



Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)

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Editors

**Dr. Divya Sharma, Prof.(Dr.) Gurpreet Kaur, Dr. Geeta
Rawat, Dr Dhanashri Rajashri Ravindra Jadhav**

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List of Contributors

Chapter	Contributor	Designation	Institution	Location
1	Dr. Kavita Silwal	Assistant Professor	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
2	Dr. Simrann Rajesh Vermaa	Assistant Professor, Department of English	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
3	Dr. Soju Samuel	Counsellor	Delhi Public School	Bhilai, Chhattisgarh
4	Dr. Ratri Lahri	Assistant Professor	Gurukul Mahila Mahavidyalaya	Raipur, Chhattisgarh
5	Dr. Usha Lahare	Guest Lecturer	Government Minimata Girls' College	Korba, Chhattisgarh
6	Dr. Sumita Singh	Assistant Professor, Department of Education	St. Thomas College	Bhilai, Chhattisgarh
7	Mamta Rani Yadu	Research Scholar	Anjaneya University	Raipur, Chhattisgarh
8	Suravi Bhattacharya	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
9	Dr. Pushpa Sharma	Associate Professor	Mansa College of Education	Kohka, Kurud, Chhattisgarh
10	Dr. Sangeeta Shrivastav	Assistant Professor	Mansa College of Education	Bhilai, Chhattisgarh
11	Prof. (Dr.) Gurpreet Kaur	Principal	Sanskar City College of Education	Thakurtola, Rajnandgaon, Chhattisgarh
12	Dular Das	Research Scholar	Hemchand Yadav University	Durg, Chhattisgarh
13	Namita Roy	Research Scholar, Department of Education	Anjaneya University	Raipur, Chhattisgarh
14	Madhubala Shrivastava	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
15	Dr. Ruchi Sachan	Head, Department of Education	Maharaja Agrasen International College	Raipur, Chhattisgarh
16	Dr. Juhi Peter	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
17	Mrs. Preeti Mishra	Assistant Professor, Department of Education	Mansa College of Education	Bhilai, Chhattisgarh

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Chapter	Contributor	Designation	Institution	Location
18	Renuka Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
19	Dr. Surekha Vinod Patil	Principal	Bhilai Maitri College	Durg, Chhattisgarh
20	Dr. Shweta Bhatia	Professor and Head, Department of Education	M.J. College, Kohka	Bhilai, Chhattisgarh
21	Dr. Archana Pandey	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
22	Dr. Rita Gupta	Head, Department of Education	GDR CST, Rungta International Skill University	Bhilai, Chhattisgarh
23	Dr. Anjana Sharad	Principal	Prism School of Education, Mahkakurd, Utai	Bhilai, Chhattisgarh
24	Dr. Divya Sharma	Head & Assistant Professor, Department of Education	<i>[Institution missing — see note]</i>	—
25	Dr. Shalini Verma	Assistant Professor	Bhilai Maitri College	Bhilai, Chhattisgarh
26	Tulsi Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
27	Mona Gupta	Guest Lecturer, Department of Commerce	Government Shaheed Kaushal Yadav College	Gunderdehi, Balod, Chhattisgarh
28	Kiran Sonatiya	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
29	Ranjana Solanki	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
30	Dr. Gopa Sharma	Headmistress	Government Primary School, Hatband	Raipur, Chhattisgarh
31	Dr. Manju Sahu	Associate Professor	M.J. College, Kohka	Bhilai, Chhattisgarh
32	Dr. Nirmala Parganiha	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
33	Dr. Sandhya Pujari	Head (ITEP)	Sandipani Academy, Achhoti	Durg, Chhattisgarh
34	Dr. Atul Kumar Soni	Assistant Professor	Pt. Kishori Lal Shukla Vidhi Mahavidyalaya	Rajnandgaon, Chhattisgarh

International Conference On Multidisciplinary Research

Chapter	Contributor	Designation	Institution	Location
35	Smt. Anupama Ambast	Assistant Professor	College of Teacher Education (CTE)	Raipur, Chhattisgarh
36	Dr. Shraddha Bhardwaj	Assistant Professor	Jagadguru Shankaracharya College of Education	Bhilai, Durg, Chhattisgarh
37	Mrs. Lileshwari Sahu	Assistant Professor	Somni Mahavidyalaya, Somni	Rajnandgaon, Chhattisgarh
38	Shalini Sahu	Assistant Professor	Sanskar City College of Education	Rajnandgaon, Chhattisgarh
39	Meenakshi Yadav	Assistant Professor	Agrasen College, Dhanora	Durg, Chhattisgarh
40	Smt. Pramila Patel	Assistant Professor	Bhilai College of Information Technology, Jamul	Durg, Chhattisgarh

