Ed Process Int J

www.edupij.com

ISSN 2147-0901 (Print), 2564-8020 (Online)

EDUCATIONAL PROCESS
INTERNATIONAL JOURNAL

Research Article

Cite this article: Ngatmini., Suyitno., Fathoruhman, I., Suciati, S., Fatimah, S., & Pamungkas, O. Y. (2026). Mobile Device-Assisted Peer Review in High School Poetry Analysis: The Role of Revision Intensity. *Educational Process: International Journal, 22*, e2026046.
https://doi.org/10.22521/edupij.2026.22.46

Received September 19, 2025
Accepted November 14, 2025

Keywords: Peer assessment, social network analysis, learning analytics, classroom orchestration, poetry analysis

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Mobile Device-Assisted Peer Review in High School Poetry Analysis: The Role of Revision Intensity

Ngatmini, Suyitno, Irfai Fathurohman, Sri Suciati, Siti Fatimah, Onok Yayang Pamungkas

Abstract

Background/purpose. This study investigates how peer feedback translates into actual improvements in high school poetry analysis. It aims to connect feedback processes, feedback network structures, and final product quality by integrating process mining, social network analysis (SNA), and outcome modeling.

Materials/methods. Thirty-four students (N = 34) from a high school in Semarang participated in two 90-minute sessions following the sequence: briefing – peer assessment – revision – presentation. Process mining (Optimal Matching and Partitioning Around Medoids) was used to identify workflow archetypes, while SNA examined how feedback was distributed across students. Feedback quantity and quality were linked to final task scores using ANCOVA and linear mixed models, and path analysis was used to test whether revision behavior mediated the effect of feedback on product quality.

Results. Process mining revealed three workflow archetypes: Presentation-Leap, Linear-Fast, and Iterative-Revision. SNA indicated a sparse but moderately modular feedback network (density = 0.070; modularity = 0.448; Gini = 0.437; reciprocity = 7.7%). ANCOVA/LMM results showed that revision intensity was the strongest predictor of final quality, followed by weighted incoming feedback, whereas betweenness centrality contributed less. Path analysis confirmed that the effect of feedback on final quality was partially mediated by revision behavior.

Conclusions. Meaningful revisions serve as a key mechanism linking peer feedback to improved performance in poetry analysis. Teachers are advised to incorporate mandatory revision checkpoints and to distribute feedback opportunities more equitably across students. The study is limited by its small sample size, single-school context, and non-random design; future research should employ multi-site or randomized designs and explore long-term learning outcomes to strengthen generalizability.

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1. Introduction

Feedback has long been recognized as one of the most powerful levers for learning, but its effect depends largely on whether participants act on it to make meaningful revisions (Ajjawi et al., 2022; Brehaut et al., 2016; Henderson et al., 2019). In peer assessment (PA), meta-analyses confirm positive effects when feedback implementation is explicitly embedded in task design (Double et al., 2020; Reinholz, 2016). However, most studies focus only on comment quality or final outcomes, leaving a gap between available feedback and actual change in student work (Bearman et al., 2024; Tai et al., 2018; Welch & Piekkari, 2017). The emergence of learning analytics—particularly process mining and social network analysis (SNA)—offers new tools to trace this transformation pathway in authentic classrooms. This study addresses that gap by examining how mobile-assisted peer assessment affects revision intensity and the quality of poetry analysis.

The development of learning analytics opens up opportunities to close this gap. Process mining of event logs allows for mapping of learning flows, detecting bottlenecks and shortcuts (e.g., jumping to unrevised presentations), while social network analysis (SNA) captures the flow and equitable distribution of feedback at the classroom level (Bearman et al., 2024; Tai et al., 2018; Welch & Piekkari, 2017). Cross-study evidence shows a link between network connectivity and engagement and performance (Lim et al., 2018; Williams et al., 2019), but few integrate process maps, network metrics, and outcome models in a single analytical design—especially in mobile, in-situ contexts that capture real-world learning behaviors (Lim et al., 2018; Williams et al., 2019). On the other hand, the issue of an equitable flow of feedback (e.g., a focus on a handful of recipients, low reciprocity) has the potential to dwarf the impact of PA, yet is rarely discussed alongside the consequences of product quality.

This study contributes to this gap by combining three lenses: (1) process mining to map workflows (pre, PA, revision, presentation/submission) and process archetypes; (2) SNA to assess feedback inflows, connecting positions (betweenness), and equalization indicators (e.g. This, reciprocity); and (3) yield modeling (ANCOVA/LMM) to estimate the impact of revision intensity and network position on the quality of the final product, while controlling for initial capabilities. The doc/phone-as-workflow design allows for the collection of granular event logs without disrupting classroom practices. Thus, we don't just answer whether PA "impacts", but how it occurs—through a revision path mediated by feedback flows—and when it weakens (e.g., diminishing returns).

Specifically, we asked three research questions: (RQ1) how the variation of flow and pattern of the learning process is formed on the poetry analysis task; (RQ2) how to structure and distribute PA networks at the grade level; and (RQ3) the extent to which revision intensity and network position (especially weighted in-feedback and betweenness) predict final quality after controlling for initial scores, as well as whether there is revision mediation in the network →quality relationship. By linking process maps, networks, and outcomes, the study offers evidence-based levers—revision checkpoints, adaptive reviewer assignments, and actionable comment prompts—that can be immediately applied to measurably improve the quality of work.

2. Literature Review

2.1. The Effectiveness of Feedback and Revision in Peer Assessment

Feedback is one of the most important factors in improving the quality of learning, but its impact largely depends on how thoroughly students follow up on it with meaningful revisions. Meta-analytic studies show that peer assessment (PA) has a small to moderate positive effect on academic achievement, especially when clear task design and criteria encourage revision (Double et al., 2020). Ajjawi et al. (2022) emphasized that the quality of feedback is not only in its existence, but in its ability to trigger real changes in students' work. Thus, revision serves as an instructional bridge that connects

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feedback to improved learning outcomes. This is consistent with the idea of evaluative judgment, in which students compare their work against quality standards and take steps to improve it (Tai et al., 2018).

