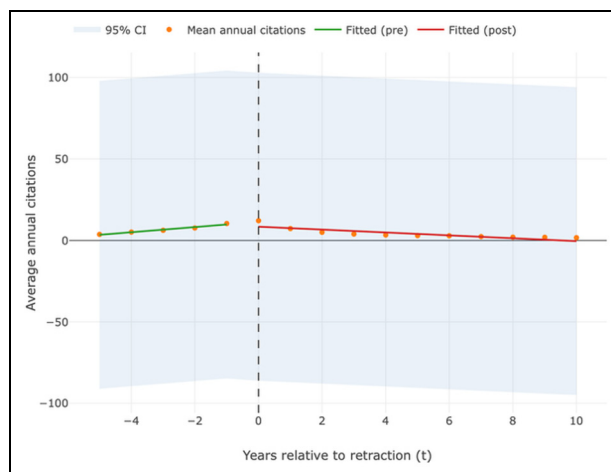


Figure 8. Interrupted time-series analysis of annual citations before and after retraction (interactive graph: <https://mugeakbulut.com/nature/graphs/fig8/>).

Note. The figure displays the average annual citations (points), the fitted regression trend lines (solid lines) and their 95% confidence intervals (shaded areas). An interactive version of this figure is available in the online supplemental materials.

Citation behaviours after retraction vary across WoS indices. Figure 9 shows that in the CCR-EXPANDED index, the post-retraction citation median slightly increases, with citations becoming more concentrated around the median, indicating more consistent citation behaviour. In the CPCI-S index (Conference Proceedings Citation Index – Science), pre- and post-retraction citation patterns remain similar, suggesting conference proceedings are less affected by retractions.

The ICI index exhibits compressed post-retraction citation distributions with fewer upper outliers, while the SCI-EXPANDED index shows citation concentration in the upper quartile, reflecting narrower citation behaviour among highly cited articles. Uniquely, the SSCI index reveals an increased post-retraction citation median and a wider citation distribution, indicating that social sciences have distinct citation practices where retracted articles persist, often as discussion subjects.

When citation counts were normalised by the age of retraction, the SSCI index still shows a distinctive pattern, though less pronounced than in the raw citation counts. The normalisation process was performed by calculating the annual

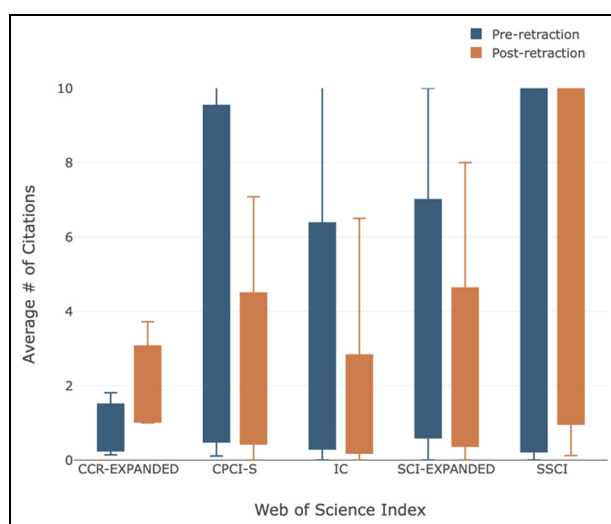


Figure 9. Distribution of pre- and post-retraction citations across indices (interactive graph: <https://mugeakbulut.com/nature/graphs/fig9/>).

Note. Current Chemical Reactions (CCR-EXPANDED), Conference Proceedings Citation Index – Science (CPCI-S), Index Chemicus (IC), Science Citation Index Expanded (SCI-EXPANDED), Social Sciences Citation Index (SSCI)

average citation rate for each article based on its age at retraction. Specifically, the total number of citations was divided by the time elapsed between the article's publication year and its retraction year (its age). For example, an article that received 50 citations more than 10 years would have an annual citation rate of five citations per year.

After normalisation, the annual post-retraction citation rate for SSCI articles (mean = 2.3 citations/year) remained higher than that of other indices (mean = 1.7 citations/year). This indicates that while the magnitude of the difference is smaller than initially observed, the tendency for continued citation in the social sciences remains notable. This pattern can be attributed to the distinct citation practices in social sciences, where retracted articles are often cited not for their original findings but as cases for discussion in research integrity studies or as examples in methodological critiques.

6.1.6. Reasons for article retractions and their impact

6.1.6.1. Distribution of retraction reasons and key patterns. Analysis of retractions in Nature Index journals shows institutional investigations (30.7%) and image duplication as the most common reasons for retraction, with a strong overlap between them. Together, these account for about half of retractions. Other key reasons include author misconduct (18%), formal investigation results (17%) and unreliable results (16%), with data manipulation and fabrication comprising 15%. This highlights that retractions arise from diverse ethical and methodological issues (see Table 2).

6.1.6.2. Relationship Between Retraction Reasons and Citation Patterns. Figure 10 presents a comparative analysis of articles' retraction reasons and their post-retraction citation rates. The figure shows that articles in the categories 'error in data' (46%), 'error in image' (44%) and 'error in results and/or conclusions' (43%) have the highest post-retraction citation rates. These data reveal that retractions categorised as 'errors' continue to receive more citations compared with retractions involving intentional misconduct.

Table 2. Annotated examples of citation sentiment classification.

Sentiment category	Example citation sentence (anonymised)	Rationale for model's classification
Positive	'Building on the groundbreaking framework proposed by Author et al. (Year), my study further explores ...'	The model identifies explicitly positive language ('groundbreaking framework') which frames the retracted work as a foundational and valuable contribution.
Neutral	'Several models have been developed to address this issue (Author et al., Year; Other et al., Year)'.	The sentence lists the retracted work as a factual reference among others, lacking any evaluative or subjective language for the model to classify as positive or negative.
Negative	'However, the methodology used by Author et al. (Year) has been questioned due to its reliance on uncorroborated data ...'	The model detects strong negative cues ('has been questioned', 'uncorroborated data') that directly challenge the validity and credibility of the retracted work.