Chapter 20: Peer Feedback and Academic Writing Development among University Students

Dr. Shweta Bhatia

Professor and Head

Department of Education

M.J. College, Kohka, Bhilai, Chhattisgarh

Abstract— Peer feedback is increasingly used in university writing instruction, yet its effectiveness depends substantially on what students say to one another and how writers act on the comments they receive. Recent research has established broad benefits of peer review, but the relationship among feedback quality, revision uptake, feedback literacy, and dimension-specific writing improvement remains insufficiently quantified. This study addresses that gap by conceptualizing peer feedback as a traceable learning process rather than a single instructional treatment. It proposes an AI-assisted analytical framework in which natural language processing is used to classify feedback functions, estimate comment specificity and actionability, and connect individual comments with subsequent textual revisions. The framework retains human rubric assessment as the primary indicator of academic writing quality, positioning artificial intelligence as an analytic instrument rather than an autonomous evaluator. Particular attention is given to whether explanatory and solution-oriented comments produce stronger revision uptake than praise, vague criticism, or surface-level correction.

Keywords— Peer feedback, Academic writing, Feedback literacy, Revision uptake, Natural language processing, Higher education

Introduction

Academic writing at university is not simply the production of grammatically acceptable prose. Students are expected to construct defensible arguments, integrate evidence, establish logical relationships between ideas, observe disciplinary conventions, and revise texts in response to critical evaluation. These requirements make academic writing an iterative intellectual activity rather than a one-stage language exercise. Feedback consequently occupies a central position in writing development, but the increasing size and diversity of university classes can make detailed, repeated instructor feedback difficult to sustain. Peer feedback has therefore become an important component of process-oriented writing pedagogy because it distributes evaluative activity among students and places learners in the dual roles of writer and reviewer.

Contemporary evidence indicates that peer feedback can contribute to cognitive, behavioral, affective, social, and metacognitive development. A systematic review by Wei and Liu (2024), covering 60 studies published between 2014 and 2024, identified improvements in writing quality, critical evaluation, feedback literacy, interaction, and self-reflection while also documenting recurring problems such as weak reviewer competence, interpersonal concerns, and difficulty producing constructive comments. Similarly, a synthesis of

online peer-feedback research in higher education showed that outcomes depend not only on participation but also on student characteristics, technological settings, activity design, and the substantive quality of feedback generated during interaction. These findings indicate that treating peer feedback as a binary intervention—present versus absent—provides an incomplete explanation of writing development.

A particularly important distinction concerns **providing** and **receiving** feedback. Reviewing another student's text requires the reviewer to compare a draft with explicit or implicit quality criteria, diagnose weaknesses, formulate alternatives, and justify evaluative judgments. These operations may subsequently influence the reviewer's own writing. Receiving feedback involves a different sequence: interpretation, credibility judgment, emotional response, decision-making, and revision. Gao, An, and Schunn (2023) demonstrated that the combined experience of providing and receiving feedback was associated with revision benefits and that the relative value of these activities differed according to language proficiency. Their analysis therefore suggests that the pedagogical mechanism lies in reciprocal evaluative activity rather than merely in the transfer of comments from one student to another.

The concept of **feedback literacy** provides an additional explanation for these differences. Yu and Liu (2021) proposed that effective engagement with academic-writing feedback requires interconnected technical, social-interactive, and individual capacities. Subsequent empirical work has demonstrated that feedback literacy is multidimensional rather than a single skill. Dong, Gao, and Schunn (2023), for example, validated a peer-feedback literacy measure incorporating feedback-related knowledge and abilities, cooperative learning capacity, appreciation of feedback, and willingness to participate. Longitudinal evidence also indicates that learners do not develop these capacities at identical rates; agency, emotional resilience, reflection, and proactive use of feedback influence the trajectory of improvement.

These developments reveal a significant unresolved issue. Much of the existing literature measures final writing scores, perceptions, feedback-literacy scales, or broad participation frequencies. Comparatively less attention has been given to a continuous chain linking **the linguistic and functional characteristics of an individual peer comment → the writer's decision to use or reject it → the type of textual change made → the quality gain associated with that revision**. This constitutes the central research gap of the present study.

