



From the ‘Best of Our Knowledge’ to the ‘Best Available Knowledge’*

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Abstract

To trust in science, both researchers and the public need to be able to trace claims to their origins. Traditionally, scholars have relied on each other to disclose their use of preexisting ideas and findings through citations, but the fast pace of modern research pressures researchers to spend less time reviewing the literature. Worse still, competition for recognition tempts authors to avoid citing potential rivals. The term *dismissive literature review* describes a claim that no answer to a question or solution to a problem exists. We here propose a distinction between a dismissive literature review, in which the author makes such claims due to insufficient search, and a *ghosting literature review*, in which the author knowingly suppresses others’ work. Better knowledge engineering, especially repositories of resource metadata with semantic markup that supports smarter and more explainable search algorithms, can help to prevent dismissive literature reviews by directing researchers to relevant information, even if it comes from outsiders to the field. However, detecting and remediating ghosting reviews will require both software tools and community commitment to communication and cooperation. In this work, we review the tools that the PORTAL-DOORS Project has developed to help researchers, reviewers, editors, and readers to assess how well authors acknowledge others’ contributions. We then call for scholarly communities to build up repositories not only of scientific data but of social knowledge that can illuminate the interpersonal context of a submission and the potential incentives to uphold or violate other researcher’s and the public’s trust in science.

Keyphrases

Data stewardship, metadata management, knowledge engineering, research ethics, citational justice.

Contents

Deficient reviews of published literature	1
Dismissive reviews	1
Ghosting reviews	1
Software from the PORTAL-DOORS Project	3
NPDS Cyberinfrastructure	3
PDP-DREAM Ontology	3
FAIR Metrics	4

Socially aware knowledge engineering	5
Social influence and ethical behavior	5
The need for metatextual context in metadata	5
Incorporating social context into NPDS records	6
Conclusion	6
Citation	6
Affiliations	7
References	7

Deficient reviews of published literature

Dismissive reviews

Primary research articles typically place the novel results that they present in the wider context of a given field by citing, summarizing, and discussing related prior literature (Steward 2004). However, many articles instead assure the reader that no prior research on a given topic exists, a practice for which (Phelps 2012) coined the term “dismissive literature review.” The same article defines a “firstness claim” as “a particular type of dismissive review in which a researcher insists that he is the first to study a topic” (Phelps 2012). They argue that false dismissive reviews dissuade readers from looking more deeply into the history of a topic, diminishing the impact of potentially valuable literature (Phelps 2012). As an example, they present several articles by prominent figures in education policy that wrongly insisted little to no information was available on the impact of academic standards and policies on outcomes, all of which appeared shortly prior to the passage of the No Child Left Behind Act in the United States (Phelps 2012).

Ghosting reviews

While (Phelps 2012) defines dismissive reviews in terms of behavior, it is useful to draw a distinction between actual and feigned ignorance. The former is correctable, while the latter is likely to reoccur no matter how often others attempt to correct the scholarly record by alerting the authors and journal editors to the presence of work undercutting a false claim of novelty. The term “dismissive literature review” includes cases when authors fail to search for prior work that introduces the same ideas or answers the same questions as their own and use their lack of knowledge as the basis for claiming novelty (Phelps 2012). In this context, common phrases like “to the best of our knowledge, no prior

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Table 1: Distinctions among valid firstness claims, dismissive literature reviews, and ghosting literature reviews.

		Authors aware of prior work?	
		No	Yes
Scope of work that firstness claim ignores	Single research result History of field	Multiple discovery or invention Dismissive literature review	Idea plagiarism Ghosting literature review

work has..." are examples of the "appeal to ignorance" fallacy (Walton 2010): We do not know of any prior work answering the same question that ours does, so no such work exists.

We here coin the term "ghosting literature review" to describe a case where authors do know that a work has precedents but intentionally suppress them to make their own work seem more impactful. See Figure 1 for a visual representation of this definition as a decision tree for deciding whether a claim is a ghosting literature review. We choose to use "ghosting" to draw an analogy with the social phenomenon of ghosting, in which one party cuts off contact with the other without warning or explanation (Teichert 2025). In both cases, one party intentionally acts as if the other does not exist.