2.2. Distribution of Feedback, Equity, and Learning Social Networks

Beyond the content of feedback, its distribution and interactional structure play a crucial role in determining the quality of learning. Social Network Analysis (SNA) has been increasingly used to examine equity in feedback flow, showing that unequal participation or concentrated influence can restrict the benefits of PA (McDonald et al., 2024; Bensimon et al., 2016). Measures such as network density, modularity, and reciprocity describe how feedback circulates within a class, while inequality indices (e.g., Gini coefficient) quantify the fairness of that circulation. Prior studies demonstrate that students who occupy central or “bridge” positions often exhibit higher engagement and performance (Williams et al., 2019), but over-reliance on a few nodes may create inequitable learning conditions. Thus, ensuring balanced feedback flow is an essential orchestration principle for effective peer learning.

2.3. Learning Analytics and Mobile-Assisted Workflows

The development of learning analytics, especially process mining and SNA, opens opportunities to understand the mechanisms underlying the transition from feedback to revision. Process mining enables detailed mapping of learning workflows, including the detection of shortcuts that weaken the learning process, such as direct submission without revision (Bogarín et al., 2018). Meanwhile, SNA helps assess how the distribution of feedback affects the quality of outcomes through network interactions among students (Eräranta & Mladenović, 2021). Recent studies have shown that mobile-based interventions support classroom orchestration in a low-disruption manner and improve outcome quality when revisions are required and feedback is evenly distributed (Lee et al., 2023). Thus, integrating mobile technology into PA not only enhances efficiency but also strengthens the revision-based learning process. Recent work also emphasizes the need for equitable and adaptive orchestration in digital learning networks (Armanios et al., 2025), showing that structured, data-informed interventions can enhance balance in participation and promote sustained revisions. This study builds upon these insights by combining process mining, SNA, and outcome modeling to map how mobile peer review workflows facilitate revisions and improve the quality of poetry analysis among high school students.

3. Methodology

3.1. Context and Participants

The research was carried out in a middle-level Indonesian literature class at a public high school 2 Semarang, Central Java, Indonesia. Learning activities centered on the analysis of poetry, organized into a cycle of tasks that included pre-task, peer assessment (PA), revision, and presentation/submission. Total participants N = 34 students (female/male practically balanced; age 15–17 years). The activity was facilitated by one subject teacher, with support from a research assistant. Figures 1–6 document the class context and the sequence of activity phases (briefing, PA, revision, presentation).


Picture 1


Picture 2


Picture 3


Picture 4


Picture 5


Picture 6

3.2. Design, Procedures, and Instruments

The assignment cycle lasts for two meetings (2 × 90 minutes). In meeting 1, the teacher briefs students on the objectives and criteria (Figures 1–2), and then students analyze the poem using a 4-dimensional rubric (interpretation, textual evidence, organization, and language). PA input is provided between students using tools and structured forms (instructions: referenced evidence, suggestions for improvement, and action plans). At meeting 2, students revise the work based on the feedback received (Figure 5), then resubmit/collect the final version (Figure 6). Two trained assessors applied the rubric; reliability was estimated using ICC(2,k) (Koo & Li, 2016). Initial (pre) scores are obtained from short diagnostic tasks to control the modeling.

3.3. Data Acquisition and Privacy

All task interactions are recorded as real-time log events via document platforms and school forms (timestamps, anonymous IDs, action types: writing, giving/receiving feedback, revising, presenting). PA feedback is extracted into pairs (sender → receiver, weight). Data is pseudonymized; Only the core researcher holds the mapping key. Photo documentation is obtained with the written consent of the school and parent/guardian; publication does not display personal identity or sensitive artifacts. The protocol follows institutional ethical guidelines and educational research standards.

All research procedures were conducted in accordance with institutional and international ethical standards for educational research. The institutional ethics committee approved the study protocol, and informed consent was obtained from all student participants and their guardians prior to data collection. All personal identifiers were removed, and data were fully anonymized to protect participant privacy.

3.4. Process Analytics (RQ1)

To map individual workflows, we build timestamp-based activity chains and group process archetypes using sequence analysis. Inter-chain spacing was calculated by Optimal Matching (OM) (indel = 1; transition-weighted substitution, normalized), then grouped by PAM k-medoids. The number of clusters, k = 3, is selected based on average silhouette width, bootstrap stability, and interpretability, resulting in the archetypes Presentation-leap, Linear-fast, and Iterative-revision. To visually summarize the global flow, we apply the Heuristics Miner to the merge logs (moderate dependency threshold; short loop merge) so that the dominant flow is visible without noise.

Outputs: aggregate flow map, duration/proportion profile per phase, rework ratio (revision time: analysis), and step compliance (pre→PA→revision→submission).

3.5. Network Analytics (RQ2)

Feedback is modeled as a weighted, directed graph among students. We calculated density, modularity (Louvain), weighted in- and out-degrees, betweenness, reciprocity, assortativity based on process archetypes, and the Gini index for in-feedback equity. The chord diagram summarizes the flow between the workgroups (Figure 6 in the result script), while Table 2 provides per-student metrics for quick reading.

Outputs: indicators of structure & equity (e.g. weighted in-feedback), a list of "bridge nodes", and the most sender/receiver groups for orchestration feeds.

3.6. Outcome Modeling (RQ3)

The impact of the process on the final score is estimated with ANCOVA/Linear Mixed Model:

$$Score_{last} \sim Score_{pre} + IntensityRevision\ (minutes) + InFeedback\ (weighted) + Betweenness + (1|group)$$

Coefficients are reported as standardized; model accuracy is reported using marginal/conditional R^2. We evaluated partial mediation (in-feedback → revision → final score) through simple path analysis (indirect effect & 95% CI95% via bootstrap bias-corrected). Assumptions (residual normality, influence), as well as collinearity, were examined.