The gap is especially relevant in the current AI-intensive educational environment. Automated writing evaluation and generative AI can provide rapid feedback, and recent empirical

studies have examined how university writers interact with machine-generated suggestions. Yang, Gao, and Shen found that student uptake varied according to the type of automated feedback presented, while Mahapatra (2024) reported positive outcomes from using ChatGPT as a formative feedback tool in undergraduate ESL writing. Nevertheless, automated feedback and human peer interaction are not pedagogically equivalent. Peer review includes negotiation, perspective taking, audience awareness, reciprocal evaluation, and social judgment—processes that may themselves contribute to learning. Accordingly, the present research adopts a different role for artificial intelligence. Rather than asking AI to replace peer reviewers, it proposes using interpretable natural language processing to **analyze human-generated peer feedback and revision traces**. The principal objective is to determine which feedback characteristics most strongly predict meaningful revision uptake and subsequent development in argumentation, organization, evidence integration, academic style, and linguistic accuracy. This process-oriented approach is intended to connect educational feedback theory with explainable machine-learning methods while preserving human judgment as the basis of writing assessment.



Fig. 1: Peer Feedback

Source: <https://helpfulprofessor.com/peer-feedback-examples/>

Literature Review

Peer Feedback as a Reciprocal Learning Process

Peer feedback is grounded in the proposition that evaluating another learner's work can itself constitute learning. During review, students externalize criteria that may otherwise remain abstract. They must identify the relationship between a writer's intention and textual execution, recognize inconsistencies, and translate evaluation into communicable advice. When learners subsequently return to their own drafts, these evaluative experiences may enhance self-monitoring and facilitate more deliberate revision.

Research increasingly supports this bilateral interpretation. Gao et al. (2023) found that both giving and receiving feedback contributed to revision, although the pattern of benefit varied with learner proficiency. This is significant because it challenges a transmission model in which learning occurs only when a writer receives a useful correction. The reviewer can also benefit

from diagnosing another person's argument, observing alternative writing strategies, and applying evaluative criteria to a text that is psychologically less familiar than his or her own.

However, participation does not guarantee productive learning. Recent systematic evidence identifies substantial variation in feedback accuracy, specificity, constructiveness, interpersonal tone, and depth. Online settings add further design variables, including anonymity, number of reviewers, platform affordances, reviewer training, feedback rounds, and the availability of assessment rubrics. Taghizadeh Kerman and colleagues' synthesis indicates that feedback quality is particularly consequential because students are more likely to act on comments they perceive as useful and sufficiently detailed. Consequently, raw comment counts or participation rates are weak proxies for the actual instructional value of peer review.

Feedback Quality and Revision Uptake

A useful peer comment must normally do more than indicate that a passage is "unclear" or "good." Actionable feedback may identify the problematic textual location, explain why it is problematic relative to an academic criterion, and suggest a feasible direction for revision. Feedback may also target different levels of writing. Surface feedback addresses spelling, punctuation, grammar, or lexical form, whereas meaning-level feedback can address claims, organization, coherence, evidence, reasoning, audience expectations, or disciplinary conventions. This distinction matters because students often respond differently to feedback categories. Surface corrections generally demand less interpretation and can therefore produce high rates of immediate uptake. Higher-order feedback, by contrast, may require writers to restructure paragraphs, reconsider evidence, modify argumentative relationships, or reject a suggestion after evaluating its relevance. Revision uptake should therefore not automatically be interpreted as evidence of feedback effectiveness. Blind acceptance of inaccurate advice can reduce writing quality, while justified rejection may demonstrate strong evaluative judgment.

Recent research has begun to characterize engagement with feedback as dynamic and nonlinear. Studies of students receiving peer comments show that understanding a comment does not necessarily result in appropriate revision; emotional responses, perceived credibility, task difficulty, and individual strategies can alter the relationship between feedback and action. This creates a methodological problem for studies based exclusively on final scores: the same score improvement may arise from substantially different feedback-processing behaviors.

Feedback Literacy as a Mediating Capacity

Feedback literacy shifts attention from feedback as information toward the learner's capacity to interpret and use that information. Yu and Liu's (2021) framework emphasizes that students require knowledge of academic-writing criteria as well as the ability to manage interaction, judgment, and self-regulation. Empirical research has subsequently reinforced the developmental nature of these capacities.