We summarize the similarities and differences between ghosting literature reviews and three related concepts in Table 1. All four are situations in which authors wrongly claim to present a novel idea. The key distinctions among them are whether the authors are aware that their firstness claim is false and whether the claim ignores the existence of only a single report of a research result or a larger body of literature.

The least similar to a ghosting literature review is multiple discovery, also known as simultaneous invention or any of several other terms, depending on the kind of research output reported (Ione 1999). The discovery or invention need not be strictly simultaneous, but the latter instance must occur independently, without knowledge of the former (Plantec et al. 2025). Such cases have remained a perennial subject of interest to scholars of the history of science and engineering from the early 20th century (Rossman 1930) to the present day (Heraud and Popielek 2024) due to their potential implications for the roles of individual insight, chance, and larger societal context in innovation (Merton 1961; Simonton 1979; Voss 1984).

When authors do know of prior instances of a research result but present it as their own novel contribution, they commit idea plagiarism (Weyland 2007). If the false firstness claim is part of a larger pattern of obfuscation and refusal to correct the scientific record when confronted with evidence of prior work, it is not merely idea plagiarism but idea-laundering plagiarism and represents an intentional effort to erase the original discoverers' identities from history (S. K. Taswell, Triggles, et al. 2020).

In (Phelps 2010), Phelps argues that dismissive literature reviews do even more damage to the scientific community's collective understanding by denying the existence of not just a single report but an entire branch of research. Furthermore, the wider scope of ignorance required to remain oblivious to a larger body of work represents a more severe failure to study the problem domain and makes claims of unintentional

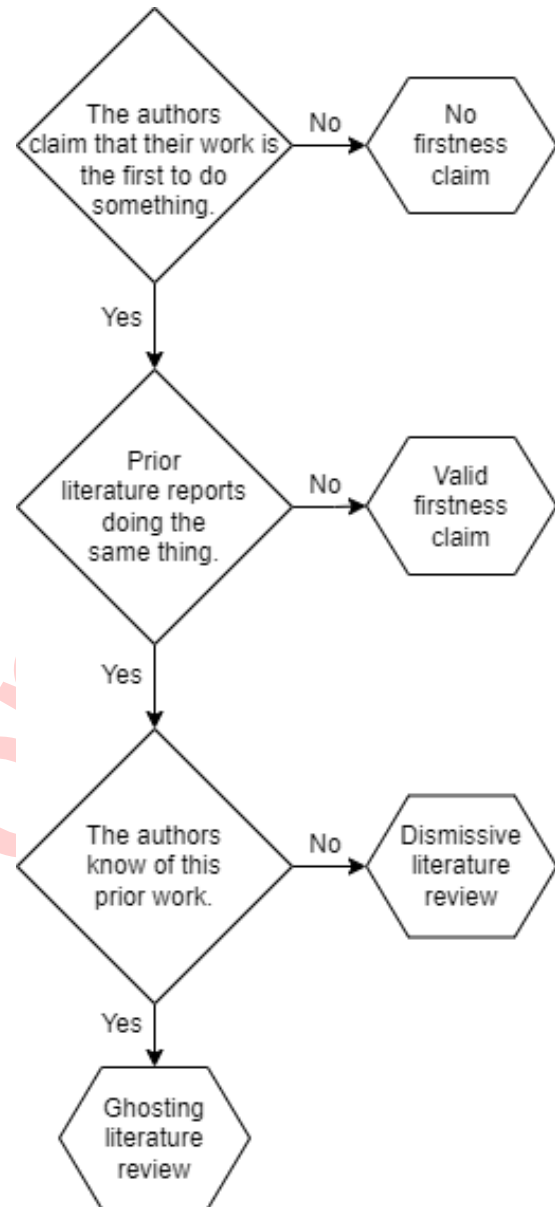


Figure 1: Decision tree for distinguishing among valid firstness claims, dismissive literature reviews, and ghosting literature reviews.

omission less plausible and intentional erasure more likely. While this is true regardless of whether the authors had any prior knowledge that the firstness claim was false, distinguishing a ghosting literature review from a merely dismissive one reflects a meaningful difference in intent. Whereas a wrongly dismissive literature review is misinformation, false information spread either knowingly or unknowingly, a ghosting review is an instance of disinformation, intentional dissemination of a falsehood (Lecheler and Egelhofer 2022).