Figure 10. Post-retraction citation rates of articles based on retraction reasons (interactive graph: <https://mugeakbulut.com/nature/graphs/fig10/>).

Table 3. Frequency of individual retraction reasons.

Reason	Number of retracted articles	%
Investigation by company/institution	305	30.7
Duplication of image	218	21.9
Concerns/Issues about data	185	18.6
Misconduct by author	180	18.1
Misconduct – Official investigation/Finding	171	17.2
Unreliable results	158	15.9
Falsification/Fabrication of data	150	15.1
Error in data	146	14.7
Manipulation of images	139	14.0
Results not reproducible	131	13.2
Error in results and/or conclusions	111	11.2
Error in analyses	101	10.2

Note. Individual articles often have multiple, overlapping reasons for retraction. Percentages sum to more than 100% due to this overlap.

Similarly, the fact that articles in the ‘results not reproducible’ category continue to receive a high rate of citations (42%) suggests that these papers may persist in the literature as objects of discussion, even after retraction. In contrast, categories that more directly reflect deliberate manipulation, such as ‘manipulation of images’ (20%) and ‘unreliable results’ (25%), show comparatively lower post-retraction citation rates. These differences are presented as descriptive patterns rather than as definitive behavioural claims, because retraction notices can list multiple overlapping reasons and the same article may contribute to more than one category.

Overall, the results indicate that retraction reasons are associated with heterogeneous post-retraction citation trajectories. However, the magnitude of these differences should be interpreted cautiously, as category construction, multi-reason cases and heterogeneity in notice clarity may influence how sharply citation behaviour appears to shift across groups.

Basic statistics for the general classification are as follows (see Table 3):

In Nature Index journal retractions, the largest share (45.81%) falls under scientific errors without academic misconduct (Type 4). However, this distribution reflects classification instances rather than unique articles, because the same article may be assigned to more than one category when multiple reasons are reported in the retraction notice. Accordingly, the total number (1070) represents classification instances derived from 994 unique retracted articles. When reporting article-level prevalence (e.g. whether an article involves any form of misconduct), the denominator is the number of unique articles ($N = 994$). Using this article-level definition, 67% (666 of 994) involved some form of misconduct, consistent with prior studies indicating that approximately two-thirds of retractions relate to misconduct [9,13]. This distinction between article-level and reason-level reporting is maintained throughout the article.

Before analysing the retraction timelines across different article types, four distinct time points in the retraction process were identified: Type 1 (date of publication), Type 2 (date when concerns were first raised), Type 3 (date of formal investigation initiation) and Type 4 (date of retraction notice publication). While these time points generally follow a sequential order (Type 1 → Type 2 → Type 3 → Type 4), they may occasionally overlap in cases where actions occur simultaneously. For instance, when concerns lead to immediate investigation, Types 2 and 3 may coincide. However, Type 4 always represents the final point in this timeline as it marks the official retraction of the article. Using these time points, analyses of retraction timelines reveal striking patterns. Articles involving academic misconduct (Types 1 and 2) take longer to be retracted compared with those without misconduct (Types 3 and 4). This difference is particularly pronounced in cases of misconduct without scientific errors (Type 2), indicating an extended average duration of 7.49 years. Conversely, articles containing scientific errors (Types 1 and 4) are retracted more quickly than those without scientific errors (Types 2 and 3). The fastest retraction time (averaging 3.13 years) is observed in articles containing neither scientific errors nor academic misconduct (Type 3). These articles are typically retracted for technical or administrative reasons, for example, duplicate publication of an article, procedural errors in the submission process, the need to comply with newly emerging ethical standards, authors’ requests for correction or expansion or legal disputes are the primary reasons for retraction in this category.

These findings demonstrate that the complexity of the retraction process varies according to the type of problem the article contains. Since detecting and proving cases of misconduct typically requires more comprehensive investigations, the retraction process for such articles can be lengthy. In contrast, technical or methodological errors can usually be detected more easily, and the process for their correction or retraction can proceed more quickly.

