AI Disclosure Without Protection: A Governance Gap in Scholarly Peer Review

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comment

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Abstract

Background: Major scholarly publishers and AI conference venues now require authors to disclose AI use in manuscript preparation. These policies rarely tell reviewers how to interpret that disclosure. The result is an asymmetric system: authors are placed under detailed disclosure obligations, while reviewers exercise their own judgement, often without procedural protections for the disclosing author.

Main text: We examine this asymmetry through a bounded corpus of 15 official policy documents from 10 major publishers and AI conference venues. Author-side obligations are specified in detail across all organizations, including what to disclose, where to disclose it, and at what threshold. Reviewer-side safeguards for handling that disclosure are almost entirely absent. Only one organization (Wiley) explicitly states that disclosed AI use is not grounds for rejection, and no organization provides an AI-specific appeal channel. We call this the *interpretive safeguard gap*. The gap has predictable consequences: when honest disclosure carries evaluative risk and non-disclosure does not, rational authors learn to under-report. This *transparency paradox* cannot be resolved by author-side reform alone. We propose four minimum conditions for the missing reviewer-side half: explicit penalty protection, positive interpretive guidance, differentiation by use type, and an AI-specific complaint channel.

Conclusions: Disclosure architecture and reviewer interpretation are two halves of one governance problem. AI policy in scholarly publishing must address both, or honest disclosure will be punished by the very system that requires it.

Keywords: AI disclosure; generative AI; peer review; research integrity; procedural fairness; publication ethics; scholarly publishing policy

1 Background

Generative AI tools spread quickly through academic writing [1], and major publishers and conference venues responded with formal policies [2]. These policies share a common orientation: they regulate what authors must do. Authors must disclose AI use; AI tools cannot be listed as authors; human authors retain full responsibility for all content, including any portions written with AI. This convergence represents real progress, establishing a baseline of transparency and assigning clear responsibility within the scholarly record. Several recent reviews have begun to map this policy landscape [3, 2, 4]. Yet this progress is partial. Existing policies focus on what authors must disclose. They remain largely silent on what happens after disclosure enters the review process [4].

Disclosure itself is not new in scholarly publishing. Authors declare competing interests so reviewers can weigh potential conflicts, and they describe methods so readers can assess validity. Each category carries its own interpretive norms [5]. However, AI disclosure is the newest addition to this catalogue, and it has not yet acquired such norms.

It is risky for authors to disclose AI usage without an interpretive norm. This is because, from some perspectives, AI disclosure is not neutral metadata. Once a disclosure statement appears in a manuscript, the reviewer's choice is consequential. Specifically, reviewers may interpret AI use as a sign of less effort, weaker scholarly independence, or less original work. They may object on principle. Or they may simply apply inconsistent standards. In a controlled experiment, Li et al. [6] found that disclosing AI assistance lowered average manuscript quality ratings and widened rating variance across evaluators. Both effects were strongest when AI was used for content generation rather than for minor editing.

This paper argues that current policy design is *asymmetric*. It tells authors to be transparent. It rarely tells reviewers or editors how to fairly interpret that transparency. We term this the *interpretive safeguard gap*. To examine it, we analyze a bounded corpus of 15 official policy documents from 10 major scholarly publishing organizations and conference venues. The corpus includes ACM, Elsevier, Springer Nature, Wiley, Taylor & Francis, COPE, ICLR 2026, NeurIPS, FAccT, and AIES 2025. The corpus reveals a consistent pattern. Author-side disclosure obligations are well specified across all organizations. Reviewer-side interpretive guidance is almost entirely absent. Only one organization, Wiley, directly states that disclosed AI use in manuscript development is not grounds for rejection. No organization provides an AI-specific appeal or complaint mechanism. Peer review has long built structural responses to other bias risks: double-blind review and conflict-of-interest declarations. Empirical work has documented their limits and their successes [7, 8]. No comparable structure yet exists for AI disclosure.