An additional dimension to consider is how the authors of the dismissive or ghosting literature review respond when asked to correct their publications: Misinformation and disinformation adequately cover the cases in which authors admit to the incorrectness of the information when others present evidence contradicting their claims, but continued insistence on propagating the misrepresentations escalates misinformation to anti-information and disinformation to caco-information (S. K. Taswell, Athreya, et al. 2021). We can use these same prefixes to

coin suitable terms in the context of false firstness claims. The authors' refusal to acknowledge the existence of relevant prior work even when others have brought it to their attention escalates a dismissive literature review to a "literature anti-review" and a ghosting literature review to a "literature caco-review".

Software from the PORTAL-DOORS Project

NPDS Cyberinfrastructure

Since the publication of the first PORTAL-DOORS Project paper in 2006 (C. Taswell et al. 2006), the goal has been to help authors identify relevant prior work. The original motivating example problem was supporting automated meta-analyses through publication of semantic descriptions of primary research articles and related resources in such a way that automated reasoning engines could identify the hypothesis being tested and the result of the test (C. Taswell 2007). These efforts have centered on the development of the Nexus-PORTAL-DOORS-Scribe (NPDS) cyberinfrastructure, originally envisioned as a messaging protocol and web API that would allow independent implementations of data and rich metadata management through a separate web service for conventional lexical metadata, the Problem-Oriented Registry of Tags And Labels (PORTAL), and for semantic descriptions, the Domain Ontology-Oriented Resource System (C. Taswell 2007). Subsequent updates have led to the inclusion of a combined semantic-lexical hybrid repository, the Nexus diristry, and a read-write service, the Scribe registrar, separate from the three read-only services (C. Taswell 2010a; Craig, S. H. Bae, et al. 2016). In contrast to the concentration of web traffic on a small number of platforms and power in the hands of a small number of companies, NPDS software can help individuals and small-to-medium-sized organizations to establish their own independent repositories of both human-readable and machine-readable information that they can share across institutional and disciplinary boundaries (Athreya, Craig, et al. 2023).

While the ideas of a peer-to-peer distributed network for managing semantic web resources (Schlosser et al. 2002) and infrastructure for producing explainable answers to questions using semantic markup (McGuinness and Da Silva 2003) preceded the PDP, NPDS is the first to implement this core set of design principles (Craig, Ambati, et al. 2019a) and has remained relevant for nearly 20 years amid major changes in the World Wide Web.

Many of the most successful projects in search infrastructure development focus on data sharing within a specific discipline. Some notable examples include the UniProt database, which integrates structural and functional information to facilitate large-scale proteomics (Jain et al. 2009), xWCPS, which combines the XQuery and the Web Coverage Processing Service standards to manage Earth science data (Liakos et al. 2015), and the Data Storage for Computation and Integration platform, which mainly facilitates collaborative research in dentistry (Brosset et al. 2021). One specific application area that has received attention from multiple projects is management of spatial location data due to its wide range of applications from environmental research (Li et al. 2011) to commercial Internet-of-things uses (Trifa et al. 2011). This stands in contrast to NPDS, which, from the beginning, emphasized applicability to multiple problem domains and supported representation of both online URL and physical locations (C. Taswell 2007). BHA collaborators have studied the applicability of NPDS to a wide variety of problems, including tracking provenance of cultural artifacts (Athreya, S. K. Taswell, et al. 2021), comparing hypotheses about neurodegenerative diseases

(Skarzynski et al. 2015a), and clinical tele-gaming (Gu and C. Taswell 2017). Some other works, such as (Ceri et al. 2011), have proposed abstract architectures for solving cross-domain search problems but have not taken concrete steps to build the necessary infrastructure.

In other cases, national governments have taken action to provide a common search infrastructure, but these systems inherently rely on centralized control, as with Finland's FinnONTO (Hyvönen et al. 2008) and the China National Knowledge Infrastructure (Ma et al. 2016). This also differs from the PDP vision of fostering communication and collaboration among independent institutions, which then opt in to a shared REST API and messaging protocol (Athreya, Craig, et al. 2023).