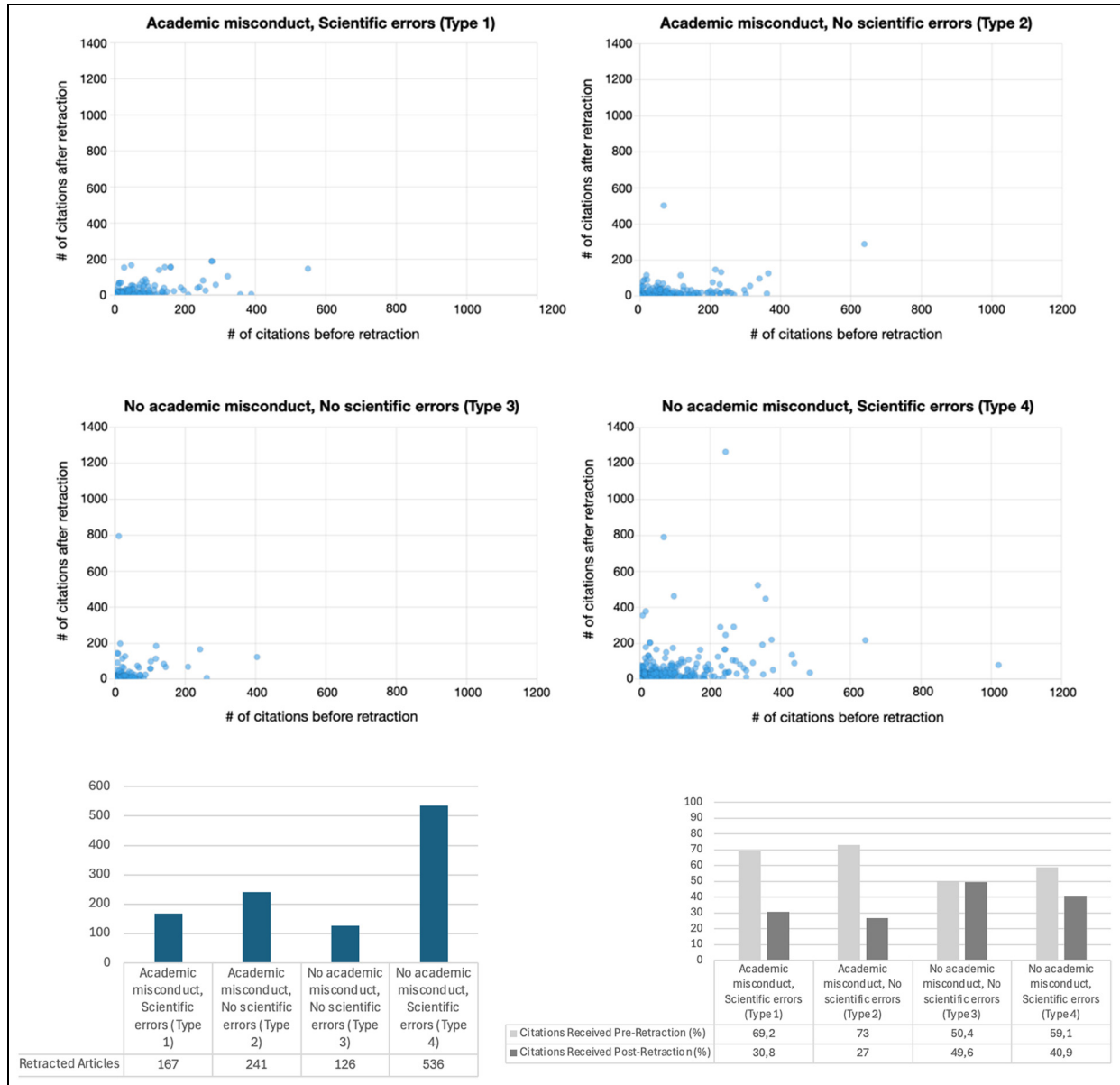


Figure 11. Retraction reasons according to the fourfold classification and pre- and post-retraction citation rates of articles² (interactive graph: <https://mugeakbulut.com/nature/graphs/fig11/>).

The facet grid visualisation and bar graphs in Figure 11 reveal citation patterns of retracted articles from different perspectives. According to the facet grid analysis, it is remarkably that articles containing only scientific errors (Type 4) have higher citation counts both before and after retraction compared with other categories. The marked decrease in post-retraction citation rates for cases of academic misconduct (Types 1 and 2) and the relatively low citation numbers for articles without scientific errors (Type 3) reflect the complex nature of how retraction decisions impact the literature.

While the quantitative analyses in this study cover all 994 retracted articles, the qualitative content analysis (i.e. sentiment and sectional analysis) is based on the subset of citations for which full-text access was possible. As detailed in the ‘Methods’ section, 15,923 in-text citation sentences (75.6% of the total) were accessible and, therefore, included in the sentiment analysis, providing a substantial basis for these findings. Nevertheless, this limitation should be considered when interpreting the findings about citation contexts and purposes, as citations in non-accessible articles might potentially show different patterns.

The distribution in the bar graphs in Figure 11 reveals the numerical and proportional distribution of retracted articles. The decline in citation rates of articles containing scientific errors (Type 4), which constitute about half of total retractions (537 articles), from 59.1% to 40.9%, is not as sharp as in articles containing academic misconduct. Particularly, the drop-in citation rates from 73% to 27% for articles containing academic misconduct but no scientific errors (Type 2) reflect researchers' strong reaction to ethical violations. The nearly stable citation rates (from 50.4% to 49.6%) of 126 articles containing neither academic misconduct nor scientific errors (Type 3) suggest these retractions are primarily due to technical or editorial reasons.

The findings presented in this section clearly demonstrate that citation patterns of retracted articles differ according to retraction reasons. The primary Hypothesis 1 (H1) of our research, formulated as 'citation patterns of retracted articles vary according to retraction reasons', is strongly supported by the findings. This is particularly evidenced by the marked decrease in citation rates of articles containing academic misconduct (Types 1 and 2) from 73% to 27%, compared with the more moderate decline (from 59.1% to 40.9%) in articles containing scientific errors but no misconduct (Type 4). These findings are consistent with previous studies examining the impact of retraction reasons on citation patterns [14,19,22].

The second Hypothesis 2 (H2), stating that 'articles with serious errors or academic misconduct receive significantly greater citation loss post-retraction, while articles retracted for minor errors experience a less drastic citation loss', has also been validated. The findings show that articles in categories involving intentional manipulation (e.g. 'manipulation of images' 20% and 'unreliable results' 25%) experienced the most significant decline in citation rates, whereas categories containing technical or methodological errors ('error in data' 46%, 'error in image' 44% and 'error in results and/or conclusions' 43%) maintained higher citation rates. These results demonstrate that the scientific community evaluates intentional misconduct differently from technical errors, and this is directly reflected in citation behaviours (RQ2).

To test the robustness of the primary finding that misconduct is associated with a greater citation loss, a stricter, binary classification scheme was implemented as suggested by the reviewer. All articles with any mention of misconduct (Type 1 or Type 2) were grouped into a single 'misconduct' category ($n = 358$ unique articles), while all others were grouped into a 'non-misconduct' category ($n = 636$ unique articles). The analysis was then re-run on these two mutually exclusive groups. The results confirm the initial findings; the 'misconduct' group experienced a much sharper decline in post-retraction citations, with their share of total citations dropping from 71.8% pre-retraction to 28.2% post-retraction (a 43.6% point decrease). In contrast, the 'non-misconduct' group saw a more moderate decline, from 57.3% to 42.7% (a 14.6% point decrease). This demonstrates that the main conclusion is robust and not an artefact of the specific classification scheme used.