The effect of this asymmetry on authors has begun to attract attention. BaHammam [9] documents a "transparency paradox": honest disclosers carry evaluative risk that non-disclosers do not, and rational authors learn to under-report. Survey data points in the same direction. A 2023 Nature poll of 1,600 researchers found sharply divided attitudes toward AI in scholarship [1]. Some welcomed productivity gains. Others raised concerns about integrity, scholarly labor, or authentic voice. A 2025 follow-up of 5,000 researchers found that 17% of mid-career respondents had used AI to write a section of a paper without disclosing it, and 47% said they would be willing to [10]. These numbers show authors already adjusting to the risks of disclosure. BaHammam proposes a tiered author-side disclosure framework as a remedy [9]. We adopt this diagnosis but argue that author-side reform is not enough on its own. Reviewers still receive no guidance on interpreting disclosures. Even a well-designed tiered framework would re-enter an evaluative process that continues to penalize transparent authors. The reviewer-side is the missing piece.

To date, reviewer-facing AI guidance has covered only reviewers' own AI use. Recent guidance addresses confidentiality, accountability for review content, and transparency about AI assistance to editors [11]. The narrower question of how a reviewer should weigh, score, or interpret a manuscript that contains an author AI disclosure does not appear to be addressed. This Comment makes that question its focus. We map current AI disclosure policies, name the reviewer-side governance gap, and propose minimum conditions for fair interpretation of AI disclosure in peer review. We treat the gap as a procedural fairness issue rather than as individual reviewer bias. The remainder of this Comment describes the corpus and analytic approach, presents the policy analysis, and proposes minimum interpretive safeguards.

2 Main text

2.1 Corpus and analytic approach

We assembled a bounded corpus of 15 official policy documents from 10 scholarly publishing organizations and conference venues: ACM, Elsevier, Springer Nature, Wiley, Taylor & Francis, COPE, NeurIPS, ICLR 2026, FAccT, and AIES 2025. The selection covers the major organizations with direct influence in the field: large commercial publishers, a key governance body, and prominent AI and computer science venues. The corpus is restricted to public-facing, organization-level documents (formal policy pages, author guidelines, reviewer guides, and calls for papers). Journal-level instructions and informal editorial communications were excluded. The selection is not exhaustive. Its purpose is to examine policy design across the most influential and publicly accountable organizations.

Each document was coded along four dimensions. *Document metadata* captured the organization, document type, and source authority (formal policy page vs. conference call for papers). *Author-side governance* recorded whether AI disclosure was required, the disclosure threshold (blanket requirement vs. conditional on significance), the specified disclosure location, whether grammar and spellcheck tools were explicitly exempted, and whether an AI authorship prohibition was stated. *Reviewer-side governance* captured whether reviewer AI use was permitted, conditionally permitted, or prohibited, and whether reviewer self-disclosure was required. *Safeguard variables* recorded three reviewer-side protections: explicit penalty protection tied to author AI disclosure (language stating that disclosed AI use is not grounds for rejection or score reduction), reviewer interpretive guidance (instruction on how disclosure should be weighed during evaluation, including whether any general anti-bias or fair-evaluation language extended to AI), and the existence of an AI-specific appeal or complaint mechanism.

We checked coding reliability through a two-stage verification process. In the first stage, all documents were retrieved and independently re-verified against live official sources in April 2026. In the second stage, four high-stakes cases were manually spot-checked against source documents: Wiley, AIES 2025, FAccT, and ICLR 2026. These cases were chosen because they matter most for the paper's central claim about safeguard presence or absence. The full coded corpus, including direct quotes and verification notes, is provided as Additional file 1.

The corpus captures what these organizations have publicly committed to in their governance documents; it does not capture internal reviewer training materials, editorial communications, or informal practice. Umbrella policies (notably Springer Nature, which covers BMC, Palgrave, and Springer imprints) may not reflect variation across individual brands or titles. Throughout the analysis, we use language that reflects these limits: findings describe what the reviewed public documents specify, not what is privately practiced.

2.2 Findings

2.2.1 Convergence on author accountability

Three norms appear without exception across all 10 organizations in the corpus. First, no organization permits an AI tool to be listed as an author. Authorship is reserved for human contributors who are accountable for the work. Second, human authors retain full responsibility for all content in a submission, including any portions produced with AI assistance. Third, some form of governance over AI-assisted writing is present in every case: nine organizations establish disclosure requirements, and one (AIES 2025) prohibits LLM-generated text outright. The convergence on these three norms suggests an emerging cross-organization agreement on the basic structure of AI governance in scholarly publishing. Transparency and human accountability are treated as non-negotiable, even though the specific rules differ.