More recent attempts at novel approaches to search often focus on scalable search within a large centralized collection of data for machine learning, as in the case of ScienceSearch (Orhean et al. 2022). Similarly, many reviews that seek to identify the remaining shortcomings of existing approaches, such as (Peek et al. 2014), emphasize challenges due to the sheer amount of data or biases inherent to the data without discussing the socio-technical problem of fostering curation of rich and mutually intelligible metadata from numerous contributors. However, (Polleres et al. 2026) argues that, while semantic web services and agentic AI set out to solve many of the same problems, both have encountered key barriers to progress due to lack of shared terminology between services and poor discoverability of resources. The authors of (Lewandowski 2019) identify the lack of an open web index as a key shortcoming of modern web infrastructure that hinders discoverability, even though NPDS repositories could serve such a function effectively if sufficiently well-populated and frequently updated with online resources. However, the labor-intensive nature of creating and updating quality metadata that reflects the true content of a resource remains one of the key barriers to populating large repositories of semantically rich records (Hitzler 2021). Attempts to automatically generate semantic markup from natural language text have achieved some success but are still computationally intensive and less accurate than human understanding of the meaning of text (Regino et al. 2026). At the same time, advances in web-scale crawling and data extraction, as illustrated by (Dlugolinsky et al. 2012), have the potential to bridge this gap but lack integration with any larger data management infrastructure. This suggests that the PDP remains unique as a multi-domain semantic-lexical hybrid data and metadata management system for the open web but also that many of the same challenges to building out such infrastructure in 2007 continue to slow progress.

While the core protocols and APIs have stabilized, Brain Health Alliance (BHA) continues to release updated versions of the free, open-source reference implementation of the NPDS server software and record curation web application annually (<https://github.com/BHAVIUS/PORTALDOORS>) and hosts live example record repositories at <https://www.portaldoors.org>, <https://brainwatch.net>, and <https://telegenetics.net/>.

PDP-DREAM Ontology

To further aid in the creation of semantic markup that can facilitate the discovery of relevant prior work, BHA has developed several formal ontologies related to domains including nuclear medicine (C. Taswell et al. 2006), clinical telegaming (C. Taswell 2010b), and progressive neurodegenerative diseases (Skarzynski et al. 2015b). Additionally, to allow the NPDS cyberinfrastructure to better serve its role as a bridge between the semantic and lexical webs, BHA has introduced a NPDS ontology to provide a clear path for translation of lexical metadata