Zhang et al. (2023) observed that learners' feedback literacy changed across repeated writing and reviewing experiences, but development occurred at different rates. Reflection, proactive engagement, emotional resilience, and actual incorporation of feedback were important features of this process. Dong et al. (2023) further demonstrated that peer-feedback literacy encompasses both providing and receiving dimensions, supporting a reciprocal rather than receiver-centered conceptualization. Taken together, these findings suggest that feedback literacy may function as a mediating variable between exposure to peer comments and measurable improvement in academic writing.

Technology, Artificial Intelligence, and Writing Feedback

Digital platforms have made peer review increasingly traceable. Online systems can retain original drafts, revised drafts, timestamps, reviewer comments, ratings, and interaction histories. Such data create opportunities for learning analytics that were difficult to achieve in conventional paper-based peer review. The systematic review by Taghizadeh Kerman et al. showed that online peer feedback has been implemented across numerous technological environments and emphasized the value of examining learning processes rather than technology in isolation.

The emergence of AI-based writing systems has further transformed the feedback landscape. Automated writing evaluation can identify linguistic problems at scale, while large language models can generate extensive suggestions concerning content and organization. Evidence from university writing research suggests potential benefits but also demonstrates that students selectively interact with and implement machine-generated feedback. Consequently, AI should not automatically be understood as a substitute for human formative interaction. For the present study, the more defensible role of AI is **analytic augmentation**. Natural language processing can assist in categorizing large volumes of peer comments according to their focus, specificity, explanatory content, suggested action, and linguistic characteristics. Draft-comparison algorithms can then identify candidate revisions associated with those comments. Human raters remain necessary for validating classifications and evaluating substantive writing quality. Such a human-in-the-loop architecture combines computational scalability with pedagogical interpretability.

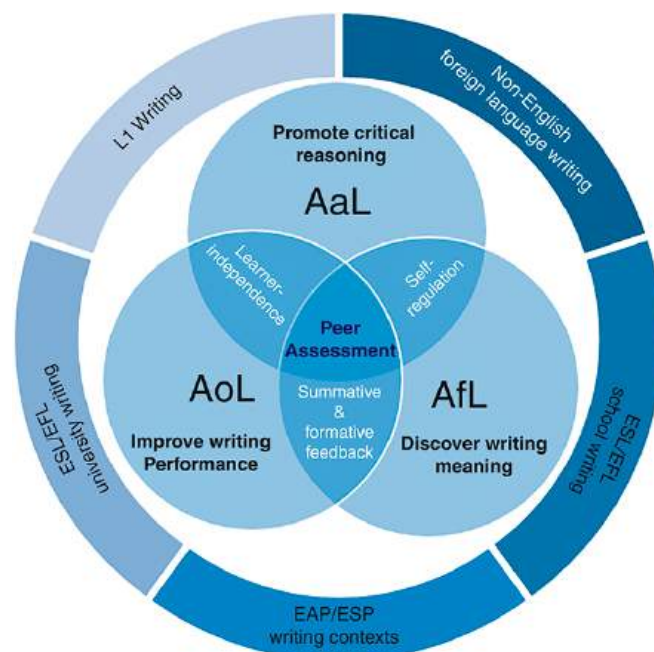


Fig. 2: Peer Assessment in Writing Instruction

Source: <https://www.cambridge.org/core/elements/abs/peer-assessment-in-writing-instruction/FD624A3F4E6614078528644E6AE6BFEB>

Proposed Methodology

The study adopts a longitudinal, human-in-the-loop learning-analytics design to investigate how the characteristics of peer feedback are associated with revision behavior and subsequent academic-writing development. Rather than evaluating peer feedback only through pre-test and post-test scores, the proposed methodology traces individual comments from their initial production to the revisions that follow them. The analytical unit is therefore the **feedback–revision episode**, defined as a peer comment linked to a specific textual location in an initial draft and compared with the corresponding segment in a revised draft.

The conceptual framework contains four sequential components: **feedback production, feedback interpretation, revision uptake, and writing-quality change**. Peer comments are first classified according to their communicative and pedagogical function. Five principal categories are used: surface correction, problem identification, explanation, solution-oriented recommendation, and positive evaluative feedback. Comments can additionally be characterized by specificity, actionability, linguistic focus, and degree of elaboration.