7. In-text citation-level analysis

Beyond examining retraction patterns and citation dynamics of retracted articles, understanding the qualitative characteristics of these citations is of great importance. For this purpose, the research went beyond macro-level analyses to conduct an in-text citation-level analysis to examine in more detail how citations are used within texts, their contexts and how authors qualify these citations. In addition to article-level analyses, detailed in-text citation-level examinations were conducted on a 20% sample (199 articles) of retracted articles. Within this scope, a total of 21,047 citations were identified from studies published in WoS-indexed journals to articles in this sample group. It was determined that 52% ($n = 10,728$) of these citations were made before the articles were retracted.

7.1. Distribution according to cited sections

Determining which sections of citing articles contain citations to retracted articles is a critical component of the study (see Table 4). However, as noted in the 'Methods' section, a substantial portion of citations (52.4%) could not be assigned to a specific section due to access or formatting issues. This high rate of missing data materially limits the evidentiary strength of section-based claims. Accordingly, the section analysis is reported as partial and conditional evidence based only on the subset of citations with identifiable section information ($n = 10,026$), while the 'N/A' category is treated as structurally unobserved rather than as ignorable missingness.

Within the identifiable subset, the majority of citations are concentrated in the background (51.2%) and discussion (31.7%) sections. At the same time, because the section location could not be determined for over half of the citation pool, any interpretation about citations 'migrating' across sections should be made cautiously and should not be generalised beyond the mapped subset. To contextualise the potential impact of the 'N/A' category, the section-based findings are interpreted under bounding logic, where the unmapped citations could, in extreme scenarios, be disproportionately concentrated either in background-oriented sections or in empirically central sections such as methods and results. Under

Table 4. Distribution of retracted articles according to general classification.

Reason for retraction (general classification)	Number of retracted articles	%	Average age of retraction
Academic misconduct, scientific errors (Type 1)	167	14.27	5.77
Academic misconduct, no scientific errors (Type 2)	241	20.60	7.49
No academic misconduct, no scientific errors (Type 3)	126	10.77	3.13
No academic misconduct, scientific errors (Type 4)	536	45.81	3.89
Total/Average	1070	22.86	5.07

Note. As articles can have multiple retraction reasons, the total number exceeds 994. In this table, percentages are reported over classification instances rather than unique articles.

Table 5. Distribution of citations to retracted articles by type and pre–post retraction change rates.

Citation type	Total		Pre-retraction		Post-retraction	
	N	%	N	%	N	%
Mentioning	15,150	93.89	11,481	94.42	3669	92.28
Supporting	652	4.04	566	4.24	86	3.42
Unclassified	232	1.44	81	0.67	151	3.80
Contradicting	102	0.63	82	0.67	20	0.50
Total	16,136	100	12,210	100	3926	100

this uncertainty, the section-based patterns are presented as suggestive rather than definitive evidence. More revealing are the changes in citation distribution before and after retraction, as visualised in Figure 11. While citations in the background section remained relatively stable (pre-retraction: 50.8% (95% CI: 49.6, 52.0); post-retraction: 49.2% (95% CI: 47.7, 50.7)), a sharp and significant decrease was observed in sections central to a paper's empirical claims. Citations in the 'Discussion' section dropped from 24.1% of pre-retraction citations to just 7.4% post-retraction. Similarly, citations in the 'Methods' and 'Results' sections experienced drastic declines. This suggests that while retracted articles may continue to be mentioned for general context, researchers actively avoid citing their specific methods, results and conclusions after retraction.

Unlike Table 5, Figure 12 presents the distribution by section only for articles where citation location could be determined. That is, it contains calculations based only on citations with identifiable locations, excluding the N/A category. Figure 12 reveals in detail the distribution of citations across sections and their pre-/post-retraction changes. The majority of citations are concentrated in background (51.5%) and discussion (31.7%) sections, with these two sections accounting for more than 80% of identifiable citations.

Notable differences are observed in the pre- and post-retraction distribution of citations across sections. While citation rates in the background section remain similar before (24.3%, $n = 2612$) and after retraction (24.4%, $n = 2516$), there is a marked decrease in the 'Discussion' section (from 22.5%, $n = 2415$ pre-retraction to 7.4%, $n = 765$ post-retraction). Similarly, citations in the 'Results' section have significantly decreased post-retraction (from 8.6%, $n = 922$ to 2.6%, $n = 264$).

The most dramatic change was recorded in the figure section: the citation rate dropped from 92.2% pre-retraction to 7.8% post-retraction. However, when interpreting this data, it should be noted that the total number of citations to the figure section was 51, representing only 0.1% of the total citation pool. When considered alongside the significant decrease in the 'Methods' section (from 82.7% to 17.3%), this indicates that researchers particularly avoid using retracted articles for methodological and visual references.

Overall, these findings show that retracted articles receive citations particularly in literature review and 'Discussion' sections, but post-retraction citations decrease substantially especially in result-based 'Discussion' and 'Conclusion' sections. This suggests that researchers adopt a more cautious approach particularly towards the empirical findings of retracted articles.

7.2. Analysis by citation types

Table 5 details the distribution of citation types to retracted articles, revealing that 93.89% are 'mentioning' citations – mostly neutral (47.86%) or positive (39.79%). This indicates that retracted articles are primarily cited for literature review or general reference (addressing RQ3).

