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Exploring Discourse Features of Peer Feedback and Their Role in Promoting Deep Learning in Blended Teaching

Ruiwen Song *, Amelia Alias , Khairul Azhar Bin Jamaludin 

Fakulti Pendidikan (FPEND), Universiti Kebangsaan Malaysia, Selangor 43300, Malaysia

ABSTRACT

Deep learning has become a central theme in contemporary educational reform, representing a critical indicator of learning quality. Peer feedback, as an interactive and learner-centered approach, has been shown to foster students' cognitive and meta-cognitive growth and holds significant potential for facilitating deep learning. This study constructed a peer assessment framework to promote deep learning in blended teaching and designed corresponding activities and implementation procedures. Drawing on CIMO-logic, the study examined how peer assessment triggered mechanisms such as personal engagement, seeking and providing relevant feedback, iterative exploration, and understanding one's own learning process. Data were collected through the SOLO taxonomy, rubrics, and questionnaires, complemented by discourse analysis of peer feedback comments. The linguistic analysis revealed that metalinguistic explanations and elicitation questions were associated with cognitive and ability development, while praise and politeness strategies primarily supported emotional engagement. The findings provide empirical evidence that peer assessment promotes deep learning across cognitive, ability, and emotional dimensions, and demonstrate that linguistic strategies in feedback are integral to how students process and internalize learning. This study provides theoretical insights into the occurrence of deep learning and offers practical implications for designing peer feedback activities to enhance learning quality in blended educational settings.

Keywords: Peer Feedback; Deep Learning; Blended Teaching; Discourse Features

*CORRESPONDING AUTHOR:

Ruiwen Song, Fakulti Pendidikan (FPEND), Universiti Kebangsaan Malaysia, Selangor 43300, Malaysia; Email: P150181@siswa.ukm.edu.my

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1. Introduction

In contemporary education, the emphasis has shifted from rote memorization and surface-level knowledge acquisition to cultivating deep learning, which prioritizes higher-order thinking, sustained engagement, and knowledge transfer across contexts. Deep learning is essential for equipping students with the adaptability and problem-solving skills required in the 21st century, as it involves not only understanding new concepts but also linking them to prior knowledge and applying them in novel situations^[1,2].

Blended learning, which strategically integrates digital technologies with traditional classroom instruction, has emerged as a key context for achieving these goals. On the one hand, it creates opportunities for personalized and resource-rich learning environments; on the other hand, its effectiveness depends largely on pedagogical design rather than the mere presence of technology^[3,4]. A central challenge for educators, therefore, lies in identifying instructional strategies that reliably foster deep learning in such hybrid settings.

Among various approaches, peer assessment has attracted increasing attention as a promising pedagogical strategy. By requiring students to evaluate the work of their peers, it promotes critical reflection, meta-cognitive awareness, and evaluative judgment, while also cultivating communication and collaboration skills. Research has consistently demonstrated its benefits: meta-analyses have shown significant gains in students' performance and critical thinking when peer feedback is integrated into instruction^[5]; further, concepts such as feedback literacy^[6] highlight how the ability to generate and act upon feedback is central to leveraging its full potential. More recent studies further suggest that the linguistic and dialogic features of feedback are not neutral but directly shape how students engage with and benefit from peer assessment^[7,8].

The significance of this inquiry is particularly salient in the Chinese context. Since the introduction of Educational Informatization 2.0 in 2018, China has shifted its strategic focus from building digital infrastructure toward integrating technology into pedagogy to improve teaching quality and cultivate deep learning. This policy remains foundational, as subsequent initiatives such as the Smart Education of China platform (2021) and the discussions at

the 2024 World Digital Education Conference reaffirmed deep learning as a core educational goal^[9]. The transition from the earlier "3C" framework (Connection, Content, Cooperation) to the "3I" framework (Integration, Intelligence, Internationalization) underscores that the ultimate aim is not technology per se but the development of higher-order competencies through its pedagogical integration. In this regard, investigating peer assessment in blended learning environments responds directly to China's educational modernization agenda while contributing to the global discourse on effective deep learning strategies.