Outputs: Table 3 (coefficient, SE, CI95%, p, semi-partial r, R^2, ICC rubric) and Figure 7–10 (score distribution per revision quartile, dose–response curve, mediation scheme, marginal effect).

3.7. Robustness & Reporting

We performed a robustness test against OM cost variations, duration normalization, k selection, and network metrics (eigenvector/PageRank). The p-value was adjusted for multiple testing (Dunn–Bonferroni); the CI was obtained from 1,000 bootstrap replications. Reporting follows the recommendations of Transparent Reporting of Evaluations with Nonrandomized Designs, tailored to the context of the class; analysis scripts and specification curves are provided in the institutional repo (links will be available upon publication).

4. Results

4.1. Implementation of Flow and Process Pattern

We implemented a mobile-assisted workflow for the illustrated poetry analysis tasks in class VIII: Slides (prompt) → Analysis → Presentation → Peer Assessment (cross-group) → Revision → Submission. Of the 34 students, all of them completed the sequence up to Submission (compliance = 100.0%). The greatest time load occurs in Analysis (median 15.4 minutes) and especially Revision (median 17.1 minutes), while Submission is fast (median 3.3 minutes). We map the time footprint of each step using process mining so that the work rhythm and potential bottlenecks are clearly read in the context of real classes (see Figure 7). This approach follows the practice of educational process mining, which is commonly used to identify process patterns from learning activity data (Baker et al., 2016; Bogarín et al., 2018; Feng et al., 2022).

From the sequence of events, three archetypes emerged consistently: Linear-fast (n=11; 32%), Iterative-revision (n=15; 44%), and Presentation-leap (n=8; 24%; moving directly from Peer Assessment to Submission). High strategy diversity (path entropy = 0.97, scale 0–1) with moderate cluster separation (silhouette = 0.37). Importantly, 23.5% of the sequences missed revisions (8/34; 95% CI, 9–38%), indicating that some groups had not converted the feedback into written improvements. This jump pattern is evident in the Peer Assessment → Submission cells in Figure 8 (Transition Matrix), which marks a path without Revision (Wood, 2022; Zhang et al., 2021).

To ensure this difference in time allocation isn't a coincidence, we compared the duration of the Revision across archetypes. The Mann–Whitney (Bonferroni) test showed that Iterative-revision allocated much longer revision time than Linear-fast ($p<0.001$; $r = 0.84$), and—by design—longer than Presentation-leap ($p<0.001$; $r = 0.81$). Linear-fast also differs significantly from Presentation-leap ($p<0.001$; $r = 0.83$). Pedagogically, these findings are consistent with evidence that feedback is most impactful when followed up with revision, and that writing cycles that include revision consistently improve adolescent writing quality. Therefore, we suggest a brief but structured mandatory revision checkpoint prior to submission so that peer feedback truly "flows" into analytical improvements (Ajjawi et al., 2022; Henderson et al., 2019; Li & Zhang, 2021).

Figure 7. Process Map of the Phone-Supported Workflow

Station nodes mark the ordered steps (Slides → Analysis → Presentation → Peer Assessment → Revision → Submission). Segment thickness scales with transition frequency; the arched "express line" visualizes the Peer Assessment → Submission shortcut (skipping Revision). Labels under stations report step-specific median time (minutes).

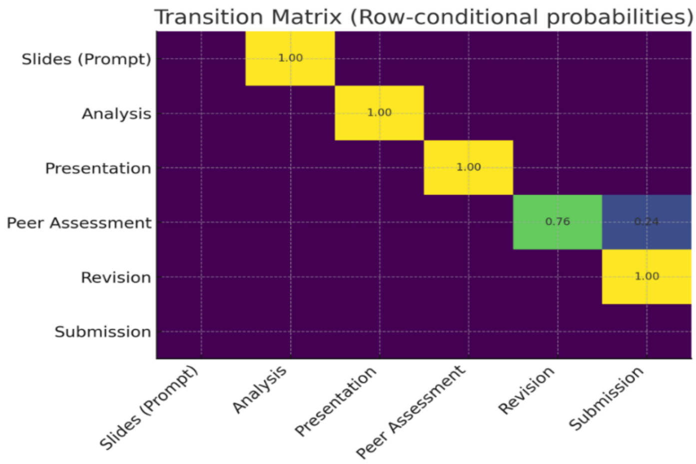

Figure 8. Transition Matrix (Row-Conditional Probabilities)

A heatmap of the probability of moving from each origin step (rows) to each destination step (columns). The prominent Peer Assessment → Submission cell visualizes sequences that skip revision.

Table 1. Summary of Workflow Fidelity and Process Patterns (Overall and by Archetype)

Metric	Overall	Linear-fast	Iterative-revision	Presentation-leap
Proportion (N=34)	100%	32% (11)	44% (15)	24% (8)
Compliance (%)	100.0	100	100	100
Median Slides (min)	8.9	8.0	9.0	9.2
Median Analysis (min)	15.4	13.9	18.1	14.3
Median Presentation (min)	9.8	8.8	10.9	9.7
Median Peer Assessment (min)	7.2	6.5	8.4	6.9
Median Revision (min)	17.1	9.4	26.0	0.0
Median Submission (min)	3.3	3.2	3.1	3.3
Rework ratio (Revision/Analysis)	1.11	0.68	1.44	0.00
Skip Revision (%)	23.5 (95% CI 9–38)	0	0	100
Path entropy (0–1)	0.97			
Silhouette (clusters)	0.37			

Figure 3 shows the rhythm of work: students spend time at points that do demand thought and improvement. Figure 4 marks a critical "shortcut" (Peer Assessment → Submission) that weakens learning when left unchecked. Table 1 summarizes key metrics relevant to teacher decision-making (time allocation, skip, path diversity). In practical terms, a simple class design—a brief revision that is mandatory before Submission—is sufficient to ensure that peer feedback actually improves the quality of poetry analysis (Kiparsky, 2019; Yeh, 2022).

