

A Comparative Analysis of Plagiarism across Written and Technical Disciplines

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Abstract

Background: Plagiarism is usually discussed as one phenomenon with one definition and one remedy. Scholarly disciplines, however, differ in what they treat as an original contribution, how they attribute knowledge, and which artefacts they produce. Those artefacts range from argumentative prose to source code, numerical data, mathematical derivations and images. This study asks whether plagiarism means the same thing in written disciplines (humanities, social sciences, law and literary studies) as in technical disciplines (engineering, computer science, mathematics and the natural sciences).

Methods: A PRISMA-guided structured narrative synthesis was carried out, drawing on the PRISMA 2020 statement and its scoping-review extension. Eligible sources were peer-reviewed reviews, meta-analyses, empirical surveys, detection-technology evaluations, linguistic analyses and policy documents published before 2026. Findings were charted against seven analytical dimensions: definition, unit of borrowing, citation culture, detection feasibility, prevalence evidence, sanction and remediation, and susceptibility to generative artificial intelligence.

Results: Written disciplines concentrate risk in textual and ideational appropriation, including patchwriting, uncredited paraphrase and contract authorship. Technical disciplines distribute risk across code, data, figures, mathematical content and reused methods text. Text-matching software serves the first group reasonably well and the second group poorly. Prevalence estimates are not comparable across fields because the underlying instruments differ. Evaluations of AI-text detectors consistently show limited accuracy and demonstrable bias against non-native writers.

Conclusions: Plagiarism is best understood as a family of discipline-conditioned integrity breaches rather than a single offence. Policy, detection and pedagogy that ignore this conditioning will over-penalise some communities and under-detect misconduct in others. A discipline-sensitive, education-first integrity framework is proposed, together with eight citable propositions to guide later empirical work.

Keywords: plagiarism; academic integrity; disciplinary differences; source-code similarity; text recycling; contract cheating; artificial intelligence detection; PRISMA

1. Introduction

1.1 Background

Few concepts in scholarly life are invoked as often, and defined as loosely, as plagiarism. The word's Latin root is the kidnapping of a person, and its modern sense of appropriating another's words or ideas without acknowledgement has passed into every code of research conduct. Yet

the apparent clarity of the definition dissolves in practice. Weber-Wulff has argued that plagiarism cannot be captured by a simple textual test, because it depends on context, on the relationship between author and source, and on the expectations of the community that receives the work [1]. Fishman made the parallel point that institutions often rely on intuition ("we know it when we see it") rather than on an operational standard that separates theft, fraud and copyright infringement [2].

The stakes of this conceptual looseness are considerable. Survey evidence pooled by Pupovac and Fanelli suggests that only a small minority of scientists admit to plagiarising, while a far larger proportion report having observed it among colleagues [3]. The same pattern appears in meta-analytic work on fabrication and falsification [4]. In the published record, an analysis of retracted biomedical articles found that misconduct, not honest error, accounted for most retractions, with plagiarism and duplicate publication together forming a substantial share [5]. At the student level, a systematic review of commercial contract cheating documented a marked increase in reported prevalence in more recent studies [6].

Technology has complicated the picture. Text-matching software, once regarded as a decisive deterrent, is now understood as a screening aid whose output requires human interpretation [7]. More recently, generative language models have blurred the boundary between assistance and authorship, prompting fresh debate about the role of artificial intelligence in both committing and combating plagiarism [8]. Practitioner-oriented discussions have also stressed that "plagiarism-free" writing is achieved through deliberate practice, meaning sound note-taking, honest paraphrase and transparent attribution, rather than through software alone [9].

1.2 Rationale: why a disciplinary comparison?

Higher education scholarship has long held that disciplines are distinct cultures. Becher and Trowler described academic "tribes" whose epistemologies, publication habits and social norms differ markedly [10]. Biglan's classic classification distinguished disciplines along dimensions such as hard versus soft and pure versus applied, and showed that these dimensions correlate with differences in how knowledge is organised and communicated [11]. Hyland's corpus work demonstrated that the very act of citation, the visible trace of attribution, varies systematically across fields in density, form and rhetorical function [12].

If citation itself is disciplinary, it follows that the *violation* of citation norms is also disciplinary. A sentence lifted without quotation marks from a sociology monograph is a different act from a block of code copied without licence attribution, or from a microscopy image reused in a second paper without disclosure. Yet integrity policies, detection tools and student inductions are usually written as if these acts were interchangeable. General reviews of the integrity literature acknowledge the breadth of the field but rarely organise their synthesis around the written/technical divide [13]. This study fills that gap.

1.3 Objectives and research questions

The study has one overarching aim: to compare the nature, manifestations, detection and governance of plagiarism across written and technical disciplines. Five research questions guide it.

- **RQ1.** How is plagiarism conceptualised in the two disciplinary families, and where do the conceptualisations diverge?
- **RQ2.** What forms of misappropriation are characteristic of each family?
- **RQ3.** What does the available evidence say about relative prevalence, and how reliable are cross-disciplinary comparisons?
- **RQ4.** How well do current detection approaches, including AI-text detectors, serve each family?
- **RQ5.** What integrated framework of prevention and governance follows from the comparison?

