Understanding Issues of Plagiarism: Forms, Causes, Detection Limits and Regulatory Responses in Higher Education and Research

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***Abstract*—Plagiarism remains one of the most frequently cited threats to academic integrity, yet universities often treat it as a single offence to be caught by software. This paper examines plagiarism as a layered problem: a set of distinct practices with different causes, uneven detectability and varying seriousness, now complicated by generative artificial intelligence. The study follows an integrative review of peer-reviewed research, meta-analyses, tool evaluations and one national regulatory instrument, the University Grants Commission (UGC) regulations of 2018. Sources were verified against publisher records and synthesised thematically. No primary data were collected; all figures reported are drawn from the cited studies. Plagiarism spans a continuum from verbatim copying and idea theft to patchwriting, text recycling and undisclosed ghost or machine authorship. Self-reported plagiarism among scientists is low (a pooled 1.7%), but 30% report having witnessed it, and plagiarism accounts for nearly one in ten biomedical retractions. Causes operate at individual, instructional, institutional and technological levels. Text-matching software finds verbatim overlap but misses paraphrase and translation, while detectors for AI-generated text are neither accurate nor reliable and misclassify non-native writing. India's UGC framework ties sanctions to similarity percentages, which risks equating a software score with misconduct. The paper proposes a four-level framework linking causes to responses and argues that institutions should move from percentage-based policing towards judgement-based, educative integrity systems.**

***Index Terms*—Plagiarism; academic integrity; patchwriting; self-plagiarism; text-matching software; generative AI; research misconduct; UGC regulations**

I. INTRODUCTION

Scholarship runs on a simple exchange. Writers borrow ideas, evidence and words from others, and in return they say where these came from. Attribution is how credit is distributed, how readers trace claims to their origins and how the reliability of a field is maintained. Plagiarism breaks that exchange by presenting another person's work or ideas as one's own, a definition the University Grants Commission of India adopted almost word for word in its 2018 regulations (UGC, 2018).

The problem is old, but its shape has changed. Digital text made copying easier and, with text-matching software, easier to detect. The arrival of large language models has disturbed that balance again, because machine-generated prose is new text with no single source to match (Cotton et al., 2024; Eaton, 2023). At the same time, research on student writing has shown that much of what is flagged as plagiarism is not deliberate theft but an unfinished stage in learning to write from sources (Howard, 1995; Pecorari, 2003).

Institutions therefore face a double risk. If they treat every textual overlap as fraud, they punish learners and second-language writers for developmental errors. If they rely on similarity scores alone, they miss the more damaging forms of misconduct, such as the appropriation of ideas or data, that software cannot see. This paper sets out to clarify what plagiarism consists of, why it happens, how well it can be detected and how regulation, with particular reference to India, responds to it.

II. REVIEW OF LITERATURE

2.1 Defining and classifying plagiarism

Definitions converge on the unacknowledged use of another's work but diverge on scope. Walker (1998) distinguished sham paraphrasing, illicit paraphrasing, verbatim copying, recycling of one's own work, ghost writing and purloining, arguing that these differ in intent and seriousness. Bouville (2008) separated the plagiarism of words from the plagiarism of ideas and questioned whether both cause the same harm. Chaddah (2014), writing from the Indian research context, made a related case: copying of text in introductory or methods sections misleads readers less than the theft of ideas or results and should not automatically attract retraction.

Howard (1995) introduced the term patchwriting for copying from a source text and then deleting some words, altering grammar or substituting synonyms. She argued that patchwriting is a normal step in learning academic discourse and that treating it as plagiarism imposes an "academic death penalty" on novices. Pecorari (2003) found the same pattern among postgraduate second-language writers, whose texts relied heavily on sources without any evident intention to deceive, and Pecorari and Petrić (2014) later reviewed the wider literature on second-language writing to the same effect.

2.2 Prevalence and consequences

Measuring plagiarism is difficult because it is concealed. Among students, McCabe et al. (2001) reported a decade of survey evidence showing that cheating, including unattributed copying, was widespread and strongly shaped by perceptions of peer behaviour. For researchers, Pupovac and Fanelli (2015) pooled 17 surveys and estimated that 1.7% of scientists admitted committing plagiarism, while 30% knew of a colleague who had. Fanelli's (2009) earlier meta-analysis on fabrication and falsification found a similar gap between self-reports and reports about colleagues, which suggests that admission rates understate the problem.