Despite the well-documented benefits of peer assessment, critical gaps remain in the literature. First, while positive outcomes are consistently reported, the causal mechanisms by which peer feedback translates into deep learning are not sufficiently explained^[10]. Second, the linguistic and pragmatic features of feedback comments remain underexplored, even though discourse moves such as questioning, hedging, and praise have been shown to influence students' cognitive and emotional engagement^[11,12]. Third, there is a lack of robust explanatory frameworks that systematically connect the context, intervention, mechanism, and outcomes of peer assessment, limiting both theoretical clarity and practical applicability^[13].

To address these gaps, this study aimed to:

RO1: Examine how peer assessment in a blended learning environment influences students' cognition, ability, and emotion.

RO2: Analyze the discourse features of peer feedback comments and explore their relationship with deep learning outcomes.

RO3: Construct a systematic framework, grounded in CIMO-logic, that explains the mechanisms through which peer assessment promotes deep learning.

By integrating multiple data sources, including SOLO taxonomy, rubrics, questionnaires, and discourse analysis, this study seeks to provide both theoretical insights and practical implications for implementing peer assessment in blended teaching environments, particularly within the context of China's educational digitalization initiatives.

2. Literature Review

2.1. Deep Learning

Deep learning in education emphasizes meaningful understanding, transfer of knowledge, and the cultivation of higher-order thinking, in contrast to surface learning, which is often limited to memorization and reproduction^[14]. Within pedagogy, deep learning is commonly conceptualized through three interrelated dimensions: cognition, ability, and emotion. Cognition refers to the development of knowledge structures and meta-cognitive awareness; ability concerns the acquisition and application of skills in authentic contexts; emotion relates to motivation and affective engagement that sustain learning processes^[4].

Recent scholarship has further refined these dimensions in blended and technology-supported settings. Weng et al.^[15] demonstrated that design-based learning effectively fosters deep learning by aligning pedagogical design with higher-order cognitive tasks. Shi and Lan^[16] highlighted the roles of self-efficacy and motivation as crucial factors influencing students' deep learning in blended courses, confirming the necessity of considering both internal learner characteristics and external instructional supports. Similarly, Tian et al.^[17] found that higher-order thinking is strongly linked to the development of digital literacy, underscoring the interplay between cognitive, affective, and technological dimensions in deep learning. Collectively, these findings establish a robust theoretical foundation for examining how peer assessment can stimulate cognition, ability, and emotion within blended teaching.

2.2. Peer Assessment

Peer assessment, where students evaluate and provide feedback on peers' work, has become a well-established strategy for promoting both formative and summative learning outcomes. A meta-analysis by Huisman et al.^[18] confirmed that formative peer feedback has significant positive effects on higher education students' performance, providing evidence that it enhances cognitive understanding, practical abilities, and motivational engagement. Importantly, peer assessment benefits not only feedback recipients but also providers, who gain meta-cognitive

awareness and internalize evaluation standards through the process of comparison^[14].

Central to this mechanism is the concept of feedback literacy, defined as the ability to interpret, act upon, and generate effective feedback^[6]. Developing feedback literacy ensures that students do not merely receive information but engage in reflective and dialogic processes, thereby deepening learning. Wu and Zhao^[8] advanced this perspective by employing multimodal data, such as eye-tracking and EEG, to examine peer feedback mechanisms in virtual environments. Their results revealed that structured peer dialogue was especially effective in fostering deep learning, offering robust empirical evidence for the role of peer interaction in activating cognitive and affective mechanisms. These studies confirm that peer assessment operates not only as an evaluative tool but also as an instructional intervention that catalyzes deep learning processes.

2.3. Blended Learning Environments

Blended learning integrates face-to-face and online learning experiences, providing both flexibility and opportunities for interaction. However, its effectiveness depends on thoughtful instructional design rather than the mere adoption of technology^[19]. Recent systematic reviews have underscored this point. De Bruijn et al.^[20] synthesized evidence on interventions that promote engagement in blended environments, highlighting strategies that balance autonomy with support. Similarly, Luo and Zhou^[21] emphasized that self-regulated learning strategies are critical for success in blended learning, as they align with the autonomy and meta-cognition required for deep learning.