1.4 Contribution

The paper makes three contributions. It consolidates review-level evidence from several literatures (research integrity, applied linguistics, computing education and information retrieval) that are rarely read together. It offers an analytical exposition of the differences between the two families along seven dimensions. And it formulates eight explicit propositions that can be tested, cited and refined by subsequent researchers.

2. Methods

2.1 Design and reporting framework

The study is a structured narrative synthesis reported in the spirit of the PRISMA 2020 statement [14] and its extension for scoping reviews (PRISMA-ScR) [15]. A scoping orientation was adopted because the question is broad, the evidence base is heterogeneous (surveys, technical benchmarks, linguistic case studies, policy analyses) and the aim is to map and compare rather than to estimate a single pooled effect. Methodological discussions of PRISMA-ScR emphasise that transparency of question, eligibility, sources and charting is what gives a scoping review its credibility, and that emerging researchers benefit from making each decision explicit [16,17]. The reporting below follows that principle.

2.2 Eligibility criteria

Sources were eligible if they met the following conditions:

- Published before 2026, in English.
- Addressed plagiarism, text or code reuse, contract authorship, image or data duplication, or the detection and governance of these, in at least one scholarly discipline or a comparison of disciplines.
- Took the form of a systematic or narrative review, meta-analysis, large-sample survey, empirical detection benchmark, linguistic or ethnographic study, or authoritative policy statement.

Sources were excluded if they were journalistic commentary without evidentiary basis, promotional material from software vendors, or documents lacking bibliographic traceability.

2.3 Information sources and search logic

The corpus was assembled purposively from research-integrity journals, applied linguistics and writing-studies journals, computing-education and software-engineering venues, information-retrieval outlets, and publication-ethics bodies. A supplied reference file of recent scholarly work on plagiarism detection, artificial intelligence in publishing, ethical issues in research and structured review methods was also consulted, and relevant items were integrated where they bore directly on the questions. The search logic combined concept blocks that can be reproduced in any bibliographic database:

- **Concept A:** plagiarism OR "text reuse" OR "text recycling" OR "source-code similarity" OR "contract cheating" OR "image duplication".
- **Concept B:** discipline OR field OR "engineering" OR "computer science" OR "humanities" OR "social science" OR "natural science".
- **Concept C:** detection OR prevalence OR attitudes OR policy OR review.

2.4 Selection and data charting

Sources were screened first on title and abstract and then on full text against the eligibility criteria. A charting form recorded, for each source, the disciplinary scope, the type of artefact studied, the design, the principal findings and the stated limitations. Findings were then coded against seven analytical dimensions: (i) definition and norms, (ii) unit of borrowing, (iii) citation culture, (iv) detection feasibility, (v) prevalence evidence, (vi) sanction and remediation, and (vii) exposure to generative AI. Conflicting findings were retained and discussed rather than averaged away.

2.5 Appraisal and synthesis

Consistent with scoping conventions, no formal risk-of-bias scoring was applied. Instead, each source was appraised qualitatively for sampling adequacy, instrument validity and transparency of reporting, and these judgements shaped the weight given to its conclusions in the synthesis. Evidence is presented narratively and organised by analytical dimension. No numerical pooling was attempted, because the underlying measures (self-report scales, similarity percentages, retraction categories, detector accuracy) are not commensurable.

3. Conceptual Foundations

3.1 What counts as plagiarism?

The most widely shared definition treats plagiarism as the use of another's words, ideas, data or creative product without appropriate acknowledgement, in a context where the audience expects original contribution. This definition hides at least four axes of variation. The first is the *object* appropriated: language, ideas, structure, data, code or images. The second is *intent*: deliberate deception versus incompetent source use. The third is *degree*: verbatim copying, near-verbatim copying, paraphrase that preserves structure, and the appropriation of an idea with no textual overlap. The fourth is the *relationship to the source*, whether the source is another person, a commercial ghostwriter, a machine, or the author's own earlier work.

Howard's analysis remains the most influential critique of the single-axis view. She argued that punitive framings conflate deceptive theft with the developmental practice of "patchwriting," in which novice writers stitch together fragments of source language while learning the discourse of a field [18,19]. Pecorari's linguistic investigation of postgraduate writing reached a complementary conclusion: much textual borrowing that would be flagged by a similarity tool reflects incomplete acquisition of academic conventions rather than a plan to deceive [20]. Bouville sharpened the distinction between plagiarism of words and plagiarism of ideas, noting that the latter is both more serious in scholarly terms and much harder to identify [21].

3.2 Self-plagiarism and text recycling

Reuse of one's own prior text presents a special case. Bird argued that the label "self-plagiarism" is problematic, since an author cannot steal from herself, and that the real harms lie in redundant publication and misleading the literature about how much independent evidence exists [23]. Roig's guidance on ethical writing recognised gradations, treating verbatim reuse of a methods description as a different matter from republishing findings under a new title [22]. Moskowitz's extended analysis of text recycling in scientific writing concluded that the issue cannot be resolved by a blanket prohibition, because some reuse (particularly of standardised methods language) is functionally benign, while other reuse (results, discussion, conclusions) undermines the integrity of the record [24]. As shown later, this nuance falls much more heavily on technical than on written disciplines.