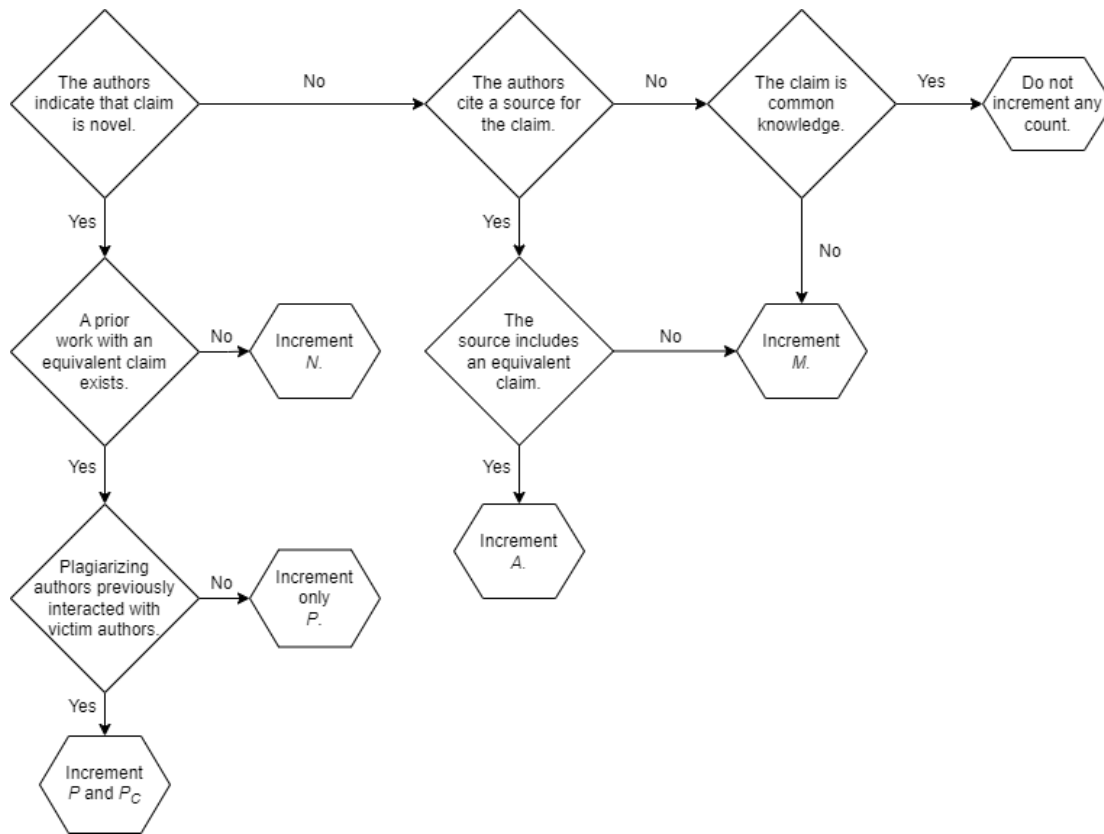


Figure 2: Decision tree for classification of claims for calculation of FAIR Metrics extended to include a 'plagiarism of known colleagues' count.

201 into semantic descriptions (Craig, S.-H. Bae, et al. 2017). The most
 202 comprehensive formal ontology that BHA has developed is the PDP-
 203 DREAM Ontology, which codifies the guiding design principles from the
 204 PORTAL-DOORS Project, the Discoverable Data with Reproducible Re-
 205 sults for Equivalent Entities with Accessible Attributes and Manageable
 206 Metadata (DREAM), and serves as a foundational ontology for more
 207 specialized modules (Craig and C. Taswell 2021). For example, the PDP
 208 Contributor Roles module offers classes and properties for recording
 209 roles in a Contributor Role Taxonomy-compatible format (Craig and
 210 C. Taswell 2023). BHA makes these ontologies available through the
 211 above-mentioned GitHub repository.

212 Other ontologies prior to the PDP-DREAM Ontology have repre-
 213 sented design and engineering principles, including (Sim and Duffy
 214 2003) and (Storga et al. 2010). Additionally, a broad class of general-
 215 purpose foundational ontologies seek to formally express core con-
 216 cepts relevant to all or most problem domains, such as "time interval"
 217 or "physical object" (Borgo et al. 2022). The key distinction is that the
 218 PDP-DREAM Ontology focuses on concepts and design principles rele-
 219 vant to data and metadata management itself, making its scope more
 220 manageable than that of a universal foundational or design principle-
 221 oriented ontology (Craig and C. Taswell 2021). If a use-case requires
 222 more wide-ranging semantic reasoning or detailed markup describing
 223 resources relevant to a specific problem, users can still use NPDS soft-
 224 ware to manage semantic descriptions using any desired foundational
 225 or domain ontology (C. Taswell 2007).

FAIR Metrics

228 BHA has previously called for not only open peer review but repro-
 229 ducible peer review, an approach in which reviewers make clear the
 230 sources of the factual claims they are using to support their recommen-
 231 dations so that an independent reviewer can evaluate the sources and
 232 claims, follow the same line of reasoning, and arrive at the same conclu-
 233 sion (Craig, Lee, et al. 2022). BHA is working to put these principles into
 234 practice in its own Brain Imaging and Computer Science (BRAINIACS)
 235 open-access journal (<https://www.brainiacsjournal.org/>).
 236 Central to this effort is the need to quantify how accurately authors
 237 present novel claims as novel and attribute preexisting claims to their
 238 sources. While numerous tools for plagiarism detection exist, some of
 239 which may be able to detect idea plagiarism even when obfuscated with
 240 paraphrasing (Gipp, Meuschke, and Beel 2011; Naik et al. 2015; Foltýnek
 241 et al. 2019), the results of any single evaluation are less important than
 242 the clear presentation of the reasoning behind evaluations. To support
 243 a more quantitative, systematic approach to evaluation, BHA has de-
 244 veloped the Fair Attribution to Indexed Reports (FAIR) Metrics (Craig,
 245 Athreya, et al. 2023). Evaluating a work according to the first family of
 246 FAIR Metrics involves identifying its substantive claims and categorizing
 247 them as either correctly attributed to a prior work, misattributed, cor-
 248 rectly presented as novel, or presented as novel but plagiarized from
 249 prior work, counting the number in each category, and computing ratios
 250 derived from these counts (Craig, Athreya, et al. 2023). The second
 251 family of FAIR Metrics supports meta-reviews of peer reviews by calling
 252 for the classification of the factual claims the reviewer uses to support
 253 their recommendation based on whether they relate to the work under
 254 review, the venue of publication, or outside domain knowledge

