BRAINIACS
BRAIN IMAGING AND COMPUTING SCIENCES

2023 Volume 4
Issue 2 Edoc D5B2734F2

Managing Lexical-Semantic Hybrid Records of FAIR Metrics Analyses with the NPDS Cyberinfrastructure*

Adam Craig, Anousha Athreya, Carl Taswell†

Abstract

Current approaches to plagiarism detection often focus on finding lexical matches rather than semantic similarities in the text content that is compared. But the more important unanswered questions remain whether similar concepts expressed in related topical contexts are semantically equivalent as idea-laundering plagiarism by humans or algorithm-generated plagiarism by machines. Now publicly available and easily accessible, text-generating algorithms have automated the process of assembling a text derived from but not attributed to published content scraped from the web. The FAIR Metrics, with FAIR an acronym for Fair Attribution to Indexed Reports and Fair Acknowledgment of Information Records, measure how appropriately a document cites prior records based on whether they contain similar claims that are equivalent in meaning. We demonstrate herein a workflow with results for manual evaluation of the FAIR Metrics to quantify the extent of plagiarism in 8 articles retracted or reported for plagiarism. We also demonstrate use of the Nexus-PORTAL-DOORS-Scribe (NPDS) Cyberinfrastructure to manage semantic descriptions of the concept mappings and entity equivalence evaluations made using concepts and relationships from the PDP-DREAM Ontology.

Keywords

Plagiarism, bibliometrics, citation analysis, knowledge engineering, semantic web, equivalent entities, concept mapping, ontology.

Contents

*Presented 2023-10-09 with slides and and video at Guardians 2023; preliminary version Craig, Athreya, et al. 2023 presented as poster at eScience 2023.

†Authors affiliated with Brain Health Alliance Virtual Institute, Ladera Ranch, CA 92694 USA; correspondence to A Craig at BHAVI.

Introduction

With the rise of generative artificial intelligence (AI), scholastic institutions and scholarly publishers have recognized the need for tools to detect AI-generated documents, initiating an arms race with AI-assisted plagiarists. Earlier this year, the journal *Science* recently updated its editorial policies to clarify that use of artificial intelligence to produce papers is plagiarism (Thorp 2023). Tools such as Copyleaks 2023, GPTZero 2023, and the OpenAI text classifier (Kirchner et al. 2023), attempt to detect the probability that a text document was produced by an AI algorithm instead of a living person (Orenstrakh et al. 2023). Manuscripts in Springer, Elsevier, IEEE, Wiley, and ProQuest utilize CrossCheck, a plagiarism detection tool by iThenticate that is available to publication editors within the journals (IEEE 2023). Per the IEEE webpage, CrossCheck compares manuscripts to a database of over 6 billion web pages of published technical papers and provides a report of the similarity to previously published work. Copyleaks 2023, which compares submitted documents against large datasets, also includes cross-language detection capabilities and may also detect image-based text plagiarism using optical character recognition technology. Scholarly publishers use Turnitin iThenticate (Young 2023) to detect plagiarism in publishing, while universities use Turnitin Similarity, another product from the same company, to check manuscripts in education. Khalil and Er 2023 tested the ability of Turnitin iThenticate and Similarity to identify plagiarism in essays written by ChatGPT and found that similarity scores ranged from 0% to 68%, indicating the need for new approaches.

Several recent surveys have documented the search for new analytic algorithms, especially for methods that look beyond superficial differences in wording to the meaning and structure of a work. Vrbanec and Meštrović 2017 evaluated plagiarism detection methods currently used by Croatian higher education institutions for measuring the quality of academic and scientific work. In a preliminary review, they discussed the use of semantic similarity techniques as an alternative for plagiarism detection by quantifying the similarity of meaning in texts. Altheneyan and Menai 2020 discussed use of paraphrase identification through word overlap and structural representations for application to automatic plagiarism detection. They compared existing methods, measuring Precision, Recall, and F-measure values. They found that the most optimal results were obtained with SVM and deep learning classifiers while the worst resulted from naive similarity-based methods. They found that all methods have worse precision than recall due to the high overlap in distributions of lexical similarity measures between false paraphrase pairs and true paraphrase pairs.

A recent survey of plagiarism detection tools by Jiffriya et al. 2021 classified plagiarism detection methods as lexical, structural, semantic, stylometric, syntactic, citation, or cross-language based. For natural language plagiarism detection, style-based identification remains difficult because web-based software typically only analyses the authors' first submissions of manuscripts. Detection tools were found to have false-positive results and inability to detect copied content due to scope of detection, paraphrasing, and cross-language plagiarism. Some promising new methods of semantic plagiarism detection include those from Javadi-Moghaddam et al. 2022 and Eisa et al. 2020. Javadi-Moghaddam et al. 2022 investigated semantic plagiarism detection methods using weighted values for matched instances within manuscript sections. The method utilizes the most frequent terms of the manuscript. They found that the model is more accurate depending on the number of surrounding terms, tested with 1-, 2-, and 3-term examples, with a larger window allowing the model to check for adjacent plagiarism. Eisa et al. 2020 proposed a method for detection of image and figure plagiarism in scientific publications. Because image-based plagiarism detection is rooted in determining the meaning of the figure, the method obtains structural and textual features to check for a similarity score between the elements. It then uses semantic mapping to relate the associated concepts between figures.

Others began their fight against AI-assisted plagiarism before the present generative AI boom. In 2013, C. Labbé and D. Labbé 2013 reported that they had identified 85 purportedly peer reviewed papers in 24 conference proceedings that were products of the SciGen text generation algorithm. As noted by C. Labbé and D. Labbé 2013, even though SciGen produces grammatically correct, properly formatted documents, a human reader can easily discern them from actual reports of scientific research due to the lack of any coherent meaning behind the concatenations of technological buzzwords. Even though C. Labbé and D. Labbé 2013 and Xiong and Huang 2009 both provided effective methods for automatically detecting SciGen-derived text, as late as 2021, Cabanac and C. Labbé 2021 identified 243 SciGen pseudo-articles, 192 of which remained in publication, neither retracted nor withdrawn.

Furthermore, the new wave of AI-assisted text generators represent a greater challenge. Gao et al. 2022 found that even human reviewers could only identify ChatGPT-generated abstracts 68% of the time and that plagiarism detection software did not flag any of them as taken from other indexed online content. This automated remixing of content in which the plagiarizing author may be completely unaware of the existence of the original work (when the black-box intermediary of the AI generator hides the sources) represents a new level of social disconnection between plagiarist and victim that was not possible when taking words or ideas from a work required that one read it and manually copy or paraphrase its content. Bibliometric analysis from Santos-d'Amorim et al. 2022 suggested a possible starting point for this trend with evidence of a rise in plagiarized work from paper mills beginning in 2015. But Gaudino et al. 2021 showed the start of a meteoric rise in retractions for research misconduct beginning as early as the late 1990s. Although plagiarism certainly did not begin with the development of the internet and web, modern information technology has made it easier to discover literature for both proper citation and referencing of sources and for the illegitimate plagiarism of those sources.