Empirical studies have also shown the pedagogical affordances of blended models. Heilporn et al.^[22] demonstrated that structuring pre-class online tasks to prepare for in-class discussions enhances both engagement and deeper understanding. Essa^[23] further confirmed that hybrid approaches can promote "academic mindfulness," integrating affective engagement with cognitive effort. Azimi^[4] argued for redesigning blended courses for the "social media generation," suggesting that integrating digital scaffolds with in-person dialogue enhances critical thinking and problem-solving. These findings position blended learning as an optimal context for implementing peer assessment, where online platforms facilitate asynchronous, reflective

peer review, and classroom sessions provide opportunities for dialogue and application.

2.4. Discourse and Linguistic Features of Peer Feedback

Beyond its structural design, the effectiveness of peer assessment critically depends on the linguistic form of feedback comments. Research shows that discourse features, such as metalinguistic explanations, elicitation questions, and praise, mediate how feedback influences cognition, ability, and emotion^[7]. Corpus-based and discourse-analytic studies confirm that specific pragmatic strategies shape feedback uptake. For example, Raphalen et al.^[24] computationally identified hedging strategies in peer tutoring and found that hedges softened criticism and increased the likelihood of feedback acceptance. Similarly, Poucke^[25] investigated appraisal strategies in higher education feedback and showed how stance-taking influenced student perceptions of feedback quality.

Computational approaches now allow for large-scale analysis of feedback discourse. Bauer et al.^[26] proposed a cross-disciplinary framework that connects linguistic features with feedback utility, while Abdi et al.^[27] developed deep learning models that integrate linguistic knowledge to evaluate student comments with high accuracy. These methods highlight the potential of natural language processing (NLP) to assess and enhance peer feedback quality.

For educational practice, mapping linguistic features to learning dimensions provides practical insights. Metalinguistic explanations promote cognitive restructuring by clarifying rules and principles^[28]; elicitation questions scaffold ability by prompting problem-solving and reflection^[29]; and praise fosters positive emotions that sustain motivation^[30]. Together, these findings affirm the centrality of discourse in understanding how peer feedback contributes to deep learning.

The literature demonstrates that deep learning is best fostered when pedagogy, learner attributes, and technology are aligned; peer assessment has robust empirical support as a catalyst for such learning; blended learning environments provide fertile ground for implementation; and discourse features critically mediate the impact of feedback. However, several gaps remain. First, while many studies confirm the effectiveness of peer assessment, fewer ex-

plicate the mechanisms that connect feedback to the three dimensions of deep learning. Second, the discourse of peer feedback has received increasing attention, but its linkage to cognition, ability, and emotion in blended teaching remains underexplored. Finally, although blended learning is widely studied, few works employ a systematic framework such as CIMO-logic to model how peer feedback interventions operate in specific contexts.

This study addresses these gaps by analyzing peer feedback discourse, examining its effects on deep learning outcomes across cognition, ability, and emotion, and constructing a CIMO-based framework to explain the mechanisms through which peer assessment fosters deep learning in blended teaching environments.

3. Methods

3.1. Research Context and Samples

This study selected 64 undergraduates majoring in Educational Technology from the Class of 2024 at a university in China as research subjects, and conducted peer feedback activities in the course Information Technology Teaching Theory. The teaching environment consisted of both face-to-face and online learning. The face-to-face environment was a traditional multimedia classroom where students could conduct classroom teaching training; the online learning environment was the “Lanmo Cloud Class” platform, which provides functions such as organization and management, interactive communication, and teaching activities. The platform is also able to record students’ learning progress, communication, discussion, Q&A, and work-related data^[31].

This group was selected for several reasons. First, the course is a core component of the teacher education curriculum, which emphasizes instructional design and classroom practice, making it closely aligned with the study’s focus on cognition, ability, and emotion in deep learning. Second, the students already possessed a foundation of disciplinary knowledge and pedagogical skills, which enabled them to produce meaningful peer feedback and engage in reflective learning. Finally, while the sample size was limited to a single class, such a design ensured consistency of instructional context and feasibility of intervention. To mitigate potential biases associated with a

single-sample design, the study employed triangulation of data sources, double coding by independent raters, and validated measurement instruments^[32,33].