Retraction data give a second view. Fang et al. (2012) examined all 2,047 biomedical and life-science articles retracted by May 2012 and attributed 67.4% to misconduct, including plagiarism (9.8%) and duplicate publication (14.2%). Horbach and Halffman (2019) analyzed 922 articles in four disciplines and found considerable problematic text recycling, especially in economics and psychology, with more productive authors more likely to reuse their own text.

2.3 Causes

Explanations cluster around several factors. Park (2003) reviewed student plagiarism and identified a lack of understanding of citation conventions, time pressure, the search for efficiency, weak deterrence and neutralizing attitudes. Gullifer and Tyson (2010) found through focus groups that students were confused about what counts as plagiarism and anxious about committing it unintentionally. Pennycook (1996) argued that ideas of textual ownership are culturally situated and that memorization and reuse of authoritative text carry different meanings across educational traditions. At the institutional level, Macfarlane et al. (2014) noted that integrity research focuses heavily on students and neglects the pressures that publication metrics place on academic staff, a point echoed by the productivity link in Horbach and Halffman (2019).

2.4 Detection and the problem of generative AI

Text-matching software is now standard. Foltýnek et al. (2019) reviewed detection research and showed that methods handle verbatim copying well but struggle with paraphrase, translation and idea plagiarism. A collaborative test of 15 systems across eight languages concluded that software cannot determine plagiarism; it can only flag similarity, and it both misses copied material and flags legitimate text (Foltýnek et al., 2020). Faculty interviewed by Bruton and Childers (2016) held inconsistent views on what the similarity reports meant.

Generative AI adds a further difficulty. Weber-Wulff et al. (2023) tested 14 detectors of AI-generated text and found them neither accurate nor reliable, with a bias towards labelling machine text as human and a sharp decline in performance when text was paraphrased. Liang et al. (2023) showed that such detectors frequently misclassify essays by non-native English writers as machine-generated. Eaton (2023) has proposed the idea of postplagiarism, in which hybrid human and machine writing becomes normal and the ethical emphasis shifts from policing sources to accepting responsibility for text one submits.

2.5 Institutional responses

Responses to plagiarism have moved between two models. The first is punitive and procedural: detect, investigate and sanction. The second is educative and cultural: teach source use, build shared norms and design assessment so that copying is neither easy nor rewarding. McCabe et al. (2001) found that institutions with honour codes and a visible culture of integrity reported lower levels of cheating, which suggests that norms shape behaviour at least as strongly as the threat of detection. Bretag (2016) and the contributors to her handbook describe academic integrity as a whole-institution responsibility that covers policy, teaching, support services and leadership. Macfarlane et al. (2014) caution that this framing still tends to place the burden on students while leaving staff practices, such as honorary authorship or text recycling, comparatively unexamined.

National regulators increasingly combine both models. The UGC (2018) regulations in India require semester-wise awareness programmes, compulsory coursework on research and publication ethics, institutional repositories and integrity panels that follow natural justice, alongside graded penalties. How far such provisions change practice depends on how panels interpret the similarity evidence placed before them, a question the present study takes up.

III. RESEARCH GAP

The literature is extensive but divided. Linguistic and pedagogical studies treat plagiarism as a learning issue; research-integrity studies treat it as misconduct; computing studies treat it as a detection problem; and regulatory documents treat it as a percentage. Few studies connect these perspectives or test regulatory approaches against the evidence on detection accuracy. In the Indian context, the UGC (2018) regulations have been widely described but rarely examined against international findings on what similarity software can and cannot establish. The implications of generative AI for such percentage-based frameworks are also largely unexamined. This paper addresses these gaps.

IV. OBJECTIVES AND RESEARCH QUESTIONS

The study has four objectives:

(1) to develop a typology of plagiarism that distinguishes forms by intent, object and seriousness;

(2) to synthesise the published evidence on prevalence and consequences;

(3) to identify the causes of plagiarism across levels of analysis; and

(4) to evaluate detection technologies and the UGC regulatory framework in the light of that evidence.