The inability of both algorithms and human reviewers to reliably detect plagiarism and the slowness, dismissiveness and/or non-response by some publishers to address reports of plagiarism shows that the scholarly publishing community needs a new approach. One such strategy proposed by Craig, Lee, et al. 2022: Publishers should improve the quality and integrity of the peer review process to provide publicly accessible living documents which track, monitor, and record continued checking of the claims made, and sources cited, by a published document. As part of this more rigorous approach, the FAIR Metrics provide a framework for appraisals of how well a scholarly work adheres to community standards by accurately attributing ideas to their sources Craig, Ambati, Dutta, Kowshik, et al. 2019. Different from approaches based solely on lexical similarity of texts, evaluation of FAIR Metrics depends on search of previously published literature for claims with equivalent meaning (Athreya et al. 2020b). Because this semantic analysis is more difficult to automate for machine algorithms than lexical analysis, and more labor intensive to perform by human persons, prior work has only demonstrated the properties of the FAIR metrics using hypothetical test cases (Craig, Ambati, Dutta, Mehrotra, et al. 2019).

However, in a recent report at eScience 2019, we introduced a practical approach to evaluating FAIR Metrics by human analysts of semantic concepts for each test document with respect to similarities found in a limited pool of comparison texts, and summarized the results of this evaluation on a set of 5 different test examples (Craig, Athreya, et al. 2023). In the present report, we provide a more thorough account of the evaluation process and discuss how the FAIR Metrics scores relate to the shared social context of the evaluated test and comparison texts. Additionally, the present report provides more detail regarding use of the PDP-DREAM Ontology to represent the results of human-analyst FAIR Metric evaluations in machine-readable resource description format (RDF) knowledge graphs. These linked graphs can then serve as openly accessible and searchable records of the assessments with the FAIR Metrics, enabling transparency and discussion of both subjective and objective evaluations of the scientific claims contributed to the historical record of published literature (S. K. Taswell et al. 2020; Craig, Lee, et al. 2022). For more about the FAIR Metrics and PDP-DREAM Ontology, see Craig, Ambati, Dutta, Kowshik, et al. 2019, Dutta, Uhegbu, et al. 2020, and Craig and C. Taswell 2021.

Methods

Craig, Ambati, Dutta, Mehrotra, et al. 2019 described 4 ratio metrics calculated from counts of 4 categories of claims: Quoted (Q) claims correctly attributed to prior work, Misquoted (M) claims misrepresenting prior work, Plagiarized (P) claims matching but not attributed to prior work, and Novel (N) claims not found in or reported as sourced from prior work. We now use subscripts with letters instead of numbers to clarify which ratio metric emphasizes which count with F_Q, F_M, F_P, F_N here corresponding respectively to F_1, F_2, F_3, F_4 in Craig, Ambati, Dutta, Kowshik, et al. 2019. In the ideal automated use case described in Craig, Ambati, Dutta, Mehrotra, et al. 2019, a semantic inference engine checks for equivalence relationships between the subject, verb, and object URIs of 2 RDF triples that reference appropriate formal ontologies. At present, creating sufficiently semantically rich descriptions of the scientific claims of a report to allow such automated comparison is a complex and labor-intensive task. We are not aware of an existing library of such descriptions extensive enough to permit a comprehensive search for equivalent statements.

As a practical interim approach to applying and using the FAIR Metrics that we can demonstrate now, we introduce limited-scope human-analyst evaluation of scientific claims for the FAIR Metric calculations.

Craig, Ambati, Dutta, Mehrotra, et al. 2019 described an earlier attempt at a pairwise comparison of scholarly articles, but the approach described there failed to produce usable results. Our new procedure differs in that we evaluate all claims with cited sources instead of discarding those that cite a source other than the comparison document, providing a more reliable and valid set of counts. In this current approach, a human evaluator compares the test document to any resources it cites and 1 or more specific references from which the authors have been proven or reported to have plagiarized previously published material. As a summary of the approach, we used the following procedure: 1) Access test T and comparison C documents and the set of references $\{R_j \mid j = 1, 2, ..., J\}$ cited by T and/or C. 2) Relabel C as R_0 so that it can be analysed in the set of references $\{R_j \mid j = 0, 1, 2, ..., J\}$. 3) List statements and select claims, ie, statements highlighted as novel or cited with a reference. 4) Initialise counts M, N, P, Q to 0 and iterate the comparison analysis over the claims. 5) If claim in T cites R_j, search R_j for equivalent claim. 6) If found, increment Q else increment M. 7) If claim in T does not cite a source, search R_j for equivalent claim. 8) If found, increment P else increment N. While this method (limited in scope to analysis of $J+2$ documents) does not suffice to detect all cases of plagiarism, it can serve as a more objective method of assessing allegations of suspected plagiarism and/or of misrepresentations of previously published references and records in the literature when there exist known test T and comparison C documents.

The distinction between statements and claims reflects the practicality that not every phrase or sentence in a document represents a substantive and meaningful contribution to scholarly knowledge. The reports we examined as test cases contain general sentiments, reiterations of common knowledge, and technical details often found in what are considered materials and methods rather than scientific claims found in results, discussions, or conclusions. The selection of key claims found in a scientific, engineering, or medical report should also reflect the current state of knowledge regarding what community standards exist for the relevant field of scholarly inquiry and research. For example, in a genome-wide association study (GWAS) producing p-values for differential expression of many genes in the human genome, we would not consider the result of each statistical p-value test a meaningful claim in isolation. Instead, in this context, the final results, inferences, and conclusions drawn by the GWAS based on the lower-level intermediate results would be considered the key claims. Craig, Ambati, Dutta, Mehrotra, et al. 2019 did not clarify such a convention for this distinction between statements and claims for evaluation purposes when calculating FAIR metrics.