The study was conducted in a university located in a region actively advancing the Educational Informatization 2.0 initiative and the Smart Education of China platform. These ongoing national strategies highlight deep learning as a key educational objective, and the selected institution had already integrated blended learning practices supported by digital platforms such as Rain Classroom. The Information Technology Teaching Theory course was chosen because it explicitly focuses on leveraging digital tools to improve instructional design and teaching performance, which naturally corresponds to the study's emphasis on peer assessment, discourse features, and deep learning. This combination of policy relevance, institutional readiness, and curricular alignment provided a representative and authentic context for the research^[34,35].

3.2. Research Design

Based on the peer feedback framework for promoting deep learning, this study designed peer feedback activities, which mainly included evaluation objectives, evaluation tasks, evaluation methods, and evaluation tools.

- (1) **Evaluation Objectives:** Students should be able to understand the meaning of each component of instructional design; design instructional plans for information technology courses in multiple ways; and master teaching skills through teaching practice to effectively implement teaching activities.
- (2) **Evaluation Tasks:** The activities included two teaching tasks. The first task was instructional design, in which students selected any knowledge point from Fundamentals of Information Technology and conducted instructional design in accordance with basic teaching principles and methods. The second task was classroom skill training, in which the teacher divided students into six groups of 6–8 people each and provided classroom teaching training.
- (3) **Evaluation Methods:** This involved evaluation subjects, evaluation content, and evaluation approaches. Evaluation subjects included individual evaluation and group evaluation. Individual evaluation referred

to students making judgments on their peers' performance, while group evaluation meant that students were randomly divided into groups of two or more, and each group evaluated the performance of the other groups. Evaluation content included students' instructional design plans and classroom teaching performance. Evaluation approaches included signed forms (real-name or anonymous) and feedback forms (scores or comments). Scores referred to students' quantitative evaluation of their peers' work using rubrics provided by the teacher. Comments referred to students' qualitative evaluation of peers' work or performance in written form, which was more easily accepted by students and could have a positive impact^[18]. In this study, during the instructional design task, students mainly used individual anonymous scoring to evaluate design plans; while in the classroom skill training task, they mainly used group real-name scoring plus comments to evaluate classroom performance.

- (4) **Evaluation Tools:** These mainly included the peer feedback platform and rubrics. The peer feedback platform was "Lanmo Cloud Class," which supported students in conducting online peer feedback. Combined with existing rubrics and evaluation content, this study designed rubrics for instructional design and classroom skill performance, consisting of evaluation elements and evaluation indicators. Before evaluation began, the teacher explained the task requirements using the rubrics to ensure the scientific nature of the evaluation results^[32].

Based on the design of the peer feedback activities to promote deep learning, this study proposed an implementation process, which included five steps: peer training, project activity, peer feedback, evaluation summary and reflection, and adjusted project activity, as shown in **Figure 1**^[36].

To strengthen the coherence of this study, each research objective (RO) was explicitly connected with the corresponding data sources and analytical methods. This section outlines how the three objectives were operationalized into concrete methodological procedures, ensuring that the research design directly addressed the aims of examining learning outcomes, analyzing discourse features, and constructing an explanatory framework (see **Table 1**).

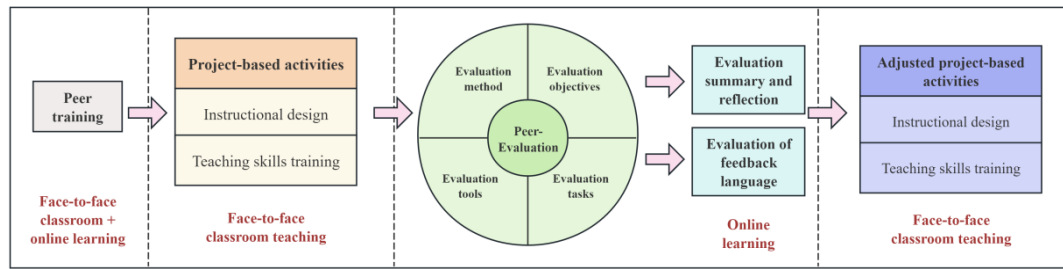


Figure 1. Implementation process of peer feedback activities.