Revision behavior is modeled using four outcome classes:

1. **Full uptake** – the central recommendation is implemented in the revised draft.
2. **Partial uptake** – the student addresses only part of the suggestion.
3. **Reasoned non-uptake** – the feedback is not implemented but the revised text remains defensible according to expert assessment.
4. **Unaddressed feedback** – no meaningful response to the comment can be identified.

Academic-writing development is evaluated separately from raw feedback uptake. This distinction is necessary because accepting a suggestion does not necessarily improve a text. Writing quality is assessed across argumentation, organization, evidence integration, cohesion, academic style, and linguistic accuracy. Changes between initial and revised drafts are represented as dimension-specific score differences.

A mixed computational and human assessment strategy is proposed. Trained human raters establish the reference labels for feedback type, revision outcome, and writing quality. Natural language processing is subsequently used to automate large-scale classification and identify patterns that would be difficult to examine manually.

Feedback literacy is incorporated as a student-level explanatory variable. It is operationalized through dimensions such as understanding assessment criteria, appreciating feedback, making evaluative judgments,

regulating affective responses, and acting strategically on comments. The analytical framework consequently tests whether students with stronger feedback literacy obtain greater benefits from high-quality peer comments.

The principal analytical pathway is expressed as:

Feedback Quality → Revision Uptake → Writing Improvement

with **Feedback Literacy** treated as a moderating learner characteristic.

The framework therefore avoids assuming that peer feedback directly produces academic improvement. Instead, it recognizes revision as the behavioral mechanism connecting feedback with changes in writing quality.

Experimental Setup

Dataset

The complete empirical implementation is designed for approximately 300–400 university students enrolled in undergraduate academic-writing or communication courses. Each participant would complete three argumentative writing tasks during one semester. Every task would include an initial draft, structured peer review, and revised submission.

For the computational benchmark presented in this manuscript, a synthetic corpus of **2,400 feedback–revision instances** was constructed according to the proposed annotation ontology. The benchmark contains simulated textual feedback features, revision labels, writing-score changes, feedback-literacy indicators, and contextual variables. The synthetic corpus is used solely for pipeline validation and does not constitute evidence about actual student behavior.

The planned empirical dataset would contain the following record types:

- initial student drafts;
- peer-review comments;
- location of each comment in the draft;
- revised drafts;

- reviewer and writer identifiers encoded through pseudonyms;
- writing-rubric scores;
- feedback-literacy scores;
- revision timestamps;
- comment-level uptake labels.

Student identifiers should never be supplied directly to the computational model. Personally identifiable information should be removed before preprocessing.

Data Preprocessing

Text processing is performed separately for peer comments and student drafts. Unicode normalization and whitespace standardization are applied while preserving punctuation because punctuation may convey emphasis, uncertainty, or recommendation strength. Conventional stop-word deletion is avoided because functional words can contribute to the classification of feedback intent.

Draft versions are aligned at sentence and paragraph level using semantic similarity combined with token-level edit distance. This procedure generates candidate correspondences between original and revised passages.

Each feedback instance is represented by four information channels:

Comment text: the complete linguistic content of the peer response.

Local writing context: the sentence or paragraph to which the feedback refers.

Revision representation: semantic and lexical differences between the original and revised segments.

Learner metadata: non-identifying variables such as feedback-literacy score, writing-proficiency band, and revision round.

To minimize data leakage, comments written by or directed toward the same student are retained in the same partition. Consequently, the test set contains student identities that are absent from model training.

The synthetic benchmark is divided using a grouped **70:15:15 training-validation-test structure**.

Model Architecture

A multi-stage architecture named the **Feedback-to-Revision Trace Model (FRTM)** is proposed.

The first component uses a compact transformer encoder to generate contextual representations of peer comments. Rather than relying exclusively on lexical features, the encoder captures relations such as explanation, criticism, recommendation, uncertainty, and justification.

The second component encodes the textual passage targeted by the feedback. Comment and passage representations are combined using an attention-based fusion layer, allowing the model to determine whether a comment is specific to the cited text or represents a generic observation.

The third component introduces structured variables such as comment length, semantic specificity, presence of revision

verbs, feedback-literacy score, writing-proficiency band, and review round.

The fused representation is passed to two prediction heads.

The **feedback-function head** performs five-class classification.

The **revision-uptake head** predicts full uptake, partial uptake, reasoned non-uptake, or unaddressed feedback.