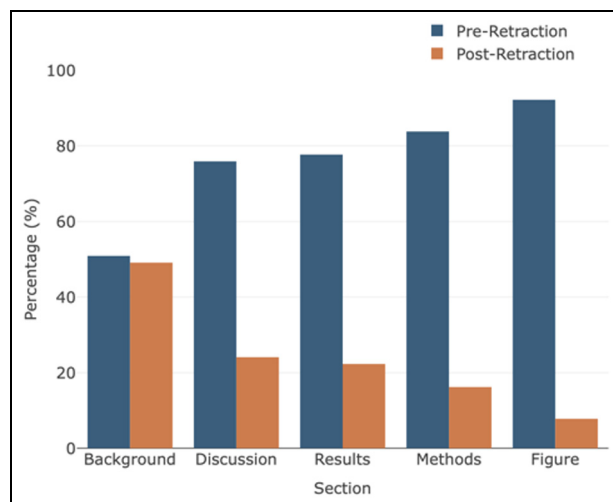


Figure 12. Pre- and post-retraction citation rates (%) to retracted articles by sections (interactive graph: <https://mugeakbulut.com/nature/graphs/fig12/>).

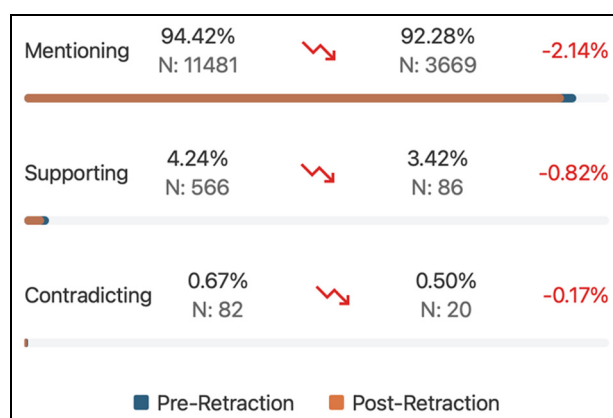


Figure 13. Shows the distribution of citations to retracted articles by type (interactive graph: <https://mugeakbulut.com/nature/graphs/fig13/>).

Despite a sharp decline in total citations after retraction, the proportional distribution of citation types remains relatively stable, as shown in Figure 13. ‘Mentioning’ citations dropped numerically (11,481–3669) but only slightly in percentage (94.42%–92.28%).

‘Supporting’ citations decreased from 4.24% to 3.42%, reflecting increased caution in using retracted papers to support claims. ‘Contradicting’ citations also declined slightly (0.67% to 0.50%). Meanwhile, ‘unclassified’ citations rose from 0.67% to 3.80%, suggesting greater ambiguity in citation contexts post-retraction.

The broad ‘mentioning’ category encompasses citations without direct engagement or evaluation of the retracted work, helping to clarify citation behaviours while recognising their complexity.

Figure 13 presents detailed changes in the ‘mentioning’, ‘supporting’ and ‘contradicting’ categories. This visualisation excludes the ‘unclassified’ category and focuses on the distribution among classifiable citations. The pre-retraction and post-retraction values shown for each citation type, along with their frequency data and percentage equivalents, allow tracking the magnitude of change. The horizontal bars for each category (navy for pre-retraction, orange for post-retraction) visually represent the percentage ratios in the relevant periods and clearly demonstrate the dominant share of the ‘mentioning’ category both before and after retraction. Therefore, while the retraction process significantly reduces the total number of citations received by articles, it does not create major changes in the qualitative distribution of citations. In other words, although retracted articles receive fewer citations, the patterns of how these citations are used remain largely similar and scientific literature patterns continue.

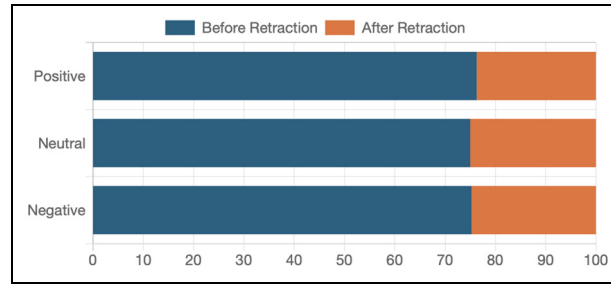


Figure 14. Distribution of citations by sentiment before and after retraction (interactive graph: <https://mugeakbulut.com/nature/graphs/fig14/>).

Table 6. Distribution of citations by sentiment before and after retraction.

Classification	Total		Pre-retraction		Post-retraction	
	N	%	N	%	N	%
Positive	6336	39.79	4834	40.18	1502	38.58
Negative	1967	12.35	1480	12.30	487	12.51
Neutral	7620	47.86	5716	47.51	1904	48.91
Total	15,923	100,00	12,030	100,00	3893	100,00

7.3. Sentiment analysis

Of the 21,047 citations to 199 articles in the sample, 15,982 provided in-text citation sentences. After excluding some sentences due to language limitations, 15,923 in-text citation sentences, corresponding to 75.6% of detected citations, were included in the sentiment analysis. According to the analysis results, the nature of citations to retracted articles was classified as follows: 47.86% neutral, 39.79% positive and 12.35% negative (see Table 6).

The sentiment analysis of citations to retracted articles shows a consistent distribution in citation quality (Figure 14). The distribution of positive and negative citations maintains similar proportions both before and after retraction. While positive citations were 40.18%, neutral citations 47.51% and negative citations 12.30% before retraction; after retraction, these rates were 38.58%, 48.91% and 12.51%, respectively.

8. Conclusion

We analyse citation patterns of retracted articles in Nature Index journals using a multidimensional approach. Although publication numbers in these journals have steadily increased, retraction rates have remained below 0.3%. The observed rise in retractions since 2000 [1,2,8,9] aligns with the shift to electronic publishing and open science practices, which enhance detection of ethical violations and speed retraction decisions [68–70].