and then according to whether or not the reviewer sites an appropriate source for the claim (Craig and C. Taswell 2024). BHA also provides PDP-DREAM Ontology modules for recording the evaluation process, including assertions of equivalence between claims in the work under review and prior works (Craig, Athreya, et al. 2023; Craig and C. Taswell 2024). See <https://npds.portalddoors.net/nexus/fidentinus/wilkinson2016fgpsdms> for an example of a Nexus record with a semantic description of a FAIR Metrics evaluation of an article and <https://npds.portalddoors.net/nexus/fidentinus/submission1review1> for an example FAIR Metrics evaluation of a peer review.

In (Craig and C. Taswell 2023), we compared the FAIR Metrics to other approaches to plagiarism detection. To summarize, the FAIR Metrics are distinctive in both their focus on equivalence of the ideas conveyed rather than lexical similarity and the semantic representation framework that allows scrutiny and improvement of the analysis. Two of the leading lexical-similarity-based plagiarism detection software tools, iThenticate for scholarly publications and Turnitin (Young 2023) for student assignments, were only partially successful at detecting plagiarizing papers generated with ChatGPT, giving similarity scores from 0% to 68% (Khalil and Er 2023). This demonstrates the need for new approaches. Support vector machines and deep learning classifiers can detect plagiarism obfuscated through paraphrasing more effectively than do simple lexical similarity measures (Altheneyan and Menai 2020), but these approaches lack interpretability. However, new machine-learning based tools intended to distinguish human writing from AI-enabled plagiarism, such as the OpenAI text classifier (Kirchner et al. 2023), Copyleaks (Copyleaks 2023), and GPTZero (GPTZero 2023), have even less transparency, rely on costly large language model technology, and do not address human-written plagiarism.

More broadly, one can classify plagiarism detection methods as lexical, structural, semantic, stylometric, syntactic, citation, or cross-language-focused, each of which has distinct strengths and weaknesses (Jiffriya et al. 2021). While our work on the FAIR Metrics so far has relied on a human reviewer to identify claims with equivalent meaning (Craig, Athreya, et al. 2023; Craig and C. Taswell 2024), the FAIR Metrics analysis framework also allows for use of automated agents to search the literature for prior work from which a work under review may have plagiarized. Semantic similarity detection methods, such as those from (Javadi-Moghaddam et al. 2022), (Eisa et al. 2020), and (Javadi-Moghaddam et al. 2022), may be especially valuable for their ability to identify specific pairs of passages in the new and prior work that have similar meaning. Ideally, publishers would apply automated agents to detect potentially equivalent claims from a larger pool of prior literature and then recruit human reviewers to judge the accuracy of the matches and recommend other matches based on their own knowledge.

Socially aware knowledge engineering

Social influence and ethical behavior

The standards to which we hold ourselves reflect not only intrinsic motivations but also our interactions with others. A recent comprehensive meta-analysis found that, while interventions using social comparison to assist people with behavioral changes, such as reducing alcohol consumption or adopting more environmentally sustainable practices, had small effect sizes, the effects were frequently significant, low-cost, and readily scalable (Hoppen et al. 2025). A recent study used a variant

of the marshmallow test to illustrate another way social interaction can support self-regulation: Children completed the challenge successfully more often when they had promised a peer that they would wait for the second marshmallow (Koomen et al. 2025).