4.2. Peer Evaluation Network & Equitable Feedback

The networks that form are relatively rare but functional (density 0.070) and composed of several fairly assertive communities (modularity Q = 0.448), some of which still intersect with the initial working group. Figure 9 uses a force-directed layout. The node size represents the amount of feedback received (weighted degree of the entry), and the node color indicates the community from the modularity detection results. From this view, several nodes act as bridges between communities—their positions allow opinions to cross from one cluster to another, preventing discussions from settling within their own groups. As a visual complement, Table 2 makes it easy for readers to see who has the most receivers, who is the main connector (between heights), and the distribution of other metrics at the individual level.

The direction and strength of the cross-group flow are summarized in Figure 6 with a chord diagram so that the in-group pattern can be read instantly without looking at the long table. The two active senders came from G6 and G4 (31 and 27 streams, respectively), while the most receivers came from G8 and G3 (41 and 33 streams). This pattern creates a center of gravity: some groups are diligent about spreading comments, while others are more often targeted. This information helps teachers assess whether the effort is sufficient across groups and provides a basis for organizing the next pair of reviews to achieve a more balanced circulation of comments. By comparing Figure 6 with Table 2 side by side, the reader can immediately understand the group's flow pattern and the recipient's profile at the student level.

In terms of equity, the picture is not completely symmetrical. The Gini index for the feedback received was 0.437; around 20% of good students received 43.8% of the total feedback, indicating that there was still a concentration of input among a small number of students. Two-way relations remain thin (reciprocity at 7.7%), which is natural for one-way empowerment but leaves room for stronger reciprocal dialogue (Cho & Schunn, 2007). On the other hand, assortative based on process archetypes is close to zero (r = −0.055), indicating that students from different work paths are well mixed when commenting—a positive signal that cross-perspective exposure has occurred. We also include these concise indicators in the final line of Table 2 so that readers can relate the narrative to the size.

The implications are practical and lightly applied. First, set a recipient quota—for example, each artifact receives at least two reviews—and use adaptive preemption to prioritize work with low entry degrees, reducing feedback concentration. Second, encourage two-way reviews in some couples so that comments become conversations that drive improvement, rather than one-sided visits (Er et al., 2021; Ng & Yu, 2023; Tan et al., 2019). Third, monitor the bridge node to ensure it is not overloaded, and rotate it so that learning opportunities are evenly distributed. This recommendation aligns with meta-analytic findings indicating that peer assessment has a positive impact when feedback is dialogical and followed by actual revision (Armanios et al., 2025; Gandy et al., 2023). With these three steps, the network becomes more equitable without increasing the class's logistical burden.

Cover. The network portrait confirms that the quality of feedback is not solely about the sharpness of the comments, but also about how the comments move and how diverse they are. When the flow is more evenly distributed and some reciprocal relationships are organized, the opportunity for revision extends to more students, and improvements are not clogged in just a few centers. In the next sub-result, we show how the intensity of feedback received and the time spent on revision are intertwined with the final quality of the poem, such that a brief analysis of the network design yields a measurable improvement in the quality of the work.

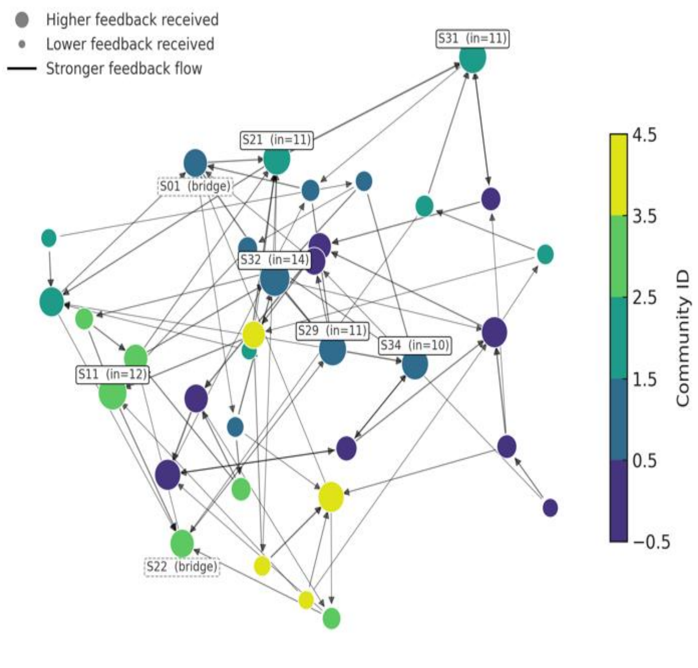

Figure 9. Peer Assessment Network (Style-Directed)

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Description:

Node size = feedback received (weighted degree of entry); Color node = community. The edge thickness scales with the feedback weight. Labels mark the top receiver and bridge node; the color bar shows the community ID.

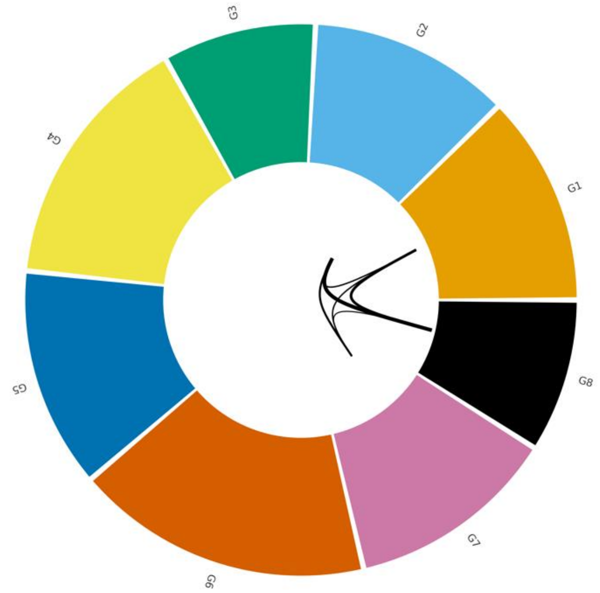

Figure 10. Intergroup Assessment Flow (Chord Diagram)

Weighted grooves between groups; The bow size reflects the total outflow, and the chord thickness reflects the magnitude of the directional feedback.