3.3 Ethics in research writing

Plagiarism sits within a wider ethical field that includes informed consent, honest reporting and respect for participants. Discussions of ethical issues in social science research place attribution alongside these obligations, treating fair acknowledgement of prior work as a component of scholarly honesty rather than a free-standing rule [25]. Park's review of student plagiarism reached a similar integrative conclusion, arguing that institutions must address the causes of plagiarism (workload, unclear rules, inadequate skills, commercial temptation) as well as its detection [26].

4. Related Research Reviews and Their Results

This section synthesises the principal review-level and large-sample studies that inform the comparison. For each, the design, the main result and its relevance to the written/technical question are summarised.

4.1 Reviews of research-misconduct prevalence

Fanelli's meta-analysis of survey data on fabrication and falsification is the anchor study for questions of scale. It found that a small percentage of scientists admitted to serious misconduct, while a much larger percentage admitted to a wider range of questionable research practices, and that reported rates rose sharply when respondents were asked about colleagues' behaviour rather than their own [4]. Pupovac and Fanelli applied the same logic specifically to plagiarism. Their pooled estimates showed self-admitted plagiarism at under two percent, and witnessed plagiarism at nearly a third of respondents [3]. The gap is instructive. It suggests that self-report seriously under-estimates behaviour, and that comparisons of self-reported prevalence between

fields may reflect differences in candour or in definitional boundaries rather than differences in conduct.

Fang, Steen and Casadevall examined retraction notices for biomedical and life-science articles. Their reclassification showed that misconduct accounted for roughly two-thirds of retractions, with fraud the largest single category, followed by duplicate publication and then plagiarism [5]. A companion analysis asked why retractions had risen and concluded that increased detection and reporting, rather than a simple rise in misconduct, was a major driver [30]. The relevance to the present question is twofold. The retraction record is heavily weighted toward the life sciences, so it cannot represent the written disciplines. And within that record, plagiarism is a minority category, which underlines that in technical fields fabrication and duplication are competing integrity threats.

4.2 Reviews of text-reuse and detection technology

Foltýnek, Meuschke and Gipp's systematic review of academic plagiarism detection is the most comprehensive technical survey. It concluded that detection methods have progressed from character and word matching, through fingerprinting and stylometry, to semantic, cross-language and citation-based approaches, but that performance falls sharply as the disguise of the borrowing increases [27]. Earlier work by Meuschke and Gipp had already pointed out that idea plagiarism, which changes wording but retains structure or argument, remained the hardest category to detect [28]. Gipp's citation-pattern approach and its extension to mathematical content are discussed below in relation to technical documents [59].

Foltýnek and colleagues subsequently tested a wide set of commercial and open tools. They reported considerable variance in coverage and usability, weak performance on paraphrased and translated text, and no tool that could be treated as a definitive arbiter [39]. Weber-Wulff, writing in a widely read commentary, went further and characterised detectors as a "crutch" that can encourage administrators to substitute a percentage for judgement [40]. Youmans's quasi-experimental study of software adoption found no clear evidence that introducing text-matching reduced plagiarism in the sampled courses, which suggests that technology alone is not a deterrent [38]. A practitioner-oriented review of detection techniques and tools adds that similarity reports are only as useful as the interpretive competence of those reading them [7].

4.3 Reviews of source-code similarity

For computing, the equivalent review is Novak, Joy and Kermek's systematic study of source-code similarity detection in academia. They found that widely used tools rely mainly on token, tree and fingerprint techniques, that they are robust against superficial edits such as renamed variables and altered whitespace, but that they can be defeated by deeper structural transformation, and that adoption practices vary greatly between institutions [29]. Earlier system-level contributions, notably JPlag's token-based comparison and the winnowing algorithm for document fingerprinting that underlies MOSS, established the technical basis of the field [60,61]. Roy and Cordy's survey of clone detection showed that the industrial problem of finding duplicated code shares its algorithmic core with academic code-plagiarism detection, though the ethical framing differs [62].

4.4 Reviews of contract cheating

Newton's systematic review of 65,000 respondents across many studies reported that self-reported commercial contract cheating was low before 2014 and substantially higher in studies published after that date, with an overall average in the mid-teens percent range, although he cautioned that sampling and question wording strongly influence estimates [6]. Curtis and Clare's Australian study found that a small but non-trivial minority had used such services and that repeat use was common [32]. Bretag and colleagues' national survey of over 14,000 students found that a minority reported at least one contract-cheating behaviour, with dissatisfaction with teaching and perceived opportunities to cheat among the correlates [33]. Lancaster and Clarke's chapter traced the commercial ecosystem and argued that outsourcing is a market phenomenon that will not be removed by detection alone [34].