For the present analysis, we consider a claim to be any statement highlighted as an important concept in the abstract, statements implicitly or explicitly declared to be novel concepts, and/or statements corresponding to concepts otherwise attributed to a cited source. It is common practice for papers to reiterate their key claims in multiple sections, so it is important to take care to avoid double-counting claims. When evaluating texts organized into the standard set of 6 sections (Abstract, Introduction, Methods, Results, Discussion, and Conclusion), we found that counting claims from the Introduction and Discussion sections was most expedient. Claims in the Abstract and Conclusion typically lack citations, whereas the purpose of the Introduction and Discussion often strives to place the goals and results of the research in the proper context of the published literature and to cite relevant sources. Claims from the Methods and Results sections may also be appropriate for consideration as Methods claims and Results claims. But most reports we have evaluated here restate the results that rise to the level of substantively meaningful claims in the Discussion. If a test T document cited multiple sources for the same claim, we considered it a quoted claim for incrementing the quoted Q count if at least 1 of the sources had an equivalent claim. Fundamentally, this comparison evaluation method depends on the ability to recognize equivalence between 2 claims, ie, when 2 claims are equivalent substantively in semantic meaning in context. For a detailed discussion of different interpretations of lexical and semantic equivalence, see Athreya et al. 2020a; Athreya et al. 2020b. For purposes of the current demonstration with analysis of 9 test cases (see Table 1), we used the following method to identify equivalent statements. For each claim indexed by i as $T_i \in T$, the human reader finds the corresponding claim indexed by k as $R_{j,k} \in R_j$ closest in meaning. The analyst then evaluates the pair of claims as either equivalent or not equivalent.

For this initial sample of 9 test cases in Table 1, representative examples of different real-world scenarios were chosen. As a negative control, we selected C. Taswell 2007 compared to Mons 2005 as an example pair on a related topic but with little overlap between T and C in terms of the concepts and ideas presented and discussed. As positive controls, 7 examples of journal articles known to have been retracted for different levels of plagiarism were selected. These reports with known plagiarism were found with a search of the Retraction Watch website and database *Retraction Watch Database User Guide* 2023. The example Uddin et al. 2022 plagiarized heavily from Foster et al. 2019, but also properly cited numerous sources. The example Gnat et al. 2022 cited Hoog et al. 2016, but also used content without citation.

Three of the examples illustrate a shared tactic for obfuscating plagiarism. Ullah et al. 2018 is a case of whole-text plagiarism with only cursory paraphrasing from Sansaniwal and Kumar 2015, a work describing a test of a solar-powered produce dryer, except that the plagiarists substituted their own home institution for the original authors' as the testing site and replaced ginger with asparagus as the vegetable being dried. The other 2, Yao et al. 2016 and Dai et al. 2015, applied the same tactics albeit with greater sophistication, replacing multiple content words from the original articles they plagiarized, G. Li et al. 2015 and Lv et al. 2015 respectively, and changed some background statements and references where simple substitution would have lead to factually incorrect statements or where the cited source referenced 1 of the replaced terms. These cases differ in that Dai et al. 2015 applied the latter tactic more thoroughly. By contrast, Guo et al. 2013 plagiarized almost all of Fischbach et al. 2009 without using this tactic of systematically swapping in meaningfully different content words. Instead, they paraphrased extensively, sometimes changing the meaning of a claim seemingly by accident.

As a positive control, we considered Su et al. 2005, an example of near-verbatim whole-text plagiarism with only minor edits of the content of Schwab et al. 2001. Finally, we examined Wilkinson et al. 2016, which has not yet been retracted for plagiarism. Previously reported in Craig, Ambati, Dutta, Kowshik, et al. 2019, all of the the Findable, Accessible, Interoperable, and Reusable (FAIR) Principles described in Wilkinson et al. 2016 plagiarized (as idea-laundering plagiarized versions) of some, but not all, of the design and practice principles described in C. Taswell 2007 The original PORTAL-DOORS Project Principles (C. Taswell 2007; C. Taswell 2010) have been renamed the PDP-DREAM Principles (Craig, Ambati, Dutta, Kowshik, et al. 2019).

For a demonstration of publishing these FAIR Metrics analyses in a machine-readable manner, we have published records of the comparison documents at PORTALDOORS.net using the reference implementation of the Nexus-PORTAL-DOORS-Scribe (NPDS) Cyberinfrastructure. NPDS provides an online information management system for sharing and distributing data records about different kinds of online and offline resources grouped by problem domain (C. Taswell 2007; Dutta, Kowshik, et al. 2019). We have scoped the Fidentinus diristry for NPDS records with descriptions of known plagiarism cases, while other documents not suspected of plagiarism, such as C. Taswell 2007, have been described in NPDS records in other diristries appropriate to their problem domains, which for C. Taswell 2007 can be found in the DaVinci diristry for semantic web technologies. In addition to including the FAIR Metric values as metadata items in the NPDS records, we developed a FAIR Metrics sub-module of the PDP-DREAM Ontology, a formal OWL ontology for codifying the relationships among concepts relevant to the PORTAL-DOORS Project (Craig, Ambati, Dutta, Kowshik, et al. 2019). This sub-module features the classes and properties needed to record the key assertions an analyst makes when evaluating the FAIR Metrics: the identification of key claims in a document, attributions of claims to other documents, scoring of equivalence matches between claims across documents, classification of each claim in the test document, total counts for the 4 categories, and the FAIR Metrics ratios calculated from those counts.

Results

While we developed the most recent version of the PDP-DREAM Ontology formatted as N-Quads (Craig and C. Taswell 2021), we have also created a version of it formatted in standard Web Ontology Language (OWL) 2.0 XML using Stanford Protégé in order to support compatibility with a broad variety of consumer applications (Drummond et al. 2005). We found that Protégé dropped the fourth element of each quad, the graph label, and treated each quad as a triple. Subsequently, when developing a new FAIR Metrics sub-module, we organized all classes under the *FairMetricsRelatedEntity* class, all object properties under *hasFairMetricObjectProperty*, and all data properties under *hasFairMetricDataProperty*. We established 2 major classes: *Document* and *Statement*. We then assigned *Statements* to the subclasses *NonClaim*, *Claim*, or *FairMetricCategorizedClaim*, which in turn has 4 subclasses: *MisquotedClaim*, *NovelClaim*, *PlagiarizedClaim*, and *QuotedClaim*. We designated 2 object properties: *hasAttribution*, to indicate a reference from a *Claim* in 1 *Document* to another, and *hasFairMetricClaimCategory*, to indicate that a *Claim* belongs to 1 of the subclasses of *FairMetricCategorizedClaim*. We used 12 distinct data properties in each RDF record of a test text. For human readbility, we embedded the title of a *Document* in its RDF description using *hasName*. Similarly, we used *hasText* to embed the original natural language representation of a *Claim* in its RDF description. We also used *hasEquivalenceScore* for the equivalence score and 4 data properties to represent the 4 FAIR Metric counts and another 4 to represent the 4 FAIR Metric ratios. While reviewing the results, we added the data property *hasEquivalentClaimText* with which to directly embed the text of a matching claim in the description of a claim being tested. We found that this procedure makes it easier for the reader to check equivalence of the claims.