Four research questions follow.

1: What forms does plagiarism take, and how do they differ?

2: What does published evidence reveal about its extent and consequences?

3: What individual, instructional, institutional and technological factors contribute to it?

4: How adequately do current detection tools and regulations respond to these forms and causes?

V. RESEARCH METHODOLOGY

The paper uses an integrative review design, which allows theoretical, empirical and policy sources to be analysed together. Sources were selected purposively under four criteria: (a) conceptual works that define or classify plagiarism; (b) systematic reviews, meta-analyses or large-sample analyses of prevalence and consequences; (c) independent evaluations of detection software; and (d) the primary text of the UGC (2018) regulations, consulted in the Gazette of India.

Each source was read in full or, for large empirical studies, in its reported results, and coded under the four research questions. Quantitative figures were extracted exactly as published and are attributed to their original authors in each table. The analysis combined thematic synthesis with a critical reading of the regulation against the detection evidence.

VI. RESULTS

6.1 A typology of plagiarism

The synthesis produced seven forms, set out in Table 1. They differ in what is taken (words, ideas, data or authorship), in the likely intent of the writer and in whether current software can detect them.

Table 1. Typology of Plagiarism by Object, Typical Intent and Software Detectability

Form	Description	Typical intent	Detectable by text matching
Verbatim copying	Text reproduced without quotation or citation (Walker, 1998)	Often deliberate	Yes, reliably

Form	Description	Typical intent	Detectable by text matching
Patchwriting	Source text lightly altered by deletion or synonym substitution (Howard, 1995; Pecorari, 2003)	Usually, developmental	Partly
Sham or illicit paraphrase	Cited source but copied wording, or paraphrase without citation (Walker, 1998)	Mixed	Partly
Idea or results plagiarism	Appropriation of concepts, data or findings (Bouville, 2008; Chaddah, 2014)	Deliberate	No
Text recycling	Reuse of one's own published text without disclosure (Horbach & Halffman, 2019)	Often strategic	Yes, if indexed
Translation plagiarism	Copying across languages (Foltýnek et al., 2019)	Deliberate	Rarely
Ghost or AI authorship	Submission of text written by another person or a language model (Eaton, 2023; Walker, 1998)	Deliberate or unclear	No

6.2 Evidence on extent and consequences

Table 2 brings together the principal quantitative findings. The consistent pattern is a large gap between what individuals admit and what they observe in others, and a measurable footprint in the published record.

Table 2. Published Evidence on the Extent of Plagiarism and Related Misconduct

Source	Evidence base	Key figure reported
Pupovac and Fanelli (2015)	Meta-analysis of 17 surveys of scientists	1.7% admitted plagiarism; 30% had witnessed it
Fanelli (2009)	Meta-analysis of surveys on fabrication and falsification	1.97% admitted; 14.12% reported colleagues
Fang et al. (2012)	All 2,047 biomedical retractions indexed in PubMed to May 2012	Plagiarism 9.8%; duplicate publication 14.2%
Horbach and Halffman (2019)	922 articles in four research fields	Considerable text recycling, highest in economics and psychology
McCabe et al. (2001)	Ten years of multi-campus student surveys	Peer behaviour the strongest predictor of cheating

Figure 1 shows the reasons for retraction reported by Fang et al. (2012). Plagiarism and duplicate publication together account for 24% of retractions, about a quarter of the total and more than the share caused by honest error.

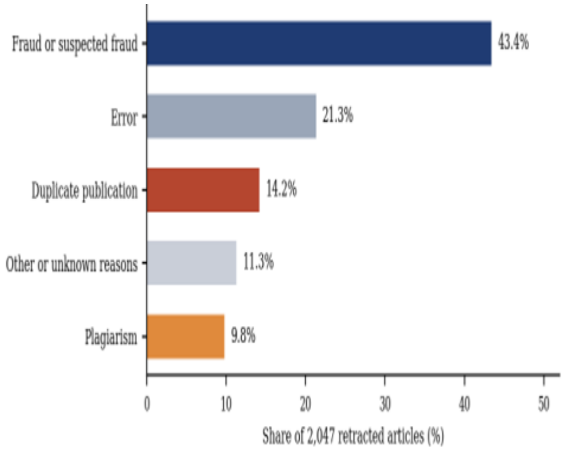

Figure 1. Reasons for retraction of 2,047 biomedical and life-science articles. Data from Fang et al. (2012); the residual category is calculated as the remainder of 100%.