Table 1. Alignment of Objectives and Methods.

Research Objective	Data Source	Analytical Approach
RO1	- Written responses to teacher-designed questions (cognition) - Instructional design and classroom teaching tasks (ability) - Questionnaire on positive emotions and intrinsic motivation (emotion)	- SOLO taxonomy coding - Rubric-based evaluation and paired-sample t-tests - Questionnaire reliability tests and Pearson correlation analysis
RO2	- 312 peer feedback comments generated on Rain Classroom	- Discourse move coding framework - Inter-rater reliability check (Cohen's) - Thematic categorization of feedback language
RO3	- Semi-structured interviews collected via Rain Classroom - Supplementary qualitative data from peer feedback	- Thematic analysis ^[33] - Integration through CIMO-logic (Context–Intervention–Mechanism–Outcome)

3.3. Data Collection

3.3.1. Cognitive Level

Students' cognitive level included knowledge mastery and thinking level. Knowledge mastery was measured through written questions raised by the course teacher based on the teaching content and objectives during the learning process. The course teacher had 18 years of teaching experience and had long been engaged in research on information technology curriculum and instruction; therefore, the validity of the questions was relatively high. This study analyzed the textual data of written questions according to Bloom's taxonomy and the cognitive behavior coding scheme developed by Hu et al. ^[37] to explore students' learning status. In Bloom's taxonomy, "remember" and "understand" were classified as shallow learning states, while "apply," "analyze," "evaluate," and "create" were classified as deep learning states ^[38]. Based on the evaluation indicators of knowledge level, the written answers of 64 students were quantitatively coded. Before coding, two coders were trained, and then formal coding was carried out. After coding, the Kappa coefficient of the two coders was calculated to be 0.8, indicating high consistency.

The thinking level was mainly measured through course tasks after completing the instruction. The task required students to evaluate the teaching performance of a given student. This study used the "Deep Understanding Assessment Scale based on the SOLO framework" developed by Svensäter and Rohlin ^[39], and applied it to code students' written answers quantitatively. In this scale, "pre-structural" represented no learning state and was assigned a value of 0; "munistructural, multistructural-low, multistructural-medium, multistructural-high" represented shallow learning states and were assigned values of 1, 2, 3, and 4; while "relational-low, relational-high, and extended abstract" represented deep learning states and were assigned values of 5, 6, and 7.

3.3.2. Ability Level

Students' ability level was mainly assessed in relation to the ability objectives of the course. The ability objectives of Information Technology Teaching Theory focused on students' teaching skills, evaluated through their instructional design plans and classroom teaching performance, as these tasks reflected students' creativity and

problem-solving ability^[32]. After completing the instructional design, students uploaded their plans to the platform for peer feedback. During face-to-face classes, students conducted skill training, recorded videos, and uploaded them to the platform for peer feedback. This study used rubrics to evaluate students' instructional design ability and classroom teaching ability. The rubrics were designed by the course teacher and demonstrated good validity. Each student's score consisted of two parts: peer scoring and teacher scoring.

3.3.3. Emotional Level

This study used a questionnaire to measure positive emotions and intrinsic motivation in order to understand students' emotional levels. The questionnaire adopted the emotional dimension from the Deep Learning Outcome Scale. The reliability and validity analysis of the scale were as follows: Cronbach's $\alpha = 0.76$, indicating good inter-

nal consistency; KMO = 0.74, Bartlett's test = 0.000, indicating significant differences and high validity^[40].

3.3.4. Language (Peer Feedback Comments)

To examine how peer feedback promotes deep learning in blended teaching, with particular attention to the linguistic features of students' feedback comments, a total of 312 comments generated during peer review activities were extracted from the Lanmo Cloud Class platform. Each comment was segmented into idea units and coded using an adapted discourse-move framework^[41,42].

The coding scheme contained six categories (see **Table 2**), which capture both cognitive-oriented and affective-oriented feedback. Two coders independently annotated 20% of the data to calculate inter-rater reliability. Cohen's coefficient was 0.8, indicating substantial agreement. Discrepancies were resolved through discussion, and the rest of the corpus was coded accordingly.

Table 2. Coding categories of peer feedback comments in the Information Technology course.