At the same time, social pressure can also induce or reinforce behaviors that harm oneself or others. For example, insular online communities can discourage members from seeking outside connections or life goals (Beckett-Herbert and Shor 2025). Even a single persuasive authority figure can sway people to act in ways they would normally find inappropriate, as illustrated in the Milgram experiments (McLeod 2017).

In the modern age, social media can amplify the reach of calls to action, but the nature of the appeal impacts the result in complex ways. A recent study found that online petitions that invoked moral outrage boosted their virality but not the number of signatures when compared to petitions with similar levels of virality, while appeals to agency, group identity, and prosociality boosted the number of signatures but not the virality of the petitions (Leach et al. 2025). At the same time, large language models have shown the potential to produce arguments that sway human opinion, especially when equipped with information about the target human (Salvi et al. 2025). Taken together, these developments suggest that a growing flood of machine-generated propaganda optimized to elicit strong emotions for the sake of virality could eventually replace more productive community-building interactions between humans. As a counterbalance to the often opaque workings of both algorithmic signal-boosting in social media and data-driven content generation by machine learning models, we propose the building of decentralized online communities in which members maintain and share their own lexical and semantic metadata records suitable for both human readers and explainable automated inference engines (Athreya, Craig, et al. 2023).

The need for metatextual context in metadata

Due to the original emphasis of the PORTAL-DOORS Project on supporting meta-analyses and other analyses of the factual claims in scholarly literature, the BHA-developed ontologies and the FAIR Metrics analysis workflows have focused on the text of scholarly works themselves rather than on the social context surrounding them (Craig, Athreya, et al. 2023; Craig and C. Taswell 2024; Craig, Ambati, et al. 2019b). However, distinguishing among misinformation and disinformation hinges on being able to infer whether the propagators of the incorrect information knew that it was incorrect at the time of writing, and distinguishing either of these from anti-information or caco-information requires information about how the propagators responded to attempts to provide correct information (S. K. Taswell, Athreya, et al. 2021). This also applies to the specific case of distinguishing between dismissive and ghosting literature reviews and distinguishing either from anti-reviews or caco-reviews, as defined above. In the context of FAIR Metrics analysis, while a high proportion of apparently plagiarized claims suggests the presence of plagiarism, the authors still have plausible deniability in the absence of clear evidence that they were aware of the existence of the work from which they plagiarized. Identifying of idea-laundering plagiarism, a pattern of behavior defined in (S. K. Taswell, Triggles, et al. 2020) in which authors obfuscate plagiarism and then not only deny having plagiarized but refuse to cite the original work, requires a record of the history of interactions among authors of original and plagiarizing works, editors, institutional ethics boards, and other stakeholders. For example, while a FAIR Metrics analysis found

that all of the Findable, Accessible, Interoperable, and Reusable data stewardship principles had appeared previously in the 2007 introductory PORTAL-DOORS schema paper (Craig, Athreya, et al. 2023), only a more detailed description of the past occasions on which the authors had attended the same conferences and Taswell's attempts to convince Wilkinson *et al.* co-authors to acknowledge the existence of this similar prior work allows characterization of the Wilkinson *et al.* FAIR-branded principles published 2016 in *Nature Scientific Data* as idea-laundering plagiarism (C. Taswell 2024).

Incorporating social context into NPDS records

Several ontology engineering efforts have incorporated potentially useful social information into semantic knowledge graphs, some specifically for the purpose of providing social context to scholarly outputs. One of the most widely used formal ontologies is the Friend-of-a-Friend (FOAF) Ontology, which several social media platforms use to manage knowledge graphs incorporating a wide variety of social interaction-relevant information about their users (Shanker 2018). A derived version called FOAF-Academic offers specialized features suitable for tracking collaborations in academia (Kalemi and Martiri 2011). The AcademiS ontology is a purpose-built ontology for tracking collaborations among researchers as an aid to assessing the performance and impact of researchers (Triperina et al. 2013). Additionally, publishers often use the Dublin Core controlled vocabulary to publish bibliographic metadata about works in a machine-readable format (Arakaki et al. 2018), which can help identify when authors have published in the same journal or conference proceedings.