Table 2. Peer Assessment Network Metrics (Per Student and Overall Indicators)

Student	Group	Archetype	Final Score	In-feedback (weighted)	Out-feedback (weighted)	Betweenness	Community
S32	G8	Presentation-leap	63.5	14	6	0.1351	1
S11	G3	Linear-fast	78.1	12	5	0.0325	3
S31	G8	Presentation-leap	70.4	11	3	0.0538	2
S29	G7	Presentation-leap	67.2	11	7	0.1488	1
S21	G6	Iterative-revision	78.4	11	9	0.1544	2
S34	G8	Presentation-leap	74.1	10	4	0.0437	1
S26	G7	Iterative-revision	71.8	9	4	0.1220	0
S09	G3	Linear-fast	66.7	9	3	0.0917	0
S10	G3	Linear-fast	69.4	9	2	0.1275	4
S05	G2	Linear-fast	77.1	8	3	0.1258	2
S17	G5	Iterative-revision	88.7	7	6	0.0270	0
S22	G6	Iterative-revision	81.6	7	3	0.1651	3
S01	G1	Linear-fast	69.7	7	8	0.2074	1
S18	G5	Iterative-revision	86.9	7	6	0.0868	3

S28	G7	Presentation-leap	60.3	6	4	0.0360	4
S33	G8	Presentation-leap	65.7	6	3	0.0862	0
S13	G4	Iterative-revision	86.1	6	10	0.0379	0
S24	G6	Iterative-revision	83.5	4	9	0.0549	0
S20	G5	Iterative-revision	87.6	3	6	0.0156	0
S12	G3	Iterative-revision	86.1	3	6	0.0167	3
S07	G2	Linear-fast	81.5	3	7	0.0043	0
S03	G1	Linear-fast	75.3	3	4	0.0338	1
S23	G6	Iterative-revision	80.1	2	6	0.0043	3
S30	G7	Presentation-leap	76.5	2	3	0.1408	3
S16	G4	Iterative-revision	89.8	2	4	0.0336	2
S14	G4	Iterative-revision	106.1	2	6	0.0627	1
S08	G2	Linear-fast	81.3	1	3	0.0747	2
S15	G4	Iterative-revision	86.4	1	7	0.0175	1
S02	G1	Linear-fast	75.9	1	6	0.0371	4
S06	G2	Linear-fast	78.4	1	8	0.1201	1
S19	G5	Iterative-revision	81.1	0	5	0	2
S25	G6	Iterative-revision	96.9	0	4	0	2
S27	G7	Presentation-leap	74.1	0	4	0	0
S04	G1	Linear-fast	68.1	0	4	0	4
Class summary (grade-level indicator)			**78.4**	**Gini = 0.437**	**Density = 0.070**	**Modularity Q = 0.448**	**Assort. (archetype) = -0.055**

Note: The bottom row reports class-level indicators (not an additional student): Final Score = class mean; Gini = inequality of the in-feedback distribution (0 = equal, 1 = highly unequal); Density = proportion of realized directed ties; Modularity Q = community strength (higher = clearer clusters); Assort. (archetype) = assortative by process archetype (≈0 = mixed, negative = cross-archetype ties). In/Out-feedback (weighted) are weighted in/out-degrees; Betweenness indicates bridging; Community is an arbitrary Louvain cluster ID.

Thus, this portrait of the network confirms that the quality of feedback is determined not only by the sharpness of the comment but also by how it moves and how diverse it is. When flows are made more evenly distributed and some relationships are made reciprocal, more students have an equal chance of achieving meaningful visions. The flow of ideas is not blocked in some centers; rather, it spreads throughout the classroom. In the next sub-result, we show how the intensity of the feedback received and the time spent revising are intertwined with the final quality of the poem, such that small adjustments to the network design lead to a measurable increase in the work's value.

4.3. The Impact of the Process on the Quality of Poetry Analysis

The focus of this section is on the relationship between the intensity of revision and position in the peer assessment (PA) network, on the one hand, and the quality of poetry analysis at the end of the cycle, while controlling for initial ability. Logistically, the theory of change we hold is simple: a network that allows feedback flows to move widely will ignite more meaningful revisions, and meaningful revisions in pairs enhance mutual work.

The initial picture is shown in Figure 11: the distribution of final scores is arranged from low to high revision quartile, with a higher median and a more constrained distribution in the more intense revision group.