Code	Category	Definition	Example (Chinese Original + English Translation)
C1	Explicit Correction	Directly provides correction of factual/technical errors.	“你在教学设计中把‘多媒体工具’写成了‘硬件设备’，这里应改为软件工具。” (“You wrote ‘hardware device’ instead of ‘multimedia tool’ in the instructional design; this should be revised to software tool.”)
C2	Metalinguistic Explanation	Explains why a point is inaccurate or incomplete.	“教学目标部分缺少可测性，因为没有结合布鲁姆的动词分类。” (“The learning objective lacks measurability because it does not use Bloom's taxonomy action verbs.”)
C3	Directive/Suggestion	Suggests specific improvements or steps.	“可以在教学流程里增加学生活动环节，例如分组操作软件。” (“You could add a student activity, such as group practice with the software, into the teaching process.”)
C4	Elicitation/Question	Asks questions to prompt reflection or elaboration.	“为什么选择 PPT 而不是交互式白板？是否考虑过学生参与度？” (“Why did you choose PowerPoint instead of an interactive whiteboard? Have you considered student engagement?”)
C5	Praise/Positive Affect	Provides encouragement or recognition.	“案例选择得很好，和信息技术主题紧密结合！” (“The chosen case is excellent and closely connected with the IT topic!”)
C6	Hedging/Politeness	Uses hedging or polite expressions to soften suggestions.	“也许在评价方式上可以更详细一点。” (“Maybe you could be more specific about the assessment method.”)

3.3.5. Mechanisms (Interviews)

This study mainly used interviews to collect data in order to reveal the mechanism of deep learning. The interview question was: “In the course ‘Information Technolo-

gy Teaching Theory,’ we mainly used peer feedback as the evaluation approach. What do you think about peer feedback?” The interview question was posted on the “Lanmo Cloud Class” platform, and interview data were collected and coded using Nvivo 11^[43].

4. Results

4.1. Effects of Peer Feedback on Cognition, Ability, and Emotion (RO1)

4.1.1. Cognitive Level

Students' knowledge mastery and thinking levels were examined through teacher-designed written tasks and SOLO-based coding. The results are presented in **Table 3**.

In terms of knowledge mastery, "application, analysis, and evaluation" behaviors accounted for 56.3%, indicating that more than half of the students demonstrated deep learning behaviors. By contrast, 45.3% of responses

reflected only the "understanding" level, suggesting that a considerable number of students remained at a surface learning state without applying knowledge further.

Regarding thinking level, students' responses ranged from "multistructural-middle" to "extended abstract," with none at the "prestructural" level. The lowest level observed was "multistructural-middle," showing that all students could understand knowledge from multiple perspectives. Notably, 12.5% of students achieved the "extended abstract" level, reflecting their ability to generalize knowledge and engage in critical reflection. Overall, 68.8% of students reached "relational-low" or above, suggesting that most were in a deep learning state.

Table 3. Description of Students' Knowledge Mastery Level and Thinking Level.

Behavior	Remember	Understand	Apply	Analyze	Evaluate	Create
Percentage	1.56%	45.31%	9.38%	40.63%	3.13%	0%
Structure	multistructural-low	multistructural-high	relational-low	relational-high	extended abstract	Mean
Percentage	10.94%	20.31%	31.25%	25.00%	12.50%	4.97

4.1.2. Ability Level

Students' instructional design and classroom teaching ability were evaluated using rubrics, with pre- and post-feedback comparisons analyzed through paired-sample t-tests (see **Table 4**).

Descriptively, mean scores increased from 14.9 to 17.5 in instructional design and from 15.8 to 17.9 in class-

room teaching after peer assessment activities.

Inferentially, the paired-sample t-tests revealed significant improvements in both dimensions. Instructional design ability increased significantly ($t(64) = 9.98, p < 0.001, d = 1.25$), while classroom teaching ability also improved significantly ($t(64) = 7.62, p < 0.001, d = 0.95$). Both effect sizes indicate large effects ^[44].

Table 4. Paired-Sample t-Test Results of Ability Levels.