We report the results of the FAIR Metrics analyses on the 9 example pairs in Table 1. The negative control, C. Taswell 2007 written as a literature review with integrated synthesis of a collection of design and practice principles, had no substantive overlap with Mons 2005 and cited all its sources adequately, resulting in F_M, F_P, and F_Q scores of 1. The ratio of novel claims to cited claims was nearly even, leading to an F_N score close to 0. Different from the other FAIR Metric ratios that have increasing values of fairness and ideal values of 1, this novelty measure F_N does not necessarily have an ideal value which can vary according to the type of manuscript, eg, primary research report versus secondary literature review. Future work will establish what values of each of the FAIR metrics should be considered acceptable for that measure and what values should meet the standards of the scholarly community in a given research field.

Both Uddin et al. 2022 and Gnat et al. 2022 attained positive FAIR Metric scores, as both appropriately citde the sources of most concepts they presented. Although F_M, F_P, and F_Q are greater than 0, they are still well below 1, which would be sufficient to alert an editor to issues requiring further scrutiny. The negative F_P score of Ullah et al. 2018 demonstrates that the FAIR Metrics are immune to conventional paraphrasing. However, the non-zero N count shows that changing actual content words to those with different meanings can decrease the apparent extent of plagiarism. Nevertheless, this tactic of random word replacement did result in misrepresentations of the content of the cited sources, including such clearly erroneous statements as "About half of the total production of Asparagus is being consumed as white and red Asparagus, whereas the remaining 30% is converted into dry Asparagus for medicinal purposes, and 20% is used as seed material" (Deshmukh, Varma, et al. 2014). We excluded 5 claims from the analysis of Ullah et al. 2018 due to inability to locate any of the texts cited as their sources. Yao et al. 2016 copied most of the content of G. Li et al. 2015, but replaced several keywords with some additional paraphrasing. They replaced "chondrosarcoma" with "glioblastoma", "Slug" with "Twist", "CXCR7" with "CXCR4", "CCL21" with "CXCL12", "SW1353" with "U87", and "transwell" with "wound healing".

However, they completed a more deliberate substitution and paraphrasing than did the authors of Ullah et al. 2018. In particular, they rewrote the first few sentences of the introduction, because replacing "chondrosarcoma" with "glioblastoma" would have resulted in clearly false statements. Where the sources that G. Li et al. 2015 cited would not support the new statements, they found other, more relevant, sources to cite. However, they were not as deliberate in their paraphrasing throughout the text. G. Li et al. 2015 cited Nieto et al. 1994, titled "Control of cell behavior during vertebrate development by Slug, a zinc finger gene", Haupt et al. 2006, titled "Clues from worms: a Slug at Puma promotes the survival of blood progenitors", Y. Li et al. 2014, titled "Axl mediates tumor invasion and chemosensitivity through PI3K/Akt signaling pathway and is transcriptionally regulated by slug in breast carcinoma", and He et al. 2012, titled "Ikaros inhibits proliferation and, through upregulation of Slug, increases metastatic ability of ovarian serous adenocarcinoma cells". Instead of finding a new, more appropriate paper to cite, they changed the titles in the references to "Control of cell behavior during vertebrate development by twist, a zinc finger gene", "Clues from worms: a twist at Puma promotes the survival of blood progenitors", "Axl mediates tumor invasion and chemosensitivity through PI3K/Akt signaling pathway and is transcriptionally regulated by Twist in breast carcinoma", and "Ikaros inhibits proliferation and, through upregulation of twist, increases metastatic ability of ovarian serous adenocarcinoma cells". The lack of capitalization of "twist" is in the citations as presented in the text. Since these attributions misrepresented not only the key claims in the text, but also the claims made in the titles of the reports cited, the attributed claims count as misquoted.

If considered naively, the numerous substitutions would greatly inflate the number of novel claims. However, in this case and with Ullah et al. 2018, it is possible to mitigate this concern by abstracting out details of the sentences. For example, we can take the claims "However, to our knowledge, the potential mechanisms of the CXCL12/CXCR4 pathway in modulation of the EMT process have been largely unknown previously." and "We were very interested in their relationships and investigated whether Slug signaling was up-regulated by CCL21/CXCR7 pathway to induce EMT in human chondrosarcoma tissues and cells." in Yao et al. 2016 to be novel claims, as they identify the specific pathway, transcription factor, and type of cancer to be studied as different from those identified in the corresponding claims in G. Li et al. 2015: "However, to our knowledge, the potential mechanisms of the CXCR7 pathway in modulation of the EMT process have been largely unknown previously." and "We were very interested in their relationships and investigated whether Slug signaling was up-regulated by CCL21/CXCR7 pathway to induce EMT in human chondrosarcoma tissues and cells." However, in all subsequent claims, we can abstract out these details and consider each substituted word equivalent to the original. For example, we can abstract both "Twist" in Yao et al. 2016 and "Slug" in G. Li et al. 2015 to "the transcription factor of interest".

When plagiarizing Lv et al. 2015, the authors Dai et al. 2015 applied the same tactics as did the authors Yao et al. 2016. Specifically, they substituted "glioma" for "glioblastoma", "(SDF-1)/CXCR4" for "EGF", and "U87" for "U251" and then rewrote some parts of the introduction to replace the resulting obvious misstatements with correctly sourced background information. We can apply the same method of abstraction in order to arrive at appropriate FAIR Metric counts. They were more deliberate about replacing references with those that included claims equivalence matching what they were asserting after the substitutions. But they still included 1 misquoted claim, that the "SDF-1 pathway mainly included the RAS/RAF/MEK/ERK and PI3K/AKT pathways." While the sources they cited do refer to MEK, ERK, PI3K, and AKT as being part of pathways that include SDF-1, they did not mention RAS or RAF.

Guo et al. 2013 did not attempt any substantive substitutions of content words and instead relied only on paraphrasing and some slight abridgement to obfuscate their plagiarism of Fischbach et al. 2009. Every claim in Guo et al. 2013 had an apparent counterpart in Fischbach et al. 2009. The 1 novel claim found is a paraphrasing that is so garbled that it completely loses the meaning of its counterpart in the original text. Specifically, "Measurement of the SNR and CNR in the images does not allow for the assessment of aesthetic appearance, the depiction of tiny structural details, the distinction of different tissues, the impairment by artifacts, and, hence, the diagnostic value of the images." in Fischbach et al. 2009 becomes "The diagnosing images can be influence by the artifacts and visualization ability of anatomical details by SNR and CNR at different tissues." in Guo et al. 2013. One of the 2 misquoted claims is due to another instance of paraphrasing that altered the meaning of the sentence in a nonsensical way, taking an original sentence about eliminating a blood vessel from an image and altering it to be about eliminating the nerves that were originally the focus of the imaging. The other is due to the addition of citations to the plagiarized version of 1 of the novel claims in Fischbach et al. 2009, but attributing it to earlier works.