Several partial agreements also appear. Elsevier, Springer Nature, Wiley, Taylor & Francis, NeurIPS, and FAccT prohibit uploading unpublished manuscript content to third-party AI services during peer review. ACM, Elsevier, Springer Nature, and NeurIPS exempt grammar and spellcheck tools from disclosure requirements. These norms are firm but not fully spelt out in scope.

2.2.2 Divergence in author-side policy design

Below this surface convergence, the corpus shows meaningful variation across three dimensions of author-side policy design (Table 1).

Table 1: Author-side policy design across the 10 organizations in the corpus. AIES 2025 shows "—" for threshold and disclosure location because it prohibits rather than regulate AI use.

Organization	Policy	Threshold	Disclosure location
ACM	Disclosure	Blanket	Public
Elsevier	Disclosure	Blanket	Public
Springer Nature	Disclosure	Blanket	Public
Wiley	Disclosure	Blanket	Cover letter
Taylor & Francis	Disclosure	Blanket	Public
COPE	Disclosure	Blanket	Public
NeurIPS	Disclosure	Conditional	Public
ICLR 2026	Disclosure	Conditional	Public
FAccT	Disclosure	Blanket	Public
AIES 2025	**Prohibition**	—	—

The clearest divergence is between organizations that allow AI use with disclosure and the one that forbids it. AIES 2025 is the only organization in the corpus that treats LLM-generated text as outright forbidden, with the narrow exception of text submitted as experimental data. This differs from all other organizations, which treat AI-assisted writing as a practice that requires transparency rather than one to be avoided. The distinction matters. Disclosure assumes that AI-assisted writing is legitimate if declared. Prohibition rejects that assumption. The two approaches are not just different procedures. They reflect different judgments about whether AI use in scholarly writing is acceptable in the first place.

Within the disclosure organizations, the threshold introduces a second source of variation. NeurIPS requires disclosure when an LLM "played a role in the development of this work that is important to that methodology," and ICLR 2026 similarly restricts mandatory disclosure to cases involving a "significant role." These threshold-based phrasings open the door to subjectivity. What counts as significant or important is left to author judgment, creating room for inconsistent application and uneven compliance. By contrast, the remaining seven disclosure venues in the corpus apply blanket requirements, removing this ambiguity by requiring disclosure regardless of how much AI was used.

A third dimension is disclosure location. Eight of the nine disclosure venues require AI disclosure to appear in the public manuscript, where it is visible to readers as well as reviewers. Wiley handles things differently: disclosures go in the cover letter, ensuring they remain private and visible only to the editors. This format limits transparency to editors rather than the entire scholarly community. It reduces the oversight provided by these disclosures, even though the requirement to provide them remains in effect.

2.2.3 Variation in reviewer AI policy

Reviewer AI policy shows a separate form of variation, less often examined in prior work. Elsevier, Taylor & Francis, and FAccT explicitly prohibit reviewer AI use in reviewing work. In contrast, COPE and AIES 2025 arrive at the same restriction indirectly: COPE through its reviewer confidentiality requirements, and AIES 2025 through its broader prohibition on LLM-generated text. ICLR 2026 takes the opposite position, permitting reviewer AI use while requiring self-disclosure in the review form. ACM, Springer Nature, Wiley, and NeurIPS allow some forms of AI assistance while discouraging its use for deep analysis. Organizations have not converged on how to govern reviewers' *own* AI use, but each does specify a position. This indicates that reviewer-side conduct is something organizations are willing and able to govern.

2.2.4 The interpretive safeguard gap

The most striking finding in the corpus is not variation in policy design but a systematic absence: across all 15 documents and 10 organizations, reviewer-side safeguards for author AI disclosure are almost entirely missing. Author obligations are specified in detail: what to disclose, where to disclose it, and at what threshold. But the institutional response to that disclosure is left almost entirely unspecified. Only one organization in the corpus, Wiley, provides any explicit AI-specific reviewer-side safeguard. Table 2 summarizes the presence of three reviewer-side safeguard types across the corpus.

Table 2: Reviewer-side safeguard types across all 10 organizations. A cell marked "None" indicates the absence of the corresponding AI-specific safeguard in the organization's public-facing policy documents.