4.5 Reviews of student attitudes and behaviour

McCabe, Treviño and Butterfield's decade of research established that institutional honour codes and peer norms predict cheating more strongly than most individual traits [35]. Whitley's review of correlates of cheating catalogued the influence of age, achievement orientation, attitudes and situational factors, and noted mixed evidence for differences by major [36]. Scanlon and Neumann's early survey of internet plagiarism found that roughly a quarter of respondents admitted some form of online copying, and that students often defined the boundaries of acceptable use differently from staff [37]. Macfarlane, Zhang and Pun's review of the wider integrity literature concluded that inquiry had moved from a narrow focus on student cheating toward a broader concern with the conduct of academics and institutions [13].

4.6 Reviews of language and plagiarism

The applied-linguistics literature offers a different kind of review evidence. Flowerdew and Li's survey of plagiarism and second-language writing argued that cultural conceptions of authorship, developmental stage in language acquisition and the ready availability of electronic text all contribute to problematic source use [45]. Pecorari and Petrić's later review reinforced the point that intentional and unintentional forms must be separated, and that the pedagogic response to the latter is instruction rather than sanction [46]. Hyland's studies of citation practice showed that the density and rhetorical form of attribution differs across fields, which means that novices entering different disciplines must learn different attribution conventions [12,41].

4.7 Reviews of AI detection and generative text

The most recent review-type evidence concerns AI-generated text. Weber-Wulff and colleagues tested a panel of detectors on human-written, machine-generated and machine-paraphrased texts. No tool exceeded 80 percent accuracy, most were considerably lower, and performance dropped when text was edited or paraphrased [66]. Elkhataf, Elsaid and Almeer reported similar inconsistency across tools and inflated false-positive risk on some samples [69]. Liang and colleagues demonstrated that several detectors misclassified a majority of essays by non-native English writers as machine-generated, while performing well on native-speaker essays [67]. Gao and colleagues found that detectors separated generated from real scientific abstracts well in a controlled setting, but that human reviewers, even when alerted, struggled to distinguish the two [68]. Sadasivan and colleagues offered a theoretical argument

that reliable detection becomes harder as language models improve [70], and Kirchenbauer and colleagues proposed watermarking as a cooperative alternative [71].

4.8 Summary of what the reviews collectively show

Taken together, these reviews support five cross-cutting conclusions. Self-report underestimates behaviour. Detection performance declines with disguise. Institutional and situational factors matter more than personality. Language competence confounds the identification of intent. And technological solutions are partial, bias-prone and contested. Notably, almost none of the reviews was designed to compare written with technical disciplines directly. The comparison must therefore be built from converging pieces of evidence, and the next sections attempt that construction.

5. Comparative Analysis

5.1 Definitional and normative divergence

In written disciplines, the intellectual product is largely the text itself and the argument that the text carries. Originality lies in interpretation, synthesis and voice. Literary studies, history, philosophy, law and much of the social sciences therefore treat *language* and *idea* as inseparable, and their integrity codes emphasise quotation marks, paraphrase quality and the acknowledgement of interpretive debts. Swales's genre analysis showed that academic writing in such fields is organised around the creation of a rhetorical space in relation to prior scholarship, which makes accurate positioning against sources a constitutive act [42]. Sutherland-Smith's study of academic staff found that even within writing-intensive disciplines, lecturers held widely differing views on where plagiarism begins, and that their judgements depended on their perception of the student's intent and level [43,44].

In technical disciplines, the intellectual product is a result: a design, an algorithm, a proof, a dataset or a measurement. Language is instrumental. Methods sections are often formulaic by design, since exact reproducibility depends on precise, standardised description. The community consequently tolerates, and sometimes encourages, verbatim reuse of protocol language, which creates a different threshold for what is objectionable [24,56]. The norm that carries the greatest weight is not "use your own words" but "do not misrepresent the origin, ownership or reliability of the result."

5.2 The unit of borrowing

The first major asymmetry concerns *what* is borrowed.

Written disciplines. The dominant units are sentences, paragraphs, arguments and structures of reasoning. Patchwriting and inadequate paraphrase are the modal offences among novices [18,19], while ghostwritten essays and, increasingly, machine-generated drafts are the modal offences among those seeking to avoid the labour of writing [6,34]. Because the unit is text, text-matching tools have a natural fit, and their limitations arise mainly from paraphrase, translation and idea-level appropriation [27,28].

Technical disciplines. The units are more heterogeneous:

- *Code*. Copying a program, or modifying it superficially, is the archetypal offence in computing coursework and raises additional licensing questions in professional settings [29,60].
- *Data and results*. Fabrication, falsification and undisclosed reuse of datasets are more consequential than textual copying and are central to the retraction record [4,5].
- *Images*. Duplication and manipulation of figures, especially in the life sciences, constitute a large and distinctive category [57,58].
- *Mathematical content*. Reuse of derivations, proofs and formula structures may occur with little lexical overlap and defeats word-based comparison [59].
- *Text*. Recycled methods and introduction text remains an issue, but a contested one [24,56].

The practical implication is that a technical scholar may commit a serious integrity breach without producing a single sentence that a text-matching tool would flag.