Among the 8 plagiarism examples analysed here, Su et al. 2005 represents the most overt and explicit plagiarism. Most of the text is a verbatim copy of Schwab et al. 2001 with only sparse rewordings. As such, all claims are either plagiarized or quoted.

In contrast, Wilkinson et al. 2016 did not copy text verbatim from C. Taswell 2007; C. Taswell 2010. Instead, Wilkinson et al. 2016 obfuscated their plagiarism of concepts and ideas by paraphrasing part of the Taswell 2007 collection without citation (Craig, Ambati, Dutta, Kowshik, et al. 2019) and the editors of *Nature Scientific Data* concealed this plagiarism by refusing to correct the omission of citation of the original sources — which constitutes both *idea-laundering plagiarism by authors and idea-bleaching censorship by editors* as defined by S. K. Taswell et al. 2020. Each of the 24 claims counted as plagiarized in Wilkinson et al. 2016 (the FAIR-named collection of principles) has a corresponding equivalent in C. Taswell 2007 (the PORTAL-DOORS Project collection of principles). Moreover, the 5 claims counted as novel in Wilkinson et al. 2016 focused merely on building consensus at workshops for their FAIR-named collection. The 6 claims counted as misquoted in Wilkinson et al. 2016 likely resulted from changes to the content of the websites cited as sources.

Discussion

The 8 cases of plagiarism in Table 1 illustrate the complexity and diversity of real-world plagiarism and demonstrate that the current version of the FAIR Metrics are useful in real-world peer reviews. The FAIR Metrics did not indicate any sign of plagiarism in the negative control case of the example pair C. Taswell 2007 and Mons 2005. Thus, the requirement of equivalence of meaning can assist in detecting plagiarism while not yielding false positives for plagiarism and possibly allegations of plagiarism in the scenario of different author groups writing about the same topics within the same field of study contemporaneously. The cases retracted for plagiarism show that the FAIR Metrics can positively identify cases of explicit plagiarism even with mild paraphrasing across problem domains as diverse as green technology (Ullah et al. 2018), dermatology (Gnat et al. 2022), and neuroscience (Uddin et al. 2022). Future work will more formally evaluate the sensitivity and specificity of the FAIR Metrics for the detection of plagiarism in various scenarios.

Although the FAIR Metrics provide helpful insights and alerts, the current version does not obviate the need for other forms of textual analysis, both lexical and semantic, to identify and understand the full nature and extent of plagiarism in research communications. In particular, the Q counts can be spuriously high in that many of the passages in the plagiarizing papers with correct attributions have nevertheless been plagiarized from the comparison papers. Since neither T nor C are the original references for the ideas presented, and since both attribute them to prior sources that do present such concepts, the FAIR Metric evaluation procedure as currently practiced deems the copies of such claims in both works to be valid quoted claims, even if they have identical wording. We originally designed the FAIR Metrics to evaluate the quality of primary research articles, which should present original results and analyses balanced with context from the existing literature (Craig and C. Taswell 2018). In their present form, they would not be suitable for a comparison of 2 pure reviews of the literature that summarize previously published content from the historical record devoid of any attempt in the literature reviews to provide commentary, analysis, or synthesis with new concepts, ideas, and claims. While we plan to develop FAIR Metrics customized for different kinds of scholarly research communications, current lexical and semantic comparison methods can still serve as complementary tools for use with the FAIR Metrics analyses. Regardless, when automated with machine algorithms these comparison evaluations for the detection of plagiarism should always be subject to final review by human analysts.

Table 1: FAIR Metrics for example comparison pairs listed in F_P descending order

Pair	Test (T) text	Retracted?	Comparison (C) text	M	N	P	Q	F_M	F_N	F_P	F_Q
1	C. Taswell 2007	no	Mons 2005	0	20	0	22	1.00	0.05	1.00	1.00
2	Uddin et al. 2022	yes	Foster et al. 2019	0	18	18	87	0.83	0.56	0.66	0.83
3	Gnat et al. 2022	yes	Hoog et al. 2016	0	3	10	30	0.75	0.63	0.50	0.75
4	Wilkinson et al. 2016	no	C. Taswell 2007	6	5	24	28	0.38	0.37	0.07	0.48
5	Yao et al. 2016	yes	G. Li et al. 2015	4	2	11	9	0.21	0.27	-0.08	0.38
6	Dai et al. 2015	yes	Lv et al. 2015	1	2	18	14	0.39	0.34	-0.12	0.42
7	Guo et al. 2013	yes	Fischbach et al. 2009	2	1	13	10	0.32	0.346	-0.12	0.40
8	Ullah et al. 2018	yes	Sansaniwal and Kumar 2015	31	3	7	2	-0.73	-0.02	-0.13	0.05
9	Su et al. 2005	yes	Schwab et al. 2001	0	0	20	12	0.38	0.38	-0.25	0.38

M Misquoted, N Novel, P Plagiarized, Q Quoted Counts; F_M Misquoted, F_N Novel, F_P Plagiarized, F_Q Quoted FAIR Metrics.

The labor-intensive evaluation process required of human analysts, as demonstrated in this report, remains another current limitation on the practical utility of the FAIR Metrics for screening large numbers of documents. Even the pairwise comparison approach used in the present work requires that the reviewer list all statements in the test text, identify which ones are significant enough to be key claims, search the comparison text for equivalent claims, and perform at least a cursory search of every cited text for equivalents of the claims attributed to them. While more work than a typical peer review, this process can nevertheless be used as an important method for keeping the provenance and development of ideas traceable and verifiable when evaluating suspected cases of plagiarism. Publishers can make it worthwhile for reviewers by publishing the evaluation documents as citable works in their own right, thus featuring the scholarship and analytical skills of the reviewers (Craig, Lee, et al. 2022). Furthermore, making these records not only readable by humans but also by machines as subject-verb-object triples and linked quads will enhance their potential application and use in both scenarios of rapid screening of large numbers of documents as well as careful evaluation of a small number of documents suspected of plagiarism. The resulting linked knowledge graph can also be explored by semantic search and reasoning engines and provides a resource for the development and testing of tools to automate parts of the FAIR Metrics evaluation process. Maintaining a corpus of test cases known to contain matching entities can be useful for testing named entity recognition approaches such as Taufiq et al. 2023 and Khadilkar et al. 2018, which could be adapted to produce matched claim pairs for piping into an automated FAIR Metrics calculator.