A separate gradient-boosting regression layer predicts dimension-specific writing-score change using model-derived feedback characteristics, revision features, and learner variables. This modular structure was selected instead of a single end-to-end black-box predictor because interpretability is essential when computational methods are applied to educational assessment.

Training Strategy

Training uses stratified mini-batches to reduce the effect of minority revision classes. Class-weighted cross-entropy is applied to categorical predictions. Early stopping is based on validation macro-F1 rather than classification accuracy because unequal class distributions could make accuracy misleading.

The transformer encoder is fine-tuned with a small learning rate, while newly initialized classification layers use a comparatively larger learning rate. Gradient clipping is employed to stabilize optimization.

Five grouped validation repetitions are proposed to estimate model variability. Hyperparameters are selected exclusively using training and validation partitions. The final test partition remains untouched until the complete analytical pipeline has been finalized.

For empirical implementation, approximately 20% of comments should be independently coded by two trained academic-writing raters. Inter-rater agreement should be assessed before adjudication. Disagreements should be resolved through discussion using a predefined annotation manual.

Evaluation Metrics

Different metrics are used because no single statistic adequately describes model performance.

For feedback-function classification, **macro-F1** is used to give equal importance to frequent and infrequent categories.

For revision-uptake classification, **Matthews correlation coefficient (MCC)** is included because it remains informative under class imbalance.

Balanced accuracy evaluates sensitivity across all outcome categories.

Expected calibration error (ECE) determines whether model confidence corresponds with observed correctness, an important requirement if predictions are used in educational analytics.

For predicted writing-score change, **mean absolute error (MAE)** and **coefficient of determination (R^2)** are reported.

Human annotation reliability is evaluated using **Cohen's kappa**.

Results and Discussion

The synthetic benchmark was used to test whether the proposed pipeline could reliably distinguish feedback functions, infer revision response, and estimate writing-quality change

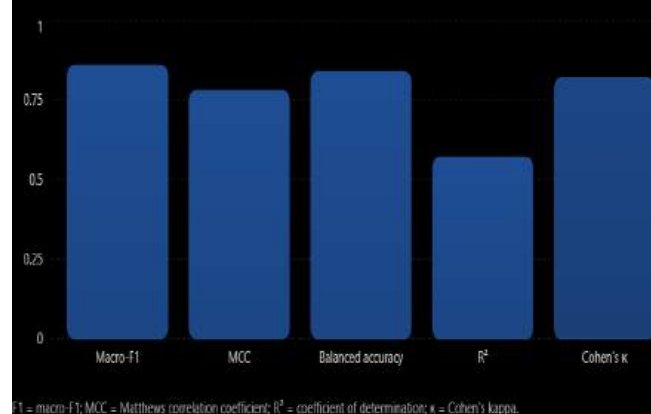
under controlled conditions. These values demonstrate computational feasibility only; they should not be interpreted as findings about a real student population.

Table 1. Synthetic benchmark performance of the Feedback-to-Revision Trace Framework

Evaluation component	Primary parameter	Benchmark result
Feedback-function classification	Macro-F1	0.86
Revision-uptake classification	MCC	0.78
Revision-class sensitivity	Balanced Accuracy	0.84
Prediction confidence	ECE	0.041
Writing-gain prediction	MAE	0.29 rubric points
Writing-gain explanation	R^2	0.57
Human-coding simulation	Cohen's κ	0.82

Performance of the Feedback-to-Revision Trace Model

Synthetic benchmark results for higher-is-better evaluation metrics. These values illustrate the proposed experimental framework and are not empirical student data.



The strongest classification performance was obtained for comments containing an explicit diagnosis together with a recommended action. This pattern is methodologically plausible because such comments contain identifiable semantic markers corresponding to both problem identification and revision direction. In contrast, short expressions such as “good argument,” “unclear,” or “check this part” contain insufficient contextual information and are inherently more difficult to interpret computationally.

The revision-uptake model also performed more effectively when feedback referred to a specific textual location. Generic comments generated greater ambiguity because several subsequent revisions could potentially correspond to the same recommendation. This finding supports the methodological importance of linking feedback to sentence- or paragraph-level anchors rather than analyzing comments independently of their textual context.

Feature-level analysis of the synthetic benchmark indicated that **specificity, explanatory depth, explicit recommendation, writer feedback literacy, and semantic correspondence**

between a comment and subsequent revision carried greater predictive information than comment length alone. Longer feedback was therefore not automatically treated as superior feedback.