While the NPDS cyberinfrastructure supports use of any desired ontology in semantic descriptions, a key ongoing effort for BHA will be incorporation of social information into FAIR Metrics analyses. A first step will be creation and testing of a new family of FAIR Metrics that takes into account the presence of prior social connections between authors. For example, we can supplement the existing P count of apparently plagiarized claims (Craig, Athreya, et al. 2023) with an additional count of claims plagiarized from works presented at conferences the authors of the evaluated work attended or from works by past collaborators, P_C , where the C stands for "plagiarism of known colleagues" (See Figure 2). We can then supplement the plagiarism-focused FAIR Metric, $F_P = (A - P)/(A + M + P)$ where A is the count of correctly attributed claims and M the count of misattributed claims, with a social context-augmented plagiarism-focused metric: $F_C = (A - P - P_C)/(A + M + P)$. However, much work remains in order to gather adequate social network information for test cases, render it in semantic markup, and evaluate the effectiveness of such social context-augmented metrics.

Another area where social context may prove valuable is development of metrics of secondary source plagiarism. Several authors, including (Abbamonte 2024), (Joy et al. 2009), and (Maxel 2013), have defined secondary source plagiarism as use of information from a literature review, meta-analysis, textbook, or other secondary source accompanied only by citations of the primary sources that it uses, not the secondary source itself. Another work, (Taylor 2024), refers to this practice as "bypass plagiarism", because the plagiarist bypasses citing the secondary source by directly citing the primary sources. The existing FAIR Metrics do not include any measure of secondary plagiarism, and incorporating one into the existing workflow may be challenging due to its emphasis on comparison of individual claims. One potentially useful approach is flagging of potential plagiarism through detection of

similar sequences of citations in the target and comparison texts (Gipp, Meuschke, and Breiting 2014), but knowing that the author of the apparently plagiarizing work was aware of the prior work and its author would strengthen the case.

A related open question is how prevalent ghosting and dismissive literature reviews are. While (Phelps 2012) discusses individual examples of dismissive reviews, it does not provide a systematic study of its prevalence. A study answering this question would face similar challenges to those seeking to assess the prevalence of plagiarism. Studies such as those included in the meta-analysis in (Pupovac 2021) analyze large bodies of scientific publications for plagiarism using automated lexical plagiarism detection tools followed by human checking of the detected matches. While independently testing articles is preferable to relying on official notices of retraction, since it provides a consistent and known methodology instead of relying on the varied approaches of the publishers, lexical plagiarism detection tools may still fail to detect paraphrased ideas or claims. Human reviewers can only remedy this if they add missed matches in addition to removing false positives. Here too, the FAIR Metrics provide a framework for a transparent recording of analysis. To detect an instance of a dismissive literature review, we must identify any firstness claim in a work and then find a matching firstness claim in a prior works. Analyzing a representative sample of the scientific literature in this way will require a new FAIR Metrics analysis workflow that incorporates automated tools for detecting potentially equivalent claims. Furthermore, to distinguish dismissive literature reviews from ghosting literature reviews, we will need to define a test of whether the authors of the work under review knew of the prior work. Because scientists can learn of each other's work through multiple channels, a possible solution would be to search for linkages in a multi-level network incorporating collaboration, institutional affiliation, and conference attendance, such as that used for recommending future collaborators in (Chen et al. 2025). We hope to address this task in future work.

Conclusion

Ghosting literature reviews represent a violation of the traditional standard of *standing on the shoulders of giants* required for citing and discussing previously published work. Furthermore, they represent a threat to the scientific literacy of readers by discouraging them from searching for potentially valuable information that the plagiarizing authors know exists. The NPDS cyberinfrastructure can help individuals and small organizations to host their own searchable repositories and share records through larger collaborative networks, providing alternate pathways by which readers can find works obfuscated by ghosting literature reviews. In particular, the FAIR Metrics module of the PDP-DREAM Ontology provides classes and properties useful for representing the key claims of scholarly publications and the equivalence relations between them. However, much work remains to build the large collections of such semantic descriptions needed to address the problem of plagiarism on a larger scale, and such efforts will require input from a wide variety of stakeholders from many disciplines and support, or at least uptake of the outputs, on the part of the institutions that employ researchers and the organizations that fund research.

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