Conclusion

We have demonstrated that the FAIR Metrics provide a quantitative method of evaluating the extent to which a scholarly commmunication adheres to a code of conduct of fairness when discussing and citing relevant research in the field, taking ideas from previously published literature, and properly crediting the original sources. We have shown that even a simple evaluation procedure against a limited pool of comparison texts yields differences in measures which can assist peer review to assess concerns about plagiarism, misrepresentation, citational justice, and fairness. We have created searchable online repositories of NPDS records with semantic representations of FAIR Metric analyses that serve as a prototype for a more reproducible, verifiable, and accountable approach to open and transparent peer review.

Citation

Brainiacs 2023 Volume 4 Issue 2 Edoc D5B2734F2
Title: "Managing Lexical-Semantic Hybrid Records of FAIR Metrics Analyses with the NPDS Cyberinfrastructure"
Authors: Adam Craig, Anousha Athreya, Carl Taswell
Dates: created 2023-06-16, received 2023-10-03, presented 2023-10-09, updated 2023-12-27, published 2023-12-27, endorsed 2023-12-31

Contact: A Craig at BHAVI
URL: BrainiacsJournal.org/arc/pub/Craig2023MLSHRFMA
PDP: /Nexus/Brainiacs/Craig2023MLSHRFMA
DOI: /10.48085/D5B2734F2

References

[1] A. Altheneyan and M. E. B. Menai. "Evaluation of state-of-the-art paraphrase identification and its application to automatic plagiarism detection." *International Journal of Pattern Recognition and Artificial Intelligence* 34.04 (2020), p. 2053004 (cited p. 1).

[2] A. Athreya, S. K. Taswell, S. Mashkoor, and C. Taswell. "Essential Question: 'Equal or Equivalent Entities?' About Two Things as Same, Similar, or Different." In: *2020 Second International Conference on Transdisciplinary AI (TransAI)*. 2020, pp. 123–124. DOI: 10.1109/TransAI49837.2020.00028 (cited p. 3).

[3] A. Athreya, S. K. Taswell, S. Mashkoor, and C. Taswell. "The Essential Enquiry 'Equal or Equivalent Entities?' About Two Things as Same, Similar, Related, or Different." *Brainiacs Journal of Brain Imaging And Computing Sciences* 1.1, PEDADC885 (1 Dec. 30, 2020), pp. 1–7. DOI: 10.48085/PEDADC885. URL: https://brainiacsjournal.org/arc/pub/Athreya2020EEEEE (cited pp. 2, 3).

[4] G. Cabanac and C. Labbé. "Prevalence of nonsensical algorithmically generated papers in the scientific literature." *Journal of the Association for Information Science and Technology* 72.12 (2021), pp. 1461–1476 (cited p. 2).

[5] Copyleaks. *AI Content Detector Continues To Be Confirmed As Most Accurate By Third-Party Studies*. Oct. 30, 2023. URL: https://copyleaks.com/blog/ai-detector-continues-top-accuracy-third-party (cited p. 1).

[6] A. Craig, A. Ambati, S. Dutta, P. Kowshik, S. Nori, S. K. Taswell, Q. Wu, and C. Taswell. "DREAM Principles and FAIR Metrics from the PORTAL-DOORS Project for the Semantic Web." In: *2019 IEEE 11th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)* (June 28, 2019). Pitesti, Romania: IEEE, June 2019, pp. 1–8. DOI: 10.1109/ECAI46879.2019.9042003. URL: https://portaldoors.org/pub/docs/ECAI2019DREAMFAIR0612.pdf (cited pp. 2–5).

[7] A. Craig, A. Ambati, S. Dutta, A. Mehrotra, S. K. Taswell, and C. Taswell. "Definitions, Formulas, and Simulated Examples for Plagiarism Detection with FAIR Metrics." In: *2019 ASIS&T 82nd Annual Meeting* (Oct. 19, 2019). Vol. 56. Melbourne, Australia: Wiley, 2019, pp. 51–57. DOI: 10.1002/PRA2.6. URL: https://portaldoors.org/pub/docs/ASIST2019FairMetrics0611.pdf (cited pp. 2, 3).

[8] A. Craig, A. Athreya, and C. Taswell. "Example evaluations of plagiarism cases using FAIR Metrics and the PDP-DREAM Ontology." *IEEE eScience 2023* (Oct. 13, 2023) (cited pp. 1, 2).

[9] A. Craig, C. Lee, N. Bala, and C. Taswell. "Motivating and Maintaining Ethics, Equity, Effectiveness, Efficiency, and Expertise in Peer Review." *Brainiacs Journal of Brain Imaging And Computing Sciences* 3.1, I5B147D9D (1 June 30, 2022), pp. 1–21. DOI: 10.48085/I5B147D9D. URL: https://BrainiacsJournal.org/arc/pub/Craig2022MMEEPR (cited pp. 2, 6).

[10] A. Craig and C. Taswell. "Formulation of FAIR Metrics for Primary Research Articles." In: *2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. Madrid, Spain: IEEE, Dec. 3, 2018, pp. 1632–1635. DOI: 10.1109/BIBM.2018.8621399 (cited p. 5).

[11] A. Craig and C. Taswell. "PDP-DREAM Software for Integrating Multimedia Data with Interoperable Repositories." *Brainiacs Journal of Brain Imaging And Computing Sciences* 2.1, HA46280EF (1 Dec. 31, 2021), pp. 1–6. DOI: 10.48085/HA46280EF. URL: https://BrainiacsJournal.org/arc/pub/Craig2021SIMDIR (cited pp. 2, 4).

[12] C. Dai, S. Lv, R. Shi, J. Ding, et al. "RETRACTED ARTICLE: nuclear protein C23 on the cell surface plays an important role in activation of CXCR4 signaling in glioblastoma." *Molecular neurobiology* 52 (2015), pp. 1521–1526 (cited pp. 3, 5, 6).

[13] A. W. Deshmukh, M. N. Varma, et al. "Investigation of solar drying of ginger (Zingiber officinale): Emprical modelling, drying characteristics, and quality study." *Chinese Journal of Engineering* 2014 (2014), pp. 1–7 (cited p. 4).

[14] N. Drummond, M. Horridge, and H. Knublauch. "Protégé-OWL tutorial." In: *8th International Protégé Conference*. 2005 (cited p. 4).