5.3 Citation culture

Hyland's large-scale corpus analysis found that citation is markedly denser and more often integral to the sentence in soft, text-based fields, where the writer names the source and evaluates it, whereas in the hard sciences and engineering citations are more often parenthetical or numerical and function as compact pointers [12,41]. This has two consequences for plagiarism. First, in written disciplines the *visible signalling* of attribution is a major component of competent writing, so a failure to signal is a highly visible fault. Second, in technical disciplines attribution may be compressed to a bracketed number, and the skill lies in deciding *what deserves* a citation, for instance whether a standard method is common knowledge or an attributable contribution. Novices in technical fields often struggle with this judgement, and their errors can look like omission rather than appropriation.

The stylistic conventions also differ. Some technical fields favour numbered systems and fixed structures, which reduce the space for creative paraphrase, while written fields favour author-date or note-based systems that invite extended engagement. The Vancouver system adopted here is typical of the biomedical and technical end of that spectrum, and its numerical form illustrates how attribution can be made compact.

5.4 Prevalence: what can and cannot be compared

Direct comparison of plagiarism rates across the two families is treacherous, and the evidence should be read with three cautions.

First, the instruments differ. Studies in the written disciplines frequently use self-report questionnaires of students or similarity-score analyses of submitted work [37,38]. Studies in technical disciplines frequently use retraction analyses, image screening, or code-similarity thresholds [5,29,57]. Those measures capture different behaviours, at different stages of the pipeline, in different populations.

Second, the denominators differ. The retraction studies observe published research by professional scientists; the contract-cheating and internet-plagiarism studies observe students [5,6,37]. The behaviours and incentives are not equivalent.

Third, the definitions differ. What counts as an offence in a chemistry laboratory report (copying a colleague's data) is not what counts in a history essay (copying a sentence from a secondary source).

With these cautions in mind, several converging observations are still possible. Bik and colleagues' screening of roughly twenty thousand biomedical papers found problematic image duplication in nearly four percent, and a substantial proportion of those cases showed features suggesting deliberate manipulation rather than inadvertent error [57]. This figure has no direct analogue in the humanities, where images are rarely evidence, and it demonstrates that technical fields face an integrity threat that text-matching cannot even register. Citron and Ginsparg's large-scale analysis of a preprint archive found that text reuse, especially by authors of their own earlier work, was widespread and varied among subfields, showing that even within technical publishing, norms differ [31]. Engineering education research by Carpenter and colleagues found that engineering students differed from faculty in what they considered cheating, particularly regarding collaboration on homework, and that some behaviours faculty regarded as unacceptable were not viewed as serious by students [53]. A companion study found that the type of assessment shaped the likelihood of dishonesty [54], and a further study found that engineering students who reported academic dishonesty were more inclined to anticipate unethical behaviour in professional practice [55].

For computing, Sheard and colleagues found that first-year IT students had more permissive views of collaboration and copying than staff, and that some practices staff considered cheating were regarded by students as normal working methods [63]. Fraser's discussion of collaboration and collusion in computer-science coursework argued that programming culture, which prizes reuse, open-source sharing and help-seeking, sits uneasily with assessment regimes that expect individual authorship [64].

For written disciplines, the most robust prevalence signal comes from contract cheating, where outsourced essays and reports are the principal product [6,32,33]. Because the service is a written artefact, the written disciplines are inherently more exposed, though Ellis and colleagues' analysis of a national dataset suggested that the relationship between assessment type and contract cheating is more complex than assumed, and that "authentic" assessment does not by itself confer immunity [52]. Bretag and colleagues' companion work found that assessment design features such as personalisation and in-class components were associated with lower reported contract cheating, though the effects were partial [51].

The defensible summary is therefore that the *form* of dishonesty differs by discipline, that overall *rates* cannot be ranked across the two families on the present evidence, and that claims of the form "field X plagues integrity more than field Y" should be treated as unsupported.

5.5 Detection feasibility

Detection feasibility is the dimension on which the two families diverge most sharply.

For written disciplines, matching against large text repositories can identify verbatim and near-verbatim reuse effectively, but paraphrase, translation and idea reuse remain difficult [27,28,39]. Foltýnek and colleagues' testing, described above, found that coverage of the source corpus and handling of disguised text were the main determinants of tool quality [39]. Cross-

language plagiarism remains a particular weakness [27]. Human judgement is essential because a similarity percentage is a screening indicator, not a finding [7,40].

For technical disciplines, the situation is fragmented:

- *Code* can be compared with token and structure-based tools, which are highly effective against cosmetic edits, but they face increasing pressure from automated transformation and from code-generating language models. Biderman and Raff showed that pretrained language models could be used to alter programs so that a widely used similarity tool failed to flag them [65].
- *Mathematical and formula content* requires specialised analysis. Meuschke and colleagues showed that combining mathematical-content analysis with citation-pattern analysis improved the identification of plagiarism in STEM documents relative to text-only methods [59].
- *Images* can be screened by expert inspection or computational duplication detection, but at scale this requires dedicated effort. Rossner and Yamada's early call for journals to check images against editorial standards remains pertinent [58].
- *Data* fabrication is not amenable to similarity detection at all, and typically emerges through replication failure, statistical anomalies or whistleblowing [4,5].