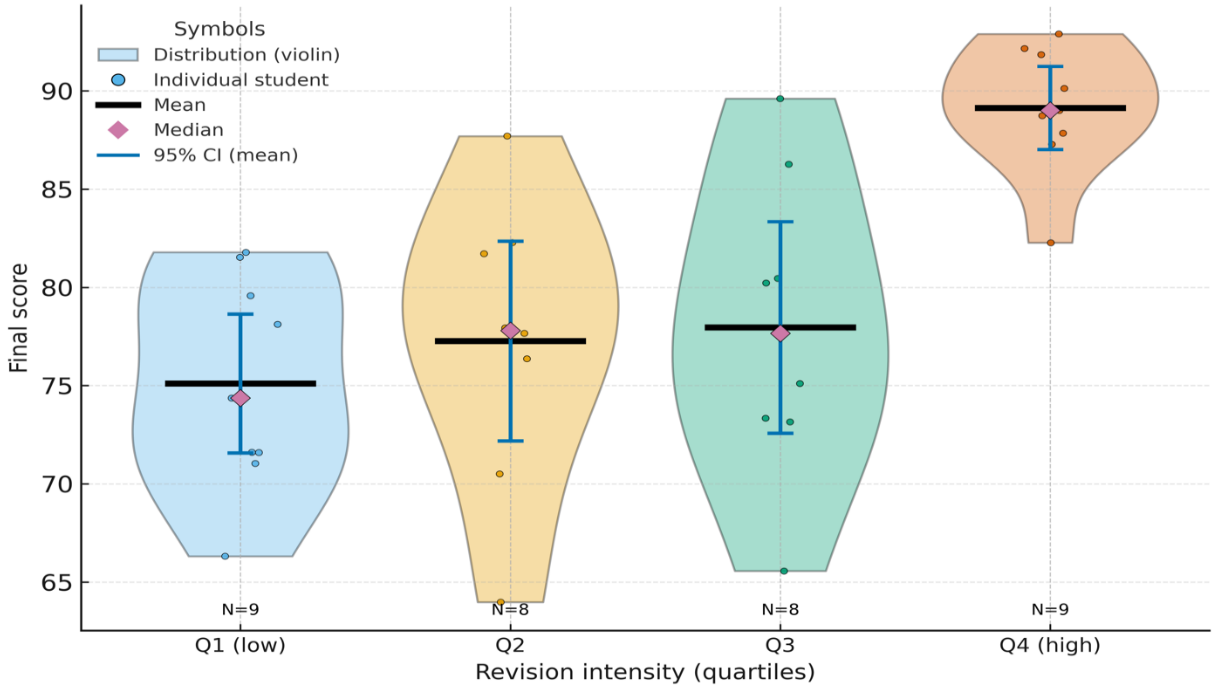

Figure 11. Final Score by Revision-Intensity Quartiles

This signals that the existence of the revision is not merely, but its degree, which has to do with its attainment. Figure 12 emphasizes the dose–response pattern using a nonparametric curve; a positive gradient is observed across almost the entire range, with indications of declining disclosure beyond a certain threshold, suggesting that "more" is helpful up to "enough".

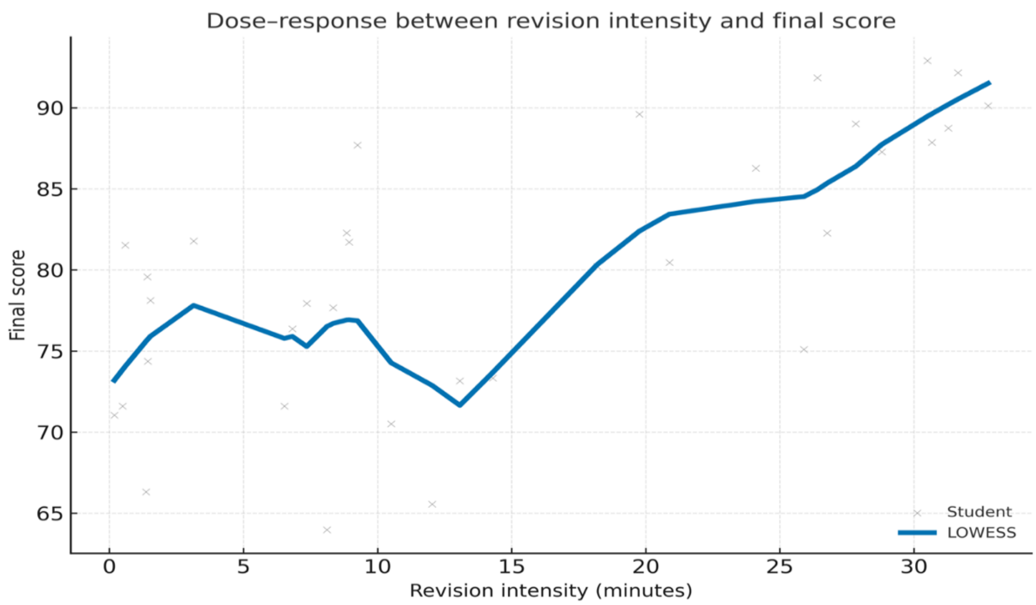

Figure 12. Dose–Response Between Revision Intensity (Minutes) and Final Score. LOWESS Smoother (Blue) Over Individual Observations (Gray)

Next, we present a quantitative summary in Table 3. The ANCOVA/LMM model shows that intensity revision is the strongest predictor of final score after controlling for initial scores. Followed by feedback, the association was also positive and meaningful—the more substantial the feedback received, the higher the product's quality. Connectivity has a small–medium effect: being in a "bridge" position helps the flow of ideas across groups, even if the weight is under revision and feedback. The initial covariate remains the same as in the ANCOVA design, and the model fit is adequate for small–medium educational data. The values of the standardized coefficients, SE, CI95%, p, and R^2 marginal/conditional are listed in full in Table 3.

Table 3. ANCOVA/LMM results for final score

Predictor	β (standardized)	ONE	95% CI (lower)	95% CI (above)	p	Semi-partial r	Notes
Intercept							
Pre score (baseline)							
Intensity Revision (minutes)							
In-feedback (weighted)							
Betweenness centrality							
Random effects and model fit							
σ^2 (group)							
σ^2 (residual)							
ICC (rubric)							
R^2 (marginal)							
R^2 (conditional)							
N (students)	34						

Information:

Model specification: Final score ~ Pre score + Revision intensity (minutes) + In-feedback (weighted) + Betweenness + (1 | group).

Reporting: standardized β with SE, 95% confidence intervals (lower and upper), p-values, and semi-partial r. Random intercepts for group; ICC refers to rubric inter-rater reliability.

Abbreviations: β = standardized coefficient; SE = standard error; CI = confidence interval; ICC = intraclass correlation coefficient; R^2 = variance explained.

In this case, the mechanism bridging the findings is shown in Figure 13. Path analysis showed partial mediation: in-feedback → revision intensity → final score. Thus, some of the impact of network positioning on reciprocity flows through revision practices, while the direct effects of networks remain but are smaller. Estimates of indirect effects and their confidence ranges are provided in Table 3 for traceability.