Ability	N	Pre-Feedback Mean	Pre-Feedback SD	Post-Feedback Mean	Post-Feedback SD	t-value	Effect Size (d)
Instructional design	64	14.93	1.66	17.50	1.20	9.98***	1.25
Classroom teaching	64	15.80	1.20	17.90	1.10	7.62***	0.95

Note: *** $p < 0.001$.

4.1.3. Emotional Level

Students' emotional engagement was measured through a questionnaire assessing positive emotions and intrinsic motivation. Descriptive statistics showed that the mean score of positive emotions was 3.68, while the mean score of intrinsic motivation was 3.75, suggesting relatively high emotional engagement levels.

Pearson correlation analysis further revealed signif-

icant positive relationships between emotions and ability measures (**Table 5**). Positive emotion was positively correlated with instructional design ability ($r = 0.49, p < 0.001$) and classroom teaching ability ($r = 0.55, p < 0.001$). Intrinsic motivation was positively correlated with classroom teaching ability ($r = 0.34, p = 0.006$), while the correlation with instructional design ability was non-significant ($r = 0.24, p = 0.052$).

Table 5. Correlation Between Emotion and Ability.

	Positive Emotion	Significance (two-tailed)	Intrinsic Motivation	Significance (two-tailed)
Instructional design ability	0.492**	$p < 0.001$	0.244	0.052
Classroom teaching ability	0.550**	$p < 0.001$	0.342*	0.006

*Note: * $p < 0.05$, ** $p < 0.001$.

4.2. Discourse Features of Peer Feedback (RO2)

A total of 312 peer feedback comments were segmented and coded into six discourse categories. **Table 6** presents the frequency distribution.

Descriptively, the most frequent category was Directive/Suggestion (28.8%), followed by Praise/Positive Affect (22.1%) and Metalinguistic Explanation (19.6%). Less common were Elicitation/Question (13.5%), Explicit Correction (10.6%), and Hedging/Politeness (5.4%).

Peer feedback comments in the Instructional Design of Information Technology course displayed distinct linguistic features that contributed to different aspects of deep learning. Three salient discourse moves were identified: metalinguistic explanations, elicitation questions, and praise. Each of these moves was closely related to one of the three dimensions of deep learning: cognition, ability, and emotion.

First, metalinguistic explanations frequently directed attention to conceptual clarity and academic standards. For example: “教学目标部分缺少可测性，因为没有结合布鲁姆的动词分类。” (“*The learning objective lacks measurability because it does not use Bloom’s taxonomy action verbs.*”).

This type of comment made peers reflect on theoretical frameworks and refine their objectives, thereby supporting cognitive restructuring.

Second, elicitation questions encouraged critical reflection and problem-solving. For instance: “为什么选择PPT而不是交互式白板？是否考虑过学生参与度？” (“*Why did you choose PowerPoint instead of an interactive whiteboard? Have you considered student engagement?*”). By posing reflective questions, peers were guided to evaluate their pedagogical decisions and consider alternative strategies, enhancing ability development.

Third, praise and positive affect played a motivational role in sustaining engagement: “案例选择得很好，和信息技术主题紧密结合！” (“*The chosen case is excellent and closely connected with the IT topic!*”). Such supportive expressions built confidence and reinforced active participation, which contributed to emotional engagement.

Overall, these findings indicate that the linguistic form of peer comments is not neutral but closely linked to how students process, apply, and internalize knowledge in blended teaching environments.

Table 6. Frequency distribution of discourse moves.

Category	Frequency	Percentage
Explicit Correction	33	10.6%
Metalinguistic Explanation	61	19.6%
Directive / Suggestion	90	28.8%
Elicitation / Question	42	13.5%
Praise / Positive Affect	69	22.1%
Hedging / Politeness	17	5.4%

4.3. Peer Assessment Triggers Deep Learning Mechanisms

Interview data analyzed using Nvivo revealed four mechanisms through which peer feedback triggered deep learning processes. **Table 7** summarizes the mechanisms

and their dimensions.

These mechanisms illustrate how peer assessment not only influenced outcomes but also activated dynamic learning processes, laying the groundwork for the framework discussed in the next section.

Table 7. Mechanisms of Deep Learning: Content and Dimensions.