6.3 Causes across four levels

The causes identified in the literature operate at four levels. At the individual level, they include limited understanding of citation conventions, poor time management and attitudes that excuse copying (Gullifer & Tyson, 2010; Park, 2003). At the instructional level, they include assignments that reward reproduction, little teaching of paraphrase and synthesis, and unclear or inconsistent expectations among teachers (Bruton & Childers, 2016; Howard, 1995). At the institutional level, publication pressure, metric-driven promotion and a permissive peer culture are prominent (Horbach & Halffman, 2019; Macfarlane et al., 2014; McCabe et al., 2001). At the technological level, easy access to digital text, paraphrasing tools and language models lowers the effort required to plagiarize and to disguise it (Cotton et al., 2024; Weber-Wulff et al., 2023). Cultural and linguistic background shapes how these pressures are felt, particularly for second-language writers (Pecorari & Petrić, 2014; Pennycook, 1996).

Table 3 organizes these causes into a four-level framework and pairs each level with the responses that the reviewed evidence supports. The framework is the paper's principal conceptual contribution: it shows that software screening addresses only one part of one level, and that most causes call for teaching, assessment design or changes to institutional incentives.

Table 3. Four-Level Framework of the Causes of Plagiarism and Matching Responses

Level	Principal causes identified	Responses supported by the evidence
Individual	Weak grasp of citation and paraphrase; time pressure; neutralizing attitudes; anxiety about unintentional copying (Gullifer & Tyson, 2010; Park, 2003)	Explicit teaching of source use with practice and feedback; clear local examples of acceptable and unacceptable reuse
Instructional	Tasks that reward reproduction; inconsistent expectations across teachers; developmental patchwriting treated as fraud (Bruton & Childers, 2016; Howard, 1995)	Process-based assessment with drafts; shared marking guidance; distinguishing learning errors from misconduct
Institutional	Publication and promotion metrics; peer culture; focus on students rather than staff (Horbach & Halffman, 2019; Macfarlane et al., 2014; McCabe et al., 2001)	Integrity codes that bind staff as well as students; disclosure rules for text reuse; fair, reasoned panel decisions
Technological	Easy digital copying; paraphrasing tools; language models; unreliable detectors (Liang et al., 2023; Weber-Wulff et al., 2023)	Similarity reports as screening only; disclosure of AI use; no sanction on detector scores alone

6.4 Detection tools and the UGC framework

Table 4 sets the UGC (2018) levels and sanctions alongside what the detection evidence implies about each. The regulations also require institutions to run awareness programmes every semester, include academic integrity in curricula, create departmental and institutional integrity panels, and exclude quotations with attribution, references, generic terms and common knowledge of up to 14 consecutive words from similarity checks (UGC, 2018).

Table 4. UGC (2018) Similarity Levels, Sanctions and Evidence-Based Concerns

Level (similarity)	Thesis or dissertation	Publication by faculty or researcher	Concern from detection evidence
0 (up to 10%)	No penalty	No penalty	Idea, translation and AI plagiarism may score near zero
1 (above 10% to 40%)	Revised script within 6 months	Withdrawal of manuscript	Scores vary across tools and settings (Foltýnek et al., 2020)
2 (above 40% to 60%)	Barred from resubmission for 1 year	Withdrawal; one increment denied; no new supervision for 2 years	Score does not show intent or where overlap occurs
3 (above 60%)	Registration cancelled	Withdrawal; two increments denied; no new supervision for 3 years	Largely verbatim cases; the rule is sound here

The comparison shows a structural mismatch. The framework is progressive in requiring education, due process and panels, but its sanctions are indexed to a single percentage that software produces. The evidence reviewed indicates that the most serious forms of plagiarism, idea theft and undisclosed machine authorship, generate low or zero similarity, while developmental patchwriting can generate high scores.