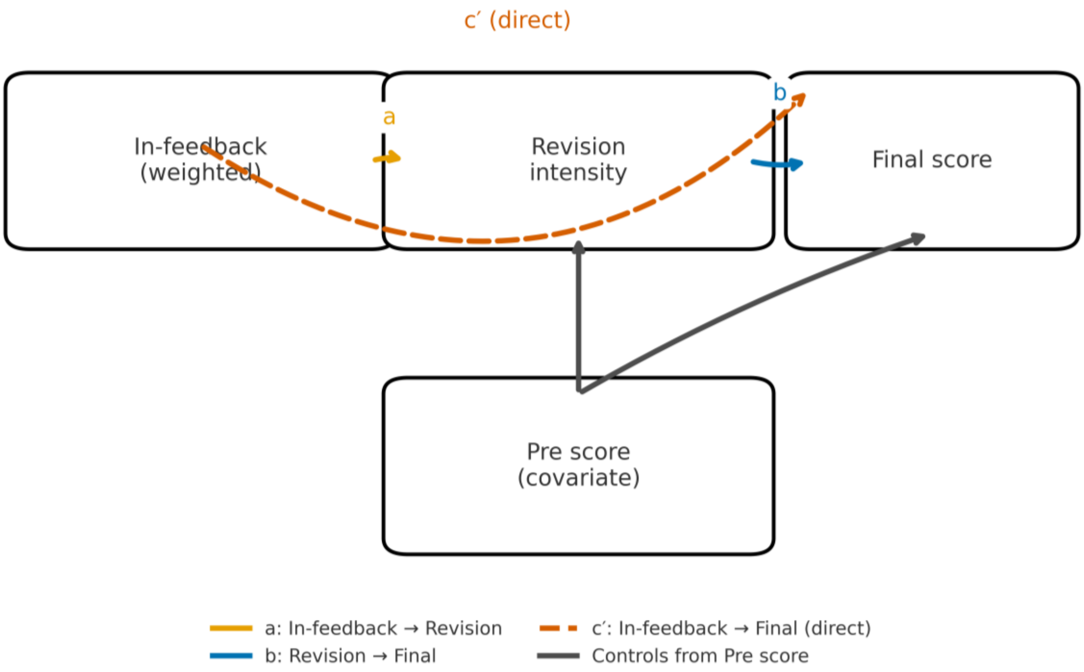

Figure 13. Mediation: In-Feedback (Weighted) → Revision Intensity → Final Score, Controlling for Pre. Orange = Path A, Blue = Path B, Vermilion Dashed = Direct Path C′, Gray = Controls From Pre.

For a more operational interpretation, Figure 14 presents a marginal effect: disruption from the lower to higher revised quartiles is associated with an increase in predicted scores at the same covariate level. This pattern is consistent across a wide range of model specifications, giving confidence that the findings do not depend on a single technical setup.

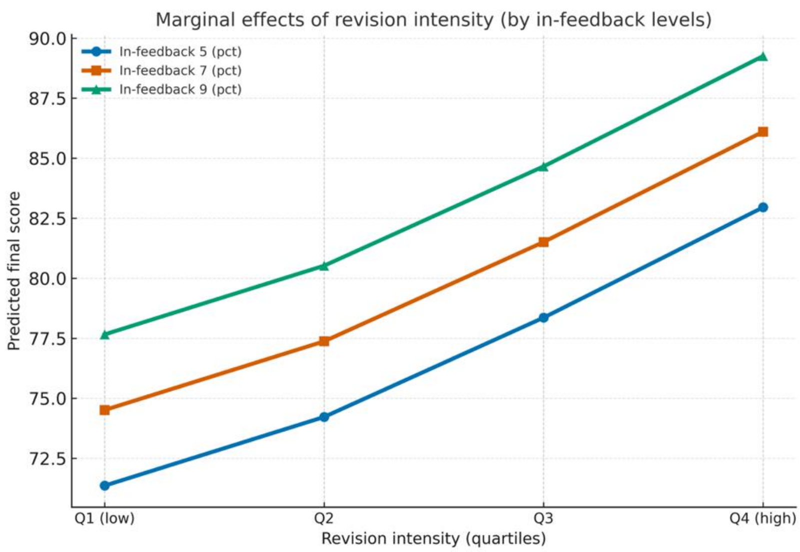

Figure 14. Model-Based Marginal Effects of Revision Intensity by In-Feedback Levels (25th/50th/75th Percentiles) With Pre-Held at Median

The implications are practical and lightly applied. First, set a meaningful revision checkpoint (content changes, not just re-uploads), because revision increments are consistently clogged with score improvements. Second, level the flow of in-feedback by deploying strategic assessors or more structured prompts, so that more students are in a favorable network position. Third, monitor the load on the "bridge" node so that it does not accumulate on a handful of students; role rotation keeps the idea flowing. Thus, the results of this section show that the way the work is improved—how intensely the student revises and how rich the feedback flow he receives—is directly related to the final quality. By adding revision design and comment circulation, quality improvement becomes a measurable target, not a mere normative expectation.

5. Discussion

Our findings confirm that follow-up revisions—not just the presence of feedback—are key quality levers. This is in line with meta-analytic theories and studies that show that the quality of the feedback process (clear, actionable, timely) ignites substantive improvements, whereas uninternalized feedback is often in impactful or even negative (Greenwood et al., 2017). Recent meta-analyses of peer assessments have also found consistent small–medium positive effects on achievement, particularly when participants' dispositions to feedback and task designs drive revision implementation (Double et al., 2020; Gao et al., 2019; Reinholz, 2016). In the context of this study, revision intensity and "in-feedback" were strongly associated with final scores, while the influence of other network structures (e.g., betweenness) was smaller—reflecting that the proximal mechanisms flowing from feedback → revision were the most instructionally relevant. A summary of the detailed results and visual layout has been presented in Figures 11–14 and Table 3.