[15] S. Dutta, P. Kowshik, A. Ambati, S. Nori, S. K. Taswell, and C. Taswell. "Managing Scientific Literature with Software from the PORTAL-DOORS Project." In: *2019 IEEE 15th International Conference on eScience (eScience)* (Sept. 24, 2019). San Diego, California: IEEE, Sept. 2019. DOI: 10.1109/eScience.2019.00081. URL: https://portaldoors.org/pub/docs/BCDC2019PdpDemo0806.pdf (cited p. 4).

[16] S. Dutta, K. Uhegbu, S. Nori, S. Mashkoor, S. K. Taswell, and C. Taswell. "DREAM Principles from the PORTAL-DOORS Project and NPDS Cyberinfrastructure." In: *2020 IEEE 14th International Conference on Semantic Computing (ICSC)*. IEEE, Feb. 4, 2020, pp. 211–216. DOI: 10.1109/ICSC.2020.00044. URL: https://portaldoors.org/pub/docs/ECAI2019DREAMFAIR0612.pdf (cited p. 2).

[17] T. A. E. Eisa, N. Salim, and A. Abdelmaboud. "Content-based scientific figure plagiarism detection using semantic mapping." In: *Emerging Trends in Intelligent Computing and Informatics*. Ed. by F. Saeed, F. Mohammed, and N. Gazem. Springer International Publishing, 2020, pp. 420–427. ISBN: 978-3-030-33582-3 (cited p. 2).

[18] F. Fischbach, M. Müller, and H. Bruhn. "High-resolution depiction of the cranial nerves in the posterior fossa (N III–N XII) with 2D fast spin echo and 3D gradient echo sequences at 3.0 T." *Clinical imaging* 33.3 (2009), pp. 169–174 (cited pp. 3, 5, 6).

[19] E. M. Foster, A. Dangla-Valls, S. Lovestone, E. M. Ribe, and N. J. Buckley. "Clusterin in Alzheimer's Disease: Mechanisms, Genetics, and Lessons From Other Pathologies." *Frontiers in Neuroscience* 13, 164 (Feb. 2019). ISSN: 1662-453X. DOI: 10.3389/fnins.2019.00164 (cited pp. 3, 6).

[20] C. A. Gao, F. M. Howard, N. S. Markov, E. C. Dyer, S. Ramesh, Y. Luo, and A. T. Pearson. "Comparing scientific abstracts generated by ChatGPT to original abstracts using an artificial intelligence output detector, plagiarism detector, and blinded human reviewers." *bioRxiv* (2022), pp. 2022–12 (cited p. 2).

[21] M. Gaudino, N. B. Robinson, K. Audisio, M. Rahouma, U. Benedetto, P. Kurlansky, and S. E. Fremes. "Trends and characteristics of retracted articles in the biomedical literature, 1971 to 2020." *JAMA internal medicine* 181.8 (2021), pp. 1118–1121 (cited p. 2).

[22] S. Gnat, A. Nowakiewicz, and P. Zięba. "Retraction of: Sebastian Gnat, Aneta Nowakiewicz, Przemysław Zięba: Taxonomy of dermatophytes – the classification systems may change but the identification problems remain the same." *Postępy Mikrobiologii - Advancements of Microbiology* 61.4 (2022), pp. 261–261. DOI: 10.2478/am-2022-013 (cited pp. 3–6).

[23] GPTZero. *Our detection technology*. 2023. URL: https://gptzero.me/technology (cited p. 1).

[24] Z.-Y. Guo, J. Chen, H.-Y. Liao, Q.-Y. Cheng, S.-X. Fu, C.-X. Chen, D. Yu, et al. *RETRACTED: High-resolution MRI of cranial nerves in posterior fossa at 3.0 T*. 2013 (cited pp. 3, 5, 6).

[25] S. Haupt, O. Alsheich-Bartok, and Y. Haupt. "Clues from worms: a Slug at Puma promotes the survival of blood progenitors." *Cell death and differentiation* 13.6 (2006), p. 913 (cited p. 4).

[26] L.-C. He, F.-H. Gao, H.-Z. Xu, S. Zhao, C.-M. Ma, J. Li, S. Zhang, and Y.-L. Wu. "Ikaros inhibits proliferation and, through upregulation of Slug, increases metastatic ability of ovarian serous adenocarcinoma cells." *Oncology reports* 28.4 (2012), pp. 1399–1405 (cited p. 4).

[27] G. S. de Hoog, K. Dukik, M. Monod, A. Packeu, et al. "Toward a Novel Multilocus Phylogenetic Taxonomy for the Dermatophytes." *Mycopathologia* 182.1–2 (Oct. 2016), pp. 5–31. ISSN: 1573-0832. DOI: 10.1007/s11046-016-0073-9 (cited pp. 3, 6).

[28] IEEE, ed. *CrossCheck Information*. 2023. URL: https://www.ieee.org/publications/rights/cross-check-main.html (cited p. 1).

[29] S. Javadi-Moghaddam, F. Roosta, and A. Noroozi. "Weighted semantic plagiarism detection approach based on AHP decision model." *Accountability in Research* 29.4 (2022), pp. 203–223 (cited p. 2).

[30] M. Jiffriya, M. Jahan, and R. Ragel. "Plagiarism detection tools and techniques: A comprehensive survey." *Journal of Science-FAS-SEUSL* 2.02 (2021), pp. 47–64 (cited p. 2).

[31] K. Khadilkar, S. Kulkarni, and P. Bone. "Plagiarism detection using semantic knowledge graphs." In: *2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA)*. IEEE. 2018, pp. 1–6 (cited p. 6).

[32] M. Khalil and E. Er. "Will ChatGPT get you caught? Rethinking of plagiarism detection." *arXiv preprint arXiv:2302.04335* (2023) (cited p. 1).

[33] J. H. Kirchner, L. Ahmad, S. Aaronson, and J. Leike. *New AI classifier for indicating AI-written text*. Jan. 31, 2023. URL: https://openai.com/blog/new-ai-classifier-for-indicating-ai-written-text (cited p. 1).

[34] C. Labbé and D. Labbé. "Duplicate and fake publications in the scientific literature: how many SCIgen papers in computer science?" *Scientometrics* 94 (2013), pp. 379–396 (cited p. 2).

[35] G. Li, Y. Yang, S. Xu, L. Ma, M. He, and Z. Zhang. "Slug signaling is up-regulated by CCL21/CXCR7 to induce EMT in human chondrosarcoma." *Medical Oncology* 32.2 (2015), p. 2 (cited pp. 3–6).