Organization	**Penalty protection**	**Interpretive guidance**	**Appeal mechanism**
ACM	None	None	None
Elsevier	None	None	None
Springer Nature	None	None	None
Wiley	**Explicit, direct**	None	None
Taylor & Francis	None	None	None
COPE	None	None	None
NeurIPS	None	None	None
ICLR 2026	None	None	None
FAccT	None	None	None
AIES 2025	None	None	None

Reading the table column by column, each safeguard type shows a distinct gap. *Penalty protection* appears in a single document. The Wiley AI guidelines state that "AI use in manuscript development is not grounds for rejection" and that editorial evaluation "should focus on the quality, integrity, disclosure, and clarity of communication in the research, regardless of the technologies used." This is the only explicit statement in the corpus stating that AI disclosure should not lead to automatic rejection. However, since this language is located in the author guidelines, it serves as a reassurance to writers rather than a strict rule that editors or reviewers must follow. No equivalent language appears in Wiley's reviewer-facing documentation. No other organization provides a comparable statement.

Interpretive guidance on how reviewers should weigh or read an AI disclosure statement is absent from every document in the corpus. Two organizations, ACM and ICLR 2026, maintain general fair-review or bias-free review language in their reviewer materials, but neither extends this language to AI disclosure specifically. The ICLR 2026 Reviewer Guide also instructs reviewers to notify their Area Chair if they suspect an author has hidden their use of AI. This procedure is designed to catch rule-breaking, but it doesn't explain how a reviewer should evaluate a paper when an author actually discloses AI use. No document in the corpus addresses the latter.

Appeal mechanisms specific to AI disclosure are absent across all 10 organizations. Several maintain general editorial appeals or complaints procedures, but none has extended these channels to cover evaluation disputes in which an author believes disclosed AI use affected the outcome. The gap is not a lack of dispute-resolution infrastructure. What is missing is its extension to AI-disclosure disputes.

This systematic absence defines the interpretive safeguard gap. Organizations have invested heavily in specifying what author-side transparency requires, while leaving the institutional response to that transparency almost entirely unspecified. As we argue in the following subsection, this asymmetry is not merely an oversight: it is a structural condition with predictable consequences for author incentives and evaluation fairness.

2.3 Discussion and recommendations

2.3.1 Mechanisms of interpretive risk

The findings point to a problem that runs deeper than mere policy incompletion. AI disclosure is not neutral metadata. In peer review, a disclosure statement can function as an evaluative and moral signal. Unlike a declaration of funding source or statistical software, a statement of AI involvement may activate judgments about the author's effort, competence, originality, or scholarly independence. None of these judgments is governed by any current policy.

Two distinct mechanisms drive this risk, each rooted in the contested status of AI described in Section 1. The first is *stigma-based*: disclosed AI use can invite judgment of the author as a practitioner. The author may be seen as lazy, less capable, or lacking in scholarly independence and originality. A tool choice is then treated as evidence about the person rather than the work. The second is *ideological*: a reviewer who objects to AI on principle, because it threatens human creativity, academic labor, education, or scholarly culture, may evaluate a disclosing paper not as a research contribution but as evidence of taking part in a contested moral practice. Both mechanisms can operate independently or together, and neither is addressed by any policy in the corpus. What sets this risk apart from other peer-review bias types is its origin in policy design: the disclosure requirement, without interpretive guidance, creates the exposure it cannot then protect against.

2.3.2 The transparency paradox

If honest disclosure carries reputational and evaluative risk while non-disclosure is relatively safe, rational authors have reason to minimize, delay, or avoid disclosure. This is not just a theoretical concern. Experimental evidence shows that revealing AI assistance systematically lowers perceived manuscript quality. Readers rate AI-assisted writing lower than otherwise identical content presented without disclosure [6]. This pattern has recently been called a "transparency paradox" in scholarly publishing [9]. A system without interpretive safeguards may reward hiding more than honesty. What looks like opportunism is often a rational way to avoid an evaluative risk that policy does not guard against. This outcome directly undermines the goals that disclosure policies are designed to achieve.

2.3.3 Minimum interpretive safeguards

Closing the interpretive safeguard gap requires targeted additions to existing policy frameworks. The proposals below are the reviewer-side counterpart to recent author-side disclosure reforms [9]. The two address different halves of the same governance gap, and either alone is not enough. We propose four minimum conditions for fair interpretation of AI disclosure in peer review.