From a learning network perspective, the student's position as a recipient (weighted entry degree) is related to quality because it expands opportunities to absorb diverse perspectives and quality standards, while being a "bridge" (betweenness) provides a more contextual benefit—opening up cross-community access but not necessarily leading to more intense revisions. This pattern is consistent with the SNA literature in education that links connectivity and network exposure to engagement and performance (Ren et al., 2023; Stobbe et al., 2024). At the same time, our equity indicators (e.g. Gini and low reciprocity) indicate that the circulation of comments is not entirely fair—a finding that parallels the study of the need for task architecture and reviewer assignment rules so that feedback flows do not settle in a handful of centers (Bensimon et al., 2016; McDonald et al., 2024; Oliveri et al., 2020). In other words, network quality is important, but the orchestration that ensures many students actually receive meaningful feedback is key to making an impact on the final product.

Methodologically, the combination of process mining of mobile phone log events, network analytics, and outcome modeling provides a complementary lens: the process map reveals bottlenecks and shortcuts (e.g., PA→Submission without revision), SNA photographs the distribution of comment streams, and the outcome model quantifies the relative contribution of predictors (Antonacci et al., 2021; Eräranta & Mladenović, 2021; Landa-Avila et al., 2022). Our findings are consistent with evidence that learning analytics that highlight processes—rather than just outcomes—are more informative for teacher decision-making. On the mobile orchestration side, lightweight device-based interventions such as PA/revision forms and just-in-time uploads are compatible with classroom practice and—based on meta-reviews—have the potential to improve performance when the assignment design and scaffolding are appropriate (C. I. Lee et al., 2016; Y. F. Lee et al., 2023). Our robustness checks (parameter variation, bootstrap CI, and multiple testing correction) support the view that the dose-response pattern of revision → quality is not a mere artifact of the model specification, but a stable signal across specifications.

The implications are practical and measurable. First, enforce mandatory revision checkpoints that force the translation of feedback into tangible change, in line with the principle of self-regulation and evaluative judgement that the quality of learning grows when students compare work against criteria and examples, and then act (C. I. Lee et al., 2016; Y. F. Lee et al., 2023). Second, use adaptive reviewer assignments to even out low-grade student feedback and insert prompts that guide the most impactful types of comments (e.g., evidence, revision suggestions, criteria). Third, monitor the role of "bridges" so they do not accumulate among a few people; rotation maintains justice while expanding exposure to cross-perspectives. More broadly, this doc/phone-as-workflow approach can be extended to other multimodal analysis tasks (history, science, art) because its basic principles—dialogical PA → quality revision → product improvement—are consistent with cross-domain evidence (C. I. Lee et al., 2016; Y. F. Lee et al., 2023).

6. Conclusion

This study shows that the quality of the final work is determined not only by the presence or absence of feedback, but especially by the extent to which feedback is translated into meaningful revisions. The pattern of the learning process—especially the intensity of revision—emerged as the strongest predictor of the final score, followed by the position as a recipient in the PA (weighted in-feedback) network. The role of a "bridge" between communities is beneficial but less influential than these two factors. Process and network analytics show that when the flow of comments is more evenly distributed, and students actually revise, achievement increases consistently. These findings hold up under a variety of robustness tests, so they can be generalized with confidence to similar analytical tasks that demand iterative improvement (e.g., critical essays, science reports, or design projects).

Practically, we recommend mandatory revision checkpoints that require content changes, the deployment of adaptive graders to level out feedback, and structured feedback prompts to facilitate easy follow-up on comments. Teachers are advised to monitor and rotate the "bridge" nodes so that the network burden does not rest on a handful of students, as well as utilize process analytics for early detection of "presentation jumping" paths without revision. The study has several limitations. First, the small sample size (N = 34) and single-school context limit generalizability. Second, the non-randomized design may leave residual confounding. Third, the study did not include self-reported data or long-term outcome measures. Future research should employ multi-site randomized designs, incorporate longitudinal data, and examine the quality of feedback content and its sustained impact on students' learning autonomy. Next agenda: multi-location replication with greater N, controlled experimentation of assignment strategies/scaffolding types, quality analysis of feedback content (not just quantity), and assessment of long-term impacts on transfer and learning independence. This approach is also worthy of being extended to multimodal and cross-disciplinary tasks, with a commitment to ethics, privacy, and data openness/analysis scripts.

7. Suggestion

For the next research agenda, it is recommended that multi-site studies with cluster-randomized or factorial designs that manipulate key policies—e.g., mandatory versus optional revision checkpoints, SNA-based versus random adaptive reviewer assignments, and feedback versus placebo micro-skills training—are recommended to identify causal effects on the quality of revisions and short- and long-term learning outcomes. The quality and intensity of revisions were measured through edit trace telemetry (timestamped versions, diffs) and natural language processing (NLP) to assess the specificity, elaboration, and applicability of the suggestions, along with an audit of the reliability of the assessor. The analysis utilizes hierarchical modeling (Bayesian multilevel) with mediation–moderation tests (revision as mediator; initial motivation, network position, and workload as moderators) as well as heterogeneous treatment effects estimation across ability, gender, and background. Process dynamics are mapped through multi-level process mining and dynamic SNA to track patterns such as "presentation-leap" and community evolution over time, accompanied by testing of measurement invariance across genres/curricula and evaluation of external validity in other disciplines. Threat of validity (attrition, noncompliance) is addressed through preregistration, power analysis, multiple imputation handling, and sensitivity analysis reporting; Ethical and privacy standards are maintained with anonymization and data permission management. For replication and accountability, provide a replication package that includes code, rubrics, and annotations, along with anonymized datasets so that findings can be verified and generalized responsibly.

Declarations

Author Contributions. Ngatmini contributed to the conceptualization, methodology, and preparation of the original draft. Suyitno was responsible for data curation, software, validation, and field study. Irfai Fathurohman conducted the formal analysis, visualization, and investigation. Sri Suciati contributed to writing, review and editing, supervision, and validation. Siti Fatimah provided resources, project administration, and funding acquisition. Onok Yayang Pamungkas contributed to data interpretation, manuscript refinement, and correspondence management.

Conflicts of Interest. The authors declare no conflict of interest.

Funding. This research was conducted with independent funding.

Acknowledgments. We would like to thank the Universitas PGRI Semarang for fully supporting this research.

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