[36] Y. Li, L. Jia, D. Ren, C. Liu, Y. Gong, N. Wang, X. Zhang, and Y. Zhao. "Axl mediates tumor invasion and chemosensitivity through PI3K/Akt signaling pathway and is transcriptionally regulated by slug in breast carcinoma." *IUBMB life* 66.7 (2014), pp. 507–518 (cited p. 4).

[37] S. Lv, C. Dai, Y. Liu, B. Sun, R. Shi, M. Han, R. Bian, and R. Wang. "Cell surface protein C23 affects EGF-EGFR induced activation of ERK and PI3K-AKT pathways." *Journal of Molecular Neuroscience* 55 (2015), pp. 519–524 (cited pp. 3, 5, 6).

[38] B. Mons. "Which gene did you mean?" *BMC Bioinformatics* 6, 142 (2005). DOI: 10.1186/1471-2105-6-142 (cited pp. 3–6).

[39] M. A. Nieto, M. G. Sargent, D. G. Wilkinson, and J. Cooke. "Control of cell behavior during vertebrate development by Slug, a zinc finger gene." *Science* 264.5160 (1994), pp. 835–839 (cited p. 4).

[40] M. S. Orenstrakh, O. Karnalim, C. A. Suarez, and M. Liut. *Detecting LLM-Generated Text in Computing Education: A Comparative Study for ChatGPT Cases*. 2023. DOI: 10.48550/ARXIV.2307.07411 (cited p. 1).

[41] *Retraction Watch Database User Guide*. Apr. 2023. URL: https://retractionwatch.com/retraction-watch-database-user-guide/ (cited p. 3).

[42] S. K. Sansaniwal and M. Kumar. "Analysis of ginger drying." *Journal of Mechanical Engineering and Sciences* 9 (2015), pp. 1671–1685. DOI: 10.15282/jmes.9.2015.13.0161 (cited pp. 3, 6).

[43] K. Santos-d'Amorim, T. Wang, B. Lund, and R. N. Macedo Dos Santos. "From plagiarism to scientific paper mills: a profile of retracted articles within the SciELO Brazil collection." *Ethics & Behavior* 34.1 (Nov. 2022), pp. 1–18. ISSN: 1532-7019. DOI: 10.1080/10508422.2022.2141747 (cited p. 2).

[44] S. Schwab, D. Georgiadis, J. Berrouschot, P. D. Schellinger, C. Graffagnino, and S. A. Mayer. "Feasibility and safety of moderate hypothermia after massive hemispheric infarction." *Stroke* 32.9 (2001), pp. 2033–2035 (cited pp. 3, 5, 6).

[45] J. Su, Y. Qiou, Z. Chen, and Y. Chen. "Feasibility and safety of moderate hypothermia after acute ischemic stroke (vol 21, pg 353, 2003)." *INTERNATIONAL JOURNAL OF DEVELOPMENTAL NEUROSCIENCE* 23.4 (2005), pp. 411–411 (cited pp. 3, 5, 6).

[46] C. Taswell. "DOORS to the Semantic Web and Grid with a PORTAL for Biomedical Computing." *IEEE Transactions on Information Technology in Biomedicine* 12.2 (2 Mar. 2007). In the Special Section on Bio-Grid published online 3 Aug. 2007, pp. 191–204. ISSN: 1089-7771. DOI: 10.1109/TITB.2007.905861 (cited pp. 3–6).

[47] C. Taswell. "A Distributed Infrastructure for Metadata about Metadata: The HDMM Architectural Style and PORTAL-DOORS System." *Future Internet* 2.2 (2010), pp. 156–189. ISSN: 1999-5903. DOI: 10.3390/FI2020156. URL: https://www.mdpi.com/1999-5903/2/2/156/ (cited pp. 3, 5).

[48] S. K. Taswell, C. Triggle, J. Vayo, S. Dutta, and C. Taswell. "The Hitchhiker's Guide to Scholarly Research Integrity." In: *2020 ASIS&T 83rd Annual Meeting* (Oct. 22, 2020). Vol. 57. Wiley, 2020, e223. DOI: 10.1002/pra2.223. URL: https://asistdl.onlinelibrary.wiley.com/doi/abs/10.1002/pra2.223 (cited pp. 2, 5).

[49] U. Taufiq, R. Pulungan, and Y. Suyanto. "Named entity recognition and dependency parsing for better concept extraction in summary obfuscation detection." *Expert Systems with Applications* (2023), p. 119579 (cited p. 6).

[50] H. H. Thorp. *ChatGPT is fun, but not an author*. 2023 (cited p. 1).

[51] M. S. Uddin, M. T. Kabir, M. M. Begum, M. S. Islam, T. Behl, and G. M. Ashraf. *Retraction Note to: Exploring the Role of CLU in the Pathogenesis of Alzheimer's Disease*. 2022. DOI: 10.1007/s12640-022-00519-1 (cited pp. 3–6).

[52] F. Ullah, M. Kang, M. K. Khattak, and S. Wahab. "Retracted: Experimentally investigated the asparagus (Asparagus officinalis L.) drying with flat-plate collector under the natural convection indirect solar dryer." *Food Science & Nutrition* 6.6 (2018), pp. 1357–1357 (cited pp. 3–6).

[53] T. Vrbanec and A. Meštrović. "The struggle with academic plagiarism: Approaches based on semantic similarity." In: *2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*. IEEE. 2017, pp. 870–875 (cited p. 1).

[54] M. D. Wilkinson, M. Dumontier, I. J. Aalbersberg, G. Appleton, et al. "The FAIR Guiding Principles for scientific data management and stewardship." *Scientific data* 3.1 (2016), pp. 1–9 (cited pp. 3, 5, 6).

[55] J. Xiong and T. Huang. "An effective method to identify machine automatically generated paper." In: *2009 Pacific-Asia Conference on Knowledge Engineering and Software Engineering*. IEEE. 2009, pp. 101–102 (cited p. 2).

[56] C. Yao, P. Li, H. Song, F. Song, Y. Qu, X. Ma, R. Shi, and J. Wu. "RETRACTED ARTICLE: CXCL12/CXCR4 Axis Upregulates Twist to Induce EMT in Human Glioblastoma." *Molecular neurobiology* 53 (2016), pp. 3948–3953 (cited pp. 3–6).

[57] L. Young. *iThenticate 2.0: Advancing research integrity with AI writing detection*. Ed. by turnitin. Nov. 1, 2023. URL: https://www.turnitin.com/blog/ithenticate-2-0-advancing-research-integrity-with-ai-writing-detection (cited p. 1).