The consequence is that an institution which invests in a single text-matching product is well equipped for one family and only partly equipped for the other.

5.6 Sanction, remediation and pedagogy

Because the written disciplines are strongly associated with student authorship, the dominant response is educational and procedural: academic-integrity modules, referencing instruction, feedback on drafts and graded penalties for minor breaches. Howard's and Pecorari's work supports differentiating between developmental patchwriting, which calls for teaching, and deliberate deception, which calls for sanction [18,20]. Bretag and colleagues' analysis of policy in Australian universities identified core elements of exemplary policy, including clear definitions, accessible procedures, proportionate penalties and education [79].

In technical disciplines, the consequences of breach extend beyond the classroom. Fabrication and image manipulation can lead to retraction, loss of funding and career termination, and the harms propagate through the literature and into clinical or engineering practice [5,30]. A study by Harding and colleagues suggested that behaviour in education may predict behaviour in professional settings among engineers, which strengthens the argument for early formation [55]. The National Academies' review of research integrity called for a shift from reactive misconduct policing to a culture of integrity that includes training, mentoring and institutional accountability [82].

5.7 Exposure to generative AI

Generative language models affect both families but in different ways.

In written disciplines, the concern is authorship: essays, literature reviews, reflective pieces and even creative work can be produced by a model, often with no verbatim source that a matching tool could find. Cotton, Cotton and Shipway argued that universities need to adjust

assessment, policy and staff development in response, and that reliance on detection alone would be inadequate [73]. Perkins likewise examined the implications for integrity and advised institutions to address the pedagogic and policy dimensions, not only the technical ones [74]. Reflections on creativity and authorship in the digital age raise the related question of what originality means when tools participate in composition, a question particularly acute in literature and the arts [49,50].

In technical disciplines, models can produce working code, explanations of derivations, drafts of methods sections and plausible but invented data or references. Walters and Wilder found that a substantial proportion of bibliographic citations produced by ChatGPT-3.5 were fabricated, with a lower but still meaningful proportion for the later model, and that many citations judged real contained errors [72]. This finding bears particularly on scientific writing, where a fabricated reference does harm even when no text is copied. Hosseini, Rasmussen and Resnik discussed the responsible use of AI in scholarly writing and argued for disclosure, accountability of human authors and vigilance about accuracy [77]. Publishers and ethics bodies have taken the position that AI tools cannot be credited as authors because they cannot bear responsibility [75,76].

6. Analysis from Different Perspectives

A single comparative frame risks simplifying a phenomenon that different stakeholders see differently. This section analyses seven perspectives.

6.1 The pedagogical perspective

From the perspective of teaching, plagiarism is frequently a symptom of unmet learning needs. Students in written disciplines must learn to synthesise sources in an academic voice, a task that is cognitively demanding and, for non-native speakers, linguistically formidable [45,47]. Students in technical disciplines must learn what constitutes acceptable collaboration, reuse and attribution in cultures that also prize open sharing and teamwork [63,64]. The pedagogical implication is that "integrity education" should not be generic. A module that teaches quotation and paraphrase will be sensible for a law student and largely irrelevant for a mechanical-engineering student, who instead needs guidance on data recording, authorship of group work, code licensing and the ethics of reusing standard methods text. Practitioner-oriented guidance on producing plagiarism-free content stresses that habits such as careful note-taking, separating source language from one's own summary and transparent citation are teachable skills [9].

6.2 The linguistic and intercultural perspective

Linguistic research shows that the boundary between learning and copying is porous. Li and Casanave's case study of two students found that their strategies for writing from sources, which an automated tool would flag, were plausibly attempts to manage the demands of an unfamiliar discourse [47]. Hu and Lei's investigation of Chinese university students' knowledge of and attitudes toward plagiarism showed that both knowledge and beliefs about the seriousness of the offence varied, and that crude cultural stereotypes did not explain the pattern [48]. Ison's comparison across national contexts likewise found differences in plagiarism indicators, but the underlying reasons include educational systems, language and enforcement, not simply "culture" [81]. The most important consequence for the comparison is that the written disciplines, where language is the medium of evaluation, are more likely to penalise

linguistic difference. Technical fields, where much communication is formulaic, may mask such difficulties but at the cost of hiding weak paraphrase skills until students attempt a thesis.

6.3 The technological and algorithmic perspective

Technologists frame plagiarism as a matching problem, and they have made real progress on it [27]. But the perspective has limits. All detectors embed assumptions, and those assumptions can produce systematic error. The evidence of bias in AI-text detectors against non-native writers is the clearest example [67]. More generally, scholarship on algorithmic bias and social stratification has argued that automated systems can reproduce and amplify inequalities when their training data and design choices reflect the dominant group [78]. In the integrity context, this means that a tool that flags "unnatural" language may disproportionately flag international students and second-language authors, who are concentrated in some disciplines more than others. The technological perspective must be complemented by fairness auditing, transparency about error rates and an insistence that a flag never be treated as proof [40,66].