VII. DISCUSSION

The results support treating plagiarism as a family of practices rather than a single offence. A doctoral candidate who patchwrites a literature review and a researcher who publishes a colleague's unpublished results have both plagiarized, yet the first needs teaching and the second has committed misconduct that damages the research record. Policies that apply one scale to both will be too harsh on the first and too lenient on the second.

The prevalence data point in the same direction. The difference between 1.7% self-reported and 30% witnessed plagiarism (Pupovac & Fanelli, 2015) suggests both under-reporting and disagreement about what counts. Clear local definitions, supported by worked examples, would narrow that disagreement. The retraction evidence (Fang et al., 2012) shows that plagiarism and duplicate publication are not trivial; they account for a larger share of retractions than error.

Detection technology is necessary but insufficient. Similarity reports are useful screening devices, and the UGC regulation rightly requires institutions to provide them. The danger lies in treating the number as the verdict. With AI-generated text, the risk becomes acute: detectors are unreliable and biased against non-native writers (Liang et al., 2023; Weber-Wulff et al., 2023), which matters in India, where much academic writing is produced in English as a second language. Assessment designs that make the writing process visible, such as drafts, oral defences and reflective accounts, offer more dependable evidence than any detector (Cotton et al., 2024). Eaton's (2023) argument that responsibility for text cannot be delegated to a machine offers a workable principle for revising regulations.

The Indian case illustrates how these issues meet in practice. The UGC (2018) regulations deserve credit for placing education and due process at the centre, and for excluding properly quoted material, references and common phrases from similarity counts. Yet the exclusion of common knowledge "up to fourteen consecutive words" and the fixed percentage bands both assume that plagiarism is a matter of counted text. A thesis can fall below 10% similarity and still borrow its central argument from an uncited source, and a thesis in a field with standard methods descriptions can exceed 10% without any intent to mislead. Chaddah's (2014) proposal to distinguish text plagiarism from the theft of ideas and results offers a way to grade seriousness that does not depend on a single number.

VIII. FINDINGS

The main findings are these. (1) Plagiarism comprises at least seven forms that differ in object, intent and detectability. (2) Self-reported plagiarism among scientists is about 1.7%, but 30% report witnessing it. (3) Plagiarism and duplicate publication account for about a quarter of biomedical retractions. (4) Causes operate at individual, instructional, institutional and technological levels, with language background shaping their effect. (5) Text-matching software reliably finds verbatim copying but not paraphrase, translation or idea theft. (6) AI-text detectors are inaccurate and disadvantage non-native writers. (7) The UGC framework combines sound educational provisions with sanctions tied to similarity percentages, which do not track seriousness or intent.

IX. CONCLUSION

Plagiarism is best understood as a problem of attribution with several distinct faces. Some forms reflect incomplete learning, others reflect pressures created by academic reward systems, and some are deliberate appropriation. No software can sort these from one another. A defensible response combines teaching, assessment design and careful human judgement, using similarity reports as evidence to be interpreted rather than as automatic grounds for sanction. With generative AI now part of ordinary writing, that principle is more urgent than before.

X. IMPLICATIONS AND RECOMMENDATIONS

For institutions, the study recommends that integrity panels treat similarity percentages as a starting point for enquiry and record the form, location and likely intent of overlap before recommending penalties. Plagiarism policies should define idea, data and AI-assisted plagiarism explicitly and require disclosure of any AI tool used in preparing a manuscript or thesis. AI-text detector scores should not be used as sole evidence of misconduct.

For teachers and supervisors, the implication is to teach paraphrase, synthesis and citation as skills, with feedback on drafts, and to design assessments that reveal process. For regulators, a revision of the UGC (2018) framework could retain its awareness and due-process provisions while replacing fixed percentage thresholds with qualitative criteria of seriousness. For researchers, disclosure of text reuse and of AI assistance should become routine practice.

XI. LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

The review is integrative, not systematic, and its source selection, though verified, may omit relevant regional studies. Much of the prevalence evidence comes from biomedical fields and Western institutions, and figures from one discipline may not transfer to others. The analysis of regulation is limited to India. Future research could survey Indian faculty and research scholars on their understanding of the UGC levels, audit how integrity panels decide cases, compare similarity scores for the same documents across tools, and test assessment designs that reduce undisclosed AI use without disadvantaging second-language writers.

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