Findings show that 93.9% of retracted articles continue to be cited post-retraction, with 47.86% of these citations classified as neutral and 39.79% positive, indicating that about 90% do not relate to the retraction event. Most citations (93.89%) are ‘mentioning’ types, used primarily for literature review without critical evaluation. This reflects low sensitivity to retracted studies, consistent with prior research [14,15,18,26]. However, citation rates decline more markedly as the time since retraction increases, a pattern likely attributable to greater ‘literature awareness’ [71].

Retracted articles due to academic misconduct show greater citation loss (from 73% to 27%) than those retracted for technical or methodological errors. Articles with only scientific errors have higher citation counts both before and after retraction, highlighting the nuanced impact of retraction reasons on citation patterns.

These findings underscore the need to improve retraction visibility and awareness through enhanced database markings and broader adoption of tools like Crossmark and retraction notifications in reference management software. As a focused case study on a prestigious subset of journals, these findings provide a critical benchmark for understanding the afterlife of retracted science at the highest level of publication.

8.1. Theoretical and practical implications

This study advances post-retraction citation analysis by using sentiment-aware machine learning, specifically BERT-based models, which capture contextual nuances better than traditional methods [19,28]. Our findings reveal that citation persistence depends on retraction reasons and rhetorical framing, highlighting the need for context-sensitive approaches in evaluating retracted articles.

Current citation databases (Web of Science, Scopus, Google Scholar) do not distinguish citation sentiments, contributing to ongoing citations of retracted papers without proper context. Automated retraction alerts and sentiment-aware citation flags could reduce this issue.

Standardising retraction notices to clearly differentiate ethical violations from scientific errors would improve clarity and reduce citation misinterpretations. Integrating sentiment classifiers into bibliometric databases would offer richer insights.

Finally, enhancing retraction notice visibility and transparency, especially with open science practices, is essential for effective scientific communication.

9. Limitations and future work

Several limitations of this study should be acknowledged. First, this work should be interpreted as a case study of a prestigious subset (Nature Index journals). While these journals represent the highest tier of scientific output, citation dynamics and retraction visibility may differ significantly in lower-tier journals, non-indexed venues or fields underrepresented in the Nature Index. Consequently, the patterns of ‘scientific ghosts’ observed here, particularly the high persistence rates, might be even more pronounced in venues with less rigorous post-publication monitoring. Second, this study could not account for the heterogeneity in the visibility of retraction notices, as these data were not systematically available. Third, as noted in the methodology, the sentiment analysis relied on a general-purpose academic sentiment model without a separate manual validation on a custom-coded subset of this specific corpus. Therefore, the reported sentiment distributions should be viewed as model-based estimates rather than human-verified classifications. Finally, the analysis does not include a matched control group of non-retracted articles to perfectly isolate the retraction effect from natural literature obsolescence, although the ITS model statistically controls for the baseline trend.

Building on these limitations, future research should focus on several key areas. Comparative studies investigating retraction impacts across different journal tiers are needed to confirm the patterns observed here. Developing explainable AI (XAI) models could enhance transparency in citation sentiment analysis. Investigating disciplinary differences would provide a richer understanding of how different fields respond to retractions. Finally, fine-tuning large language models (LLMs) specifically for citation analysis, balancing interpretability with contextual depth, will be a crucial next step in strengthening research integrity.

Acknowledgement

The author would like to thank Dilanur Karakurluk for her assistance during the data collection phases and Dr. Sümeyye Akça for her valuable suggestions after reading an early version of the study.

Declaration of conflicting interests

The author declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The author received no financial support for the research, authorship and/or publication of this article.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT (OpenAI) to improve the language and readability of the manuscript. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

ORCID iD

Müge Akbulut  <https://orcid.org/0000-0003-0026-6485>

Data availability statement

The datasets generated and analyzed during the current study are available in the Zenodo repository, with the article-level dataset accessible at <https://doi.org/10.5281/zenodo.15023330> and the in-text citation dataset available at <https://doi.org/10.5281/zenodo.15023397>. Additional visual materials and project documentation can be found at the project website: <https://mugeakbulut.com/nature/>.

Supplemental material

Supplementary materials for this article, including analytical code and additional figures, are available on Zenodo at <https://doi.org/10.5281/zenodo.15023330> and <https://doi.org/10.5281/zenodo.15023397>.

Notes

1. Three articles retracted at years 27, 32 and 33 are not included in the graph, as they received no citations before or after retraction.
2. The total number of retracted articles exceeds 994, because articles can have multiple reasons for retraction. As these reasons can fall into multiple general categories, the total number of articles is reflected as 1070 in the graph.