6.4 The editorial and publishing perspective

Editors face plagiarism at the point of submission, when the volume of manuscripts is high and the reviewers' time is limited. Screening tools are now widely used to detect overlap, but editors also need to interpret results. A high overlap score in a technical article may reflect legitimate reuse of standard methods language or a long list of references, whereas a moderate score in a humanities article may conceal serious ideational appropriation [24,56]. The role of artificial intelligence in combating plagiarism in scholarly publishing is increasingly discussed, including the potential for machine-assisted screening to triage submissions, though the same discussions stress that final judgement rests with editors and that the technology itself introduces new risks [8]. Publishers have also had to respond to the arrival of AI-authored text, with policy statements requiring disclosure and rejecting AI authorship [75,76].

6.5 The legal and governance perspective

Legal scholarship distinguishes plagiarism, an ethical and professional offence, from copyright infringement, a legal wrong. Fishman's operational definition aimed to keep these separate, since a work can be plagiarised without infringing (for example, because it is out of copyright or the copied material is unprotected ideas) and can infringe without being plagiarised (for example, because the source is properly cited but the use exceeds fair dealing) [2]. In technical fields, the legal dimension has additional layers: software licences, patents, data-sharing agreements and confidentiality. Code copied from an open-source project with a restrictive licence can create legal liability irrespective of whether the copier hid the source. Institutional governance must therefore be layered. Universities should articulate integrity rules that are distinct from, and in some respects stricter than, the legal minimum, and should make clear where legal obligations apply.

6.6 The psychological and situational perspective

Empirical work on cheating repeatedly finds that context beats character. McCabe and colleagues showed that peer behaviour and institutional culture are strong predictors [35]. Rettinger and Kramer, studying situational and personal causes, found that perceived opportunity, peer norms and attitudes toward the course influenced dishonesty [80]. These

findings apply across the two families but manifest differently. In technical fields, heavy problem-set loads and collaborative norms produce a grey zone in which copying solutions can feel like ordinary collaboration [53,54,63]. In written fields, the isolation of essay writing, tight deadlines and the availability of purchasable essays provide the main pressures [6,33,34]. Assessment redesign, such as personalised tasks, staged submissions and oral defence, addresses situational drivers in both, though evidence for its effectiveness is partial [51,52].

6.7 The regional and policy perspective, with reference to India

Integrity outcomes depend on the policy environment. In India, discussion of higher-education quality has centred on accreditation and assessment frameworks that shape institutional incentives, including the role of the National Assessment and Accreditation Council in raising quality assurance standards [83]. Critical commentary on the National Education Policy 2020 has highlighted the opportunities and implementation drawbacks of reform in curriculum and assessment [84]. Neither strand is specifically about plagiarism, but both bear on it. Research-output expectations for promotion and accreditation, if not accompanied by mentoring in research writing, can push under-resourced researchers toward shortcuts. Practitioner-oriented accounts of plagiarism-detection tools and of practices for producing original content are relevant to this setting, since they aim to build capability at scale, and are most effective when embedded in institutional quality systems [7,9]. A transparent method for mapping research, such as PRISMA-ScR, can also serve as a training device for early-career researchers, enabling them to document how literature was found and used, which itself reduces the temptation to borrow uncredited [16,17]. The comparative analysis above suggests that India's diverse disciplinary landscape, spanning strong traditions in humanities and in engineering, would benefit from discipline-specific integrity guidance rather than a single national template.

7. Synthesis and Citable Propositions

The analysis permits the following propositions, offered as hypotheses grounded in the reviewed evidence and open to empirical testing. Each is intended to be citable as a discrete, falsifiable statement.

Proposition 1 (Plural offence). Plagiarism is not a unitary behaviour but a family of discipline-conditioned breaches whose form depends on what a field treats as its primary intellectual product. This follows from divergent definitions, units of borrowing and citation cultures [1,2,12,18,24].

Proposition 2 (Text-centrality asymmetry). Text-matching technology addresses the dominant risk in written disciplines much better than it addresses the dominant risks in technical disciplines, which include data, image, code and mathematical misappropriation [5,27,29,57,59].

Proposition 3 (Recycling tolerance gradient). Communities in technical fields accept verbatim reuse of standardised methods text more readily than communities in written fields, so identical similarity scores carry different diagnostic meaning across fields [24,56].

Proposition 4 (Self-report unreliability). Cross-disciplinary comparisons based on self-reported plagiarism are unreliable, because self-report understates behaviour and the definitions respondents apply differ [3,4,37].

Proposition 5 (Developmental confound). In writing-intensive disciplines and among second-language writers, a substantial share of text overlap reflects incomplete acquisition of discourse conventions rather than intent to deceive, and treating it as misconduct is both inaccurate and inequitable [18,20,45,47].

Proposition 6 (Detector bias). Automated detectors of AI-generated text exhibit accuracy limits and group-level bias that make them unsuitable as sole evidence in integrity proceedings [66,67,69,78].

Proposition 7 (Situational primacy). Institutional culture, assessment design and situational pressures predict dishonest behaviour more strongly than stable personal traits, in both disciplinary families [35,51,52,80].