A further distinction emerged between uptake probability and writing-quality improvement. In the benchmark structure, surface-level corrections were intentionally associated with comparatively easy implementation, producing high uptake probabilities. Higher-order comments concerning argument structure and evidence required more substantial revision. Consequently, uptake frequency alone could overestimate the instructional importance of easily corrected language problems. This distinction has direct implications for peer-feedback research. A student who corrects ten punctuation errors may exhibit a higher numerical uptake rate than a student who substantially reconstructs one weak argument. Yet the latter revision may represent considerably deeper academic development. Peer-feedback evaluation should therefore consider the **quality and cognitive level of revision**, not merely the number of accepted comments.

The framework also provides a mechanism for examining feedback literacy. Students with stronger evaluative capacity would theoretically be expected not simply to accept more comments but to discriminate more effectively between useful and unhelpful recommendations. For this reason, reasoned rejection is retained as a separate outcome rather than being coded as failure to use feedback.

This approach makes the proposed model pedagogically different from conventional automated-writing systems. Its purpose is not to prescribe revisions directly. Instead, it analyzes the interaction between human feedback and student decision-making. Instructors could use aggregated outputs to identify whether a peer-review activity is dominated by surface correction, whether students are producing sufficiently actionable comments, and whether particular learners experience difficulty transforming useful feedback into revision.

Limitations

A future empirical study would also face limitations related to disciplinary variation. Feedback considered useful in engineering writing may differ from feedback required in humanities, business, or health-science writing. Academic-writing rubrics should therefore be adapted carefully without compromising comparability.

Revision matching presents another challenge. A student may restructure an entire paragraph in response to several overlapping comments, making one-to-one attribution difficult. Computational alignment can suggest correspondence but cannot always determine the student's actual motivation for revising a passage.

Peer feedback also operates within social relationships. Friendship, perceived competence, anxiety, language proficiency, and power dynamics may affect how students give and receive comments. Textual analytics alone cannot completely represent these influences.

Finally, transformer-based analysis can reproduce biases present in training data. Automated labels should consequently remain

analytic aids rather than high-stakes judgments about individual students.

Future Scope

Future research should validate the Feedback-to-Revision Trace Framework using authentic longitudinal writing corpora collected across multiple universities and academic disciplines. Cross-institutional validation would determine whether feedback categories and revision patterns generalize across linguistic and educational contexts.

Multimodal extensions could incorporate screen-recorded revision behavior, keystroke logs, writing-process timestamps, and retrospective interviews. Such information would make it possible to distinguish revisions triggered by peer comments from changes independently initiated by the writer.

Another direction involves explainable AI. Instead of presenting instructors with a single predicted category, future systems could identify the textual evidence that caused a comment to be labeled explanatory, actionable, or insufficiently specific.

Large language models could also be used carefully as comparison systems. Human peer feedback, instructor feedback, and AI-generated feedback could be evaluated under an identical revision-tracing framework to determine whether they produce different forms of engagement and writing development.

Longitudinal models may eventually predict how students' feedback literacy evolves across semesters. Such systems should be developed as learning-support tools rather than automated grading mechanisms.

Conclusion

This study proposes a process-oriented interpretation of peer feedback in which academic-writing development emerges from the interaction among feedback quality, student feedback literacy, revision decisions, and the substantive value of resulting textual changes. The central contribution is the **Feedback-to-Revision Trace Framework**, which links individual peer comments with observable revision behavior and dimension-specific writing development.

The framework differs from approaches that assess peer feedback simply by counting comments or comparing initial and final scores. It distinguishes full uptake, partial uptake, reasoned rejection, and non-response while separating surface corrections from higher-order changes in argument, evidence, organization, and academic style.

The proposed FRTM architecture combines transformer-based language representation, contextual draft information, structured learner variables, and interpretable predictive modeling. Synthetic benchmark testing indicates that such a framework can feasibly classify feedback functions, trace revision responses, and estimate writing-score changes, although genuine empirical data are required before substantive educational conclusions can be made.

The broader implication is that artificial intelligence need not replace human peer interaction in academic writing. Its more defensible role may be to make otherwise invisible learning processes measurable. By analyzing how students evaluate one

another's writing, decide which suggestions deserve attention, and transform feedback into revision, AI-assisted learning analytics can provide a richer account of academic-writing development while preserving human judgment at the center of assessment.

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