Mechanism (Content)	Dimension
Personal engagement	Mutual understanding; enhanced motivation
Seeking and providing relevant feedback	Learning new perspectives; reflection
Repeated exploration	Quick asynchronous interaction; asking in-depth questions or suggestions
Understanding one's own learning process	Comparing one's arguments with peers' arguments

5. Discussion

5.1. Peer Feedback Enhances Deep Learning

The findings demonstrated that peer assessment in a blended learning context significantly improved students' cognitive engagement, professional abilities, and emotional motivation. In terms of cognition, more than half of the students moved beyond knowledge retention to demonstrate application, analysis, and evaluation behaviors, which indicates a shift toward higher-order thinking. This resonates with Wen and Pei ^[45], who found that structured peer learning is central to achieving deep learning in blended environments. Moreover, the dual role of providing and receiving feedback encouraged students to internalize evaluation criteria and apply them to their own work, which is consistent with recent findings that peer interaction enhances both cognitive presence and self-regulation ^[46].

The development of professional abilities was also evident, with students' instructional design and classroom teaching scores improving significantly after peer feedback. The use of rubrics in this study provided clear standards for evaluation, which helped students better understand expectations and identify areas for improvement. Similar effects have been observed in pre-service teacher education, where rubric-guided peer feedback supported reflective practice and improved communication skills ^[47,48]. These results confirm that structured peer assessment can function as a powerful tool for professional growth.

Emotional outcomes were likewise positive, with higher levels of enjoyment and motivation correlating with better teaching performance. According to Control-Value Theory, positive emotions arise when students perceive control over tasks and recognize their value ^[30]. This study's results are consistent with large-scale research showing that emotional engagement strongly predicts performance in blended learning ^[49]. By creating a supportive environment where peer interactions were framed con-

structively, peer assessment helped sustain students' motivation and confidence, both of which are crucial for deep learning.

5.2. Linguistic Features of Peer Feedback Shape Learning Outcomes

The analysis of 312 peer comments revealed that the form of feedback, not only its content, played a key role in shaping learning outcomes. Three discourse moves stood out. First, metalinguistic explanations helped students clarify conceptual frameworks and refine their understanding, directly supporting cognitive development. For example, when peers pointed out the lack of measurable verbs in teaching objectives, students were prompted to rethink their alignment with Bloom's taxonomy. This finding echoes research showing that explicit explanations in peer feedback enhance conceptual clarity and meta-cognitive awareness ^[28].

Second, elicitation questions stimulated problem-solving and ability development by encouraging students to critically examine their design and teaching choices. This aligns with Shaltaeva ^[50], who noted that questioning strategies in oral feedback are valued because they guide learners to generate solutions rather than merely accept corrections. In this study, such moves supported the iterative refinement of teaching plans and classroom practices.

Third, praise and positive affect reinforced students' confidence and emotional engagement. Positive reinforcement was especially important for sustaining participation and willingness to revise work, which aligns with growth-mindset supportive discourse that has been shown to increase students' motivation to embrace challenges ^[51]. These results extend the concept of feedback literacy ^[52] by demonstrating that it is not only the ability to understand and use feedback but also the ability to craft feedback in effective linguistic forms that drives deep learning.

5.3. CIMO-Logic Framework

Beyond individual outcomes and discourse features, this study identified four mechanisms—personal engagement, seeking and providing feedback, repeated exploration, and understanding one’s own learning process—that explain how peer assessment promotes deep learning. These mechanisms clarify why students not only improved their skills but also developed a deeper awareness of their own learning. Similar mechanisms have been observed in previous studies, where repeated feedback cycles encouraged reflection and iterative improvement^[53].

To synthesize these findings, this study constructed an integrative framework grounded in CIMO-logic^[54] (see

Figure 2). The Context was the blended teaching environment, which combined online platforms with face-to-face interaction. The Intervention was structured peer feedback, supported by rubrics and guided by linguistic features such as explanations, questions, and praise. The Mechanisms included the four identified processes, which illuminate why feedback prompted deeper engagement. The Outcomes were the observed improvements in cognition, ability, and emotion. This framework responds to recent calls for more explicit theorization of feedback processes^[55] and extends the literature by connecting discourse features, psychological mechanisms, and measurable learning outcomes in a single model.