References

- [1] Brainard J. Rethinking retractions. *Science* 2018; 362(6413): 390–393.
- [2] Madlock-Brown CR and Eichmann D. The (lack of) impact of retraction on citation networks. *Sci Eng Ethics* 2015; 21: 127–137.
- [3] Fanelli D, Costas R, Fang FC, et al. Why do scientists fabricate and falsify data? A matched-control analysis of papers containing problematic image duplications [Preprint]. *Biorxiv*, 2017. DOI: 10.1101/126805.
- [4] Lu SF, Jin GZ, Uzzi B, et al. The retraction penalty: evidence from the Web of Science. *Sci Rep* 2013; 3: 3146.
- [5] Steen RG. Retractions in the scientific literature: do authors deliberately commit research fraud? *J Med Ethics* 2011; 37(2): 113–117.
- [6] Grieneisen ML and Zhang M. A comprehensive survey of retracted articles from the scholarly literature. *PLoS ONE* 2012; 7(10): e44118.
- [7] Shuai X, Rollins J, Moulinier I, et al. A multidimensional investigation of the effects of publication retraction on scholarly impact. *J Assoc Inf Sci Technol* 2017; 68(9): 2225–2236.
- [8] Noorden RV. Science publishing: the trouble with retractions. *Nature* 2011; 478: 26–28.
- [9] Steen RG, Casadevall A and Fang FC. Why has the number of scientific retractions increased? *PLoS ONE* 2013; 8: e68397.
- [10] Wakefield AJ, Murch SH, Anthony A, et al. [RETRACTED] Ileal-lymphoid-nodular hyperplasia, non-specific colitis and pervasive developmental disorder in children. *Lancet* 1998; 351(9103): 637–641.
- [11] Heibi I and Peroni S. A qualitative and quantitative analysis of open citations to retracted articles: the Wakefield 1998 et al.'s case. *Scientometrics* 2021; 126(10): 8433–8470.
- [12] Retraction Watch. The retraction watch leaderboard: Top 10 most highly cited retracted papers, 2023, <https://retractionwatch.com/the-retraction-watch-leaderboard/top-10-most-highly-cited-retracted-papers/> (accessed 14 March 2025).
- [13] Fang FC, Steen RG and Casadevall A. Misconduct accounts for the majority of retracted scientific publications. *USA Proc Natl Acad Sci* 2012; 109(42): 17028–17033.
- [14] Bar-Ilan J and Halevi G. Post retraction citations in context: a case study. *Scientometrics* 2017; 113(1): 547–565.
- [15] Bornemann-Cimenti H, Szilagyi IS and Sandner-Kiesling A. Perpetuation of retracted publications using the example of the Scott S. Reuben case: incidences, reasons and possible improvements. *Sci Eng Ethics* 2015; 22: 1063–1072.
- [16] Chen C and Leydesdorff L. Patterns of connections and movements in dual-map overlays: a new method of publication portfolio analysis. *J Assoc Inf Sci Technol* 2014; 65(2): 334–351.
- [17] Jan R, Bano S, Mehraj M, et al. Context analysis of top seven retracted articles: should Retraction Watch revisit the list? *Libr Philos Pract*, 2018, <https://digitalcommons.unl.edu/libphilprac/2016> (accessed 14 March 2025).
- [18] Kochan CA and Budd JM. The persistence of fraud in the literature: the darsee case. *J Am Soc Inf Sci* 1992; 43(7): 488–493.
- [19] Schneider J, Ye D, Hill AM, et al. Continued post-retraction citation of a fraudulent clinical trial report, 11 years after it was retracted for falsifying data. *Scientometrics* 2020; 125(3): 2877–2913.
- [20] van der Vet PE and Nijveen H. Propagation of errors in citation networks: a study involving the entire citation network of a widely cited paper published in, and later retracted from, the journal nature. *Res Integr Peer Rev* 2016; 1: 3.
- [21] Mongeon P and Larivière V. Costly collaborations: the impact of scientific fraud on co-authors' careers. *J Assoc Inf Sci Technol* 2016; 67(3): 535–542.
- [22] Furman JL, Jensen K and Murray F. Governing knowledge in the scientific community: exploring the role of retractions in biomedicine. *Res Policy* 2012; 41: 276–290.
- [23] Neale AV, Dailey RK and Abrams J. Analysis of citations to biomedical articles affected by scientific misconduct. *Sci Eng Ethics* 2010; 16(2): 251–261.