1. **Explicit penalty protection.** Every organization that requires AI disclosure should state, in its reviewer guidelines, that disclosed AI use in manuscript preparation is not itself grounds for rejection or score reduction. The Wiley wording works as a model: editorial evaluation should focus on "the quality, integrity, disclosure, and clarity of communication in the research, regardless of the technologies used." Critically, this language must appear in reviewer guidelines, not only in author-facing pages where it reads as reassurance rather than instruction.
2. **Positive interpretive guidance.** Beyond ruling out penalization, policies should give reviewers positive guidance on how to read a disclosure statement. The right response is to evaluate the work on its merits. Disclosure should be read as evidence of the author's transparency and integrity, not as a signal about research quality. Brief reviewer training materials or checklist items can put this into practice without adding significant burden.
3. **Differentiation by use type.** Current policies treat AI disclosure as a single category, but the interpretive meaning of writing assistance differs from that of AI used as a core methodological tool. BaHammam [9] proposes a four-level tiered disclosure framework that puts this difference into practice on the author side,

distinguishing basic technical assistance from substantive content generation. The matching reviewer-side step is to specify that interpretive guidance applies *at every tier*: no level of declared AI use, from minor editing assistance to substantive content generation, should trigger evaluative penalty without a specific, named concern about the quality or integrity of the work itself.

4. **An AI-specific complaint channel.** Organizations that already run general editorial appeals or complaints procedures should extend them explicitly to cover evaluation disputes in which an author has reason to believe that disclosed AI use influenced the outcome. Without any such mechanism across the entire corpus, authors currently have no institutional channel, even if they can show that a disclosure statement led to biased evaluation.

3 Conclusions

AI disclosure policies have spread quickly across scholarly publishing, but they ask almost everything of authors and very little of reviewers. Across 15 policy documents from 10 major publishing organizations and conference venues, author-side obligations are well specified while reviewer-side interpretive safeguards are nearly absent: only one organization makes any explicit commitment that disclosed AI use is not grounds for rejection, and none provides an AI-specific appeal mechanism. This asymmetry is consequential. Without interpretive guidance, honest disclosers carry evaluative risk that non-disclosers do not. Recent author-side reform [9] alone cannot resolve this transparency paradox. Disclosure architecture and reviewer interpretation are two halves of a single governance problem, and the field will need to build both. The central question is no longer only whether authors should disclose AI use, but how that disclosure is made legible within a fair evaluative process.

List of abbreviations

ACM	Association for Computing Machinery
AI	Artificial intelligence
AIES	AAAI/ACM Conference on AI, Ethics, and Society
COPE	Committee on Publication Ethics
FAccT	ACM Conference on Fairness, Accountability, and Transparency
ICLR	International Conference on Learning Representations
NeurIPS	Conference on Neural Information Processing Systems

Declarations

Ethics approval and consent to participate

Not applicable. This study did not involve human participants, human data, or human tissue.

Consent for publication

Not applicable. This manuscript does not contain data from any individual person.

Availability of data and materials

The full coded corpus of 15 policy documents from 10 publishing organisations and conference venues, including direct quotes, verification notes, and a codebook, is provided as Additional file 1. All policy documents analysed are publicly available online; the URLs and access dates are recorded in the corpus. No other datasets were generated or analysed during the current study.

Competing interests

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Authors' contributions

GXL conceived the study, assembled and coded the corpus, performed the analysis, and wrote the manuscript. The author read and approved the final manuscript.

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Use of large language models

This Comment was prepared with the assistance of large language models. The author used Manus AI for an initial pass of corpus document collection and policy coding; all retrievals and codes were then independently re-verified by the author against live official sources, as described in Section 2.1. The author additionally used Claude (Anthropic) and ChatGPT (OpenAI) for: (i) language refinement, including grammar and stylistic editing; (ii) structural editing, including suggestions for paragraph organisation and section ordering; and (iii) drafting of candidate phrasings that were subsequently reviewed, revised, and approved by the author. A separate AI-assisted pass was used to verify reference metadata; all cited sources were then checked by the author against the original publications. Corpus selection, coding decisions, the analytical argument, and the final wording of the manuscript are the author's own. LLMs are not listed as authors, consistent with current authorship norms. The author takes full responsibility for the content of the manuscript, including any portions developed with AI assistance.

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