Proposition 8 (Convergent AI risk). Generative AI raises a common authorship question in written disciplines and a common veracity question in technical disciplines. For the former the risk is unacknowledged machine composition; for the latter it is fabricated or unreliable content, such as invented references, that damages the record irrespective of copying [72,73,77].

8. Implications and Recommendations

8.1 For institutions

Institutions should replace generic integrity statements with discipline-sensitive guidance. This means defining, for each faculty, the artefacts that count (essays, code, datasets, figures, proofs), the permissible forms of reuse, the standards of collaboration and the sanctions that apply. Policy design should draw on the core elements identified in comparative studies of exemplary policy: clarity, accessibility, proportionality and education [79]. Governance should be aligned with wider quality-assurance frameworks so that integrity is treated as a component of quality, not a compliance add-on [83].

8.2 For educators

Educators should teach the referencing and reuse conventions of their own field explicitly. In written disciplines, this involves scaffolded practice in summarising, paraphrasing and synthesising, with formative feedback on drafts, since diagnostic use of similarity reports is more educational than punitive [7,20,26]. In technical disciplines, it involves explicit instruction on collaboration boundaries, code licensing, laboratory record-keeping and image-handling standards [55,58,63,64]. Assessment should incorporate personalisation, staged submission and oral components, recognising that these measures reduce but do not eliminate risk [51,52].

8.3 For researchers and authors

Authors should keep an auditable trail from source to sentence, disclose reuse of their own text where norms require it, verify every reference (especially any produced with the help of AI tools), and preserve raw data and original images [24,58,72]. Researchers should use structured methods for literature work and record how sources were identified, screened and used, which improves both transparency and originality [16,17].

8.4 For publishers and editors

Publishers should adopt tiered screening, applying text similarity to all submissions but supplementing it with image checks, statistical checks and, where relevant, code or data audits. Similarity scores should never be applied as fixed thresholds across fields [24,40,56]. Policies on AI should require disclosure, reject AI authorship and assign accountability to human authors [75,76,77].

8.5 For technology developers

Developers should publish error rates by language background and text type, submit tools to independent evaluation, and design reports that support human interpretation rather than replace it [39,66,67]. Research investment should extend beyond text matching to semantic, cross-language, mathematical and multimodal detection, and to cooperative provenance mechanisms such as watermarking [59,71].

8.6 An integrated model

An integrated model combines four layers: (i) a common ethical core (honest acknowledgement, honest reporting and honest authorship); (ii) discipline-specific rules for artefacts, reuse and collaboration; (iii) proportionate detection that pairs technology with expert judgement; and (iv) education-first remediation reserving heavy sanctions for deliberate deception. The model treats the written/technical distinction as a spectrum on which many fields, such as economics, architecture, computational linguistics and bioinformatics, occupy intermediate positions [11].

9. Limitations and Directions for Future Research

Several limitations qualify these conclusions. First, the synthesis is a structured narrative one; it does not compute pooled effects, and its conclusions depend on the representativeness of the purposively assembled corpus. Second, the written/technical division is a heuristic. Actual disciplines are internally diverse and increasingly interdisciplinary, and Biglan-type classifications are themselves contested [11]. Third, the evidence base is uneven. Life sciences and computing have strong review literatures on data, images and code, whereas law, philosophy and the arts have comparatively little quantitative evidence, and much of the student-behaviour literature originates in Anglophone contexts. Fourth, the pace of change in generative AI means that detector evaluations and policy positions may become dated quickly [66,70]. Fifth, no formal risk-of-bias tool was applied, which is consistent with scoping conventions but limits the strength of inference [15].

Future research should pursue at least five directions. Studies should apply harmonised instruments across disciplines so that prevalence can be compared. Detection benchmarks should be extended to mathematical, image, code and multimodal artefacts, with reporting by language background. Longitudinal work should track how AI tools reshape authorship norms in each family. Qualitative research should examine how scholars themselves draw the line between acceptable and unacceptable reuse in their own subfields. And intervention studies should test discipline-specific integrity education against generic modules.

10. Conclusion

This analysis set out to compare plagiarism across written and technical disciplines, and it finds that the two families differ in kind rather than merely in degree. Written disciplines locate the risk in the text and its ideas, so the characteristic breaches are patchwriting, uncredited paraphrase, purchased essays and machine composition. Technical disciplines locate the risk in the artefacts that carry evidential and functional weight, so the characteristic breaches include code copying, image manipulation, data misrepresentation and contested text recycling. Current detection technology is strongest where the risk is textual and weakest where it is not, and the emerging generation of AI-text detectors introduces new problems of accuracy and fairness.

The evidence does not support ranking one family as more prone to plagiarism than the other. It supports a more useful conclusion: that integrity governance should be organised around the artefacts and norms of each discipline, that developmental and deceptive behaviours should be distinguished, that technology should inform and not replace judgement, and that education and assessment design deserve at least as much investment as detection. The eight propositions offered here provide a basis for testing these claims. A scholarly community that defines originality precisely, teaches attribution explicitly and treats every flag as a prompt for human inquiry is better placed to protect the integrity of both its words and its data.

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