- [24] Neale AV, Northrup J, Dailey RK, et al. Correction and use of biomedical literature affected by scientific misconduct. *Sci Eng Ethics* 2007; 13(1): 5–24.
- [25] Pfeifer MP and Snodgrass GL. The continued use of retracted, invalid scientific literature. *JAMA* 1990; 263: 1420–1423.
- [26] Luwel M, van Eck NJ and van Leeuwen TN. The Schön case: analyzing in-text citations to papers before and after retraction. *Int Sci Tech Indic* 2018; 23: 1025–1030.
- [27] Cor K and Sood G. Propagation of error: approving citations to problematic research, 2018, <http://www.gsood.Com/research/papers/error.pdf> (accessed 14 March 2025).
- [28] Azoulay P, Bonatti A and Krieger JL. The career effects of scandal: evidence from scientific retractions. *Res Policy* 2017; 46(9): 1552–1569.
- [29] Dinh L, Sarol J, Cheng YY, et al. Systematic examination of pre-and post-retraction citations. *Proc Assoc Inf Sci Technol* 2019; 56(1): 390–394.
- [30] Rubbo P, Pilatti LA and Picinin CT. Citation of retracted articles in engineering: a study of the Web of Science database. *Ethics Behav* 2018; 29(8): 661–679.
- [31] Redman BK, Yarandi HN and Merz JF. Empirical developments in retraction. *J Med Ethics* 2008; 34(11): 807–809.
- [32] Campanario JM. Fraud: Retracted articles are still being cited. *Nature* 2000; 408(6810): 288.
- [33] Bolland MJ, Grey A and Avenell A. Citation of retracted publications: a challenging problem. *Account Res* 2022; 29(1): 18–25.
- [34] Heibi I and Peroni S. A protocol to gather, characterize and analyze incoming citations of retracted articles. *PLoS ONE* 2022; 17(7): e0270872.
- [35] Avenell A, Stewart F, Grey A, et al. An investigation into the impact and implications of published papers from retracted research: systematic search of affected literature. *BMJ Open* 2019; 9(10): e031909.
- [36] Bozzo A, Bali K, Evaniew N, et al. Retractions in cancer research: a systematic survey. *Res Integr Peer Rev* 2017; 2(1): 5.
- [37] Moylan EC and Kowalczyk MK. Why articles are retracted: a retrospective cross-sectional study of retraction notices at BioMed Central. *BMJ Open* 2016; 6(11): e012047.
- [38] Vuong QH. The limitations of retraction notices and the heroic acts of authors who correct the scholarly record: an analysis of retractions of papers published from 1975 to 2019. Learned Publishing, 2020, https://www.researchgate.net/publication/338178850_The_limitations_of_retraction_notices_and_the_heroic_acts_of_authors_who_correct_the_scholarly_record_An_analysis_of_retractions_of_papers_published_from_1975_to_2019
- [39] Guengerich FP. Some changes in submission and handling policies at the JBC. *J Biol Chem* 2015; 290(46): 28018–28019.
- [40] Marcus A and Oransky I. The paper is not sacred. *Nature* 2011; 480(7378): 449–450.
- [41] Schmidt M. An analysis of the validity of retraction annotation in PubMed and the Web of Science. *J Assoc Inf Sci Technol* 2018; 69(2): 318–328.
- [42] Elia N, Wager E and Tramèr MR. Fate of articles that warranted retraction due to ethical concerns: a descriptive cross-sectional study. *PLoS ONE* 2014; 9(1): e85846.
- [43] Davis PM. The persistence of error: a study of retracted articles on the Internet and in personal libraries. *J Med Libr Assoc* 2012; 100(3): 184–189.
- [44] Teixeira da, Silva JA and Bornemann-Cimenti H. Why do some retracted papers continue to be cited? *Scientometrics* 2017; 110(1): 365–370.
- [45] Decullier E, Huot L, Samson G, et al. Visibility of retractions: a cross-sectional one-year study. *BMC Res Notes* 2013; 6: 238.
- [46] Cheng YY, Parulian N, Hsiao TK, et al. ReTracker: actively and automatically matching retraction metadata in Zotero. *Proc Assoc Inf Sci Technol* 2019; 56: 372–376.
- [47] Stillman D. Retracted item notifications with Retraction Watch integration, <https://www.zotero.org/blog/retracted-item-notifications/> (2019, accessed 14 March 2025).
- [48] Crossref. Crossmark, <https://www.crossref.org/documentation/crossmark/> (2020, accessed 14 March 2025).
- [49] Schmidt M. Why do some retracted articles continue to get cited? *Scientometrics* 2024; 129: 7535–7563.
- [50] Budd JM, Sievert M and Schultz TR. Phenomena of retraction: reasons for retraction and citations to the publications. *JAMA* 1998; 280(3): 296.
- [51] Barbour V, Kleinert S, Wager E, et al. Guidelines for retracting articles. *Committee on Publication Ethics*, 2009, <https://publicationethics.org/guidance/guideline/retraction-guidelines>
- [52] Balhara YPS and Mishra A. Compliance of retraction notices for retracted articles on mental disorders with COPE guidelines on retraction. *Curr Sci* 2014; 107(5): 757–760.
- [53] Kim SY, Yi HJ, Cho HM, et al. How many retracted articles indexed in KoreaMed were cited 1 year after retraction notification. *Sci Ed* 2019; 6(2): 122–127.
- [54] Fanelli D, Costas R and Larivière V. Misconduct policies, academic culture and career stage, not gender or pressures to publish, affect scientific integrity. *PLoS ONE* 2015; 10(6): e0127556.
- [55] Fanelli D. Why growing retractions are (mostly) a good sign. *PLoS Med* 2013; 10(12): 1–6.
- [56] Nature Index. Frequently asked questions, 2024, <https://www.nature.com/nature-index/faq> (accessed 14 March 2025).
- [57] Feng L, Yuan J and Yang L. An observation framework for retracted publications in multiple dimensions. *Scientometrics* 2020; 125(2): 1445–1457.

- [58] Sandacian T. BERT sentiment analysis [GitHub repository], 2023, <https://github.com/tamasandacian/BERT-Sentiment-Analysis> (accessed 14 March 2025).
- [59] Devlin J, Chang M, Lee K, et al. BERT: pre-training of deep bidirectional transformers for language understanding. In: *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, Minneapolis, MN, 2–7 June 2019.
- [60] Madabushi H, Kochkina E and Castelle M. Cost-sensitive BERT for generalisable sentence classification on imbalanced data. In: *Proceedings of the Second Workshop on Natural Language Processing for Internet Freedom: Censorship, Disinformation, and Propaganda*, Hong Kong, China, 4 November 2019, pp. 125–134.
- [61] Palomino D. Breaking the state of the art in dialects of Spanish sentiment analysis, 2020, <https://doi.org/10.52591/lxai202007134>
- [62] Sayeed M. BERT: a review of applications in sentiment analysis. *Hightech Innov J* 2023; 4(2): 453–462.
- [63] Whitlock EP, Selby JV, Dunham KM, et al. Examining the role of funders in ensuring value and reducing waste in research: an organizational case-study of the patient-centered outcomes research institute. *F1000Res* 2019; 8: 288.
- [64] Horbach SPJM and Halfman W. The ability of different peer review procedures to flag problematic publications. *Scientometrics* 2019; 118(1): 339–373.
- [65] Kraft DH and Polacsek RA. Biomedical literature dynamics. *Methods Inf Med* 1974; 13(04): 242–248.
- [66] Moed HF, Van Leeuwen TN and Reedijk J. A new classification system to describe the ageing of scientific journals and their impact factors. *J Doc* 1998; 54: 387–419.
- [67] van de, Weert M and Stella L. The dangers of citing papers you did not read or understand. *J Mol Struct* 2019; 1186: 102–103.
- [68] Hsiao T and Schneider J. Continued use of retracted papers: temporal trends in citations and (lack of) awareness of retractions shown in citation contexts in biomedicine. *Quant Sci Stud* 2021; 2(4): 1144–1169.
- [69] McNutt M, Bradford M, Drazen JM, et al. Transparency in authors' contributions and responsibilities to promote integrity in scientific publication. *Proc Natl Acad Sci USA* 2018; 115(11): 2557.
- [70] Prager EM, Chambers KE, Plotkin JL, et al. Improving transparency and scientific rigor in academic publishing. *J Neurosci Res* 2018; 97(4): 377–390.
- [71] Risnes S. Need for a change in scientific publishing. *Nord Perspect Open Sci* 2018; 3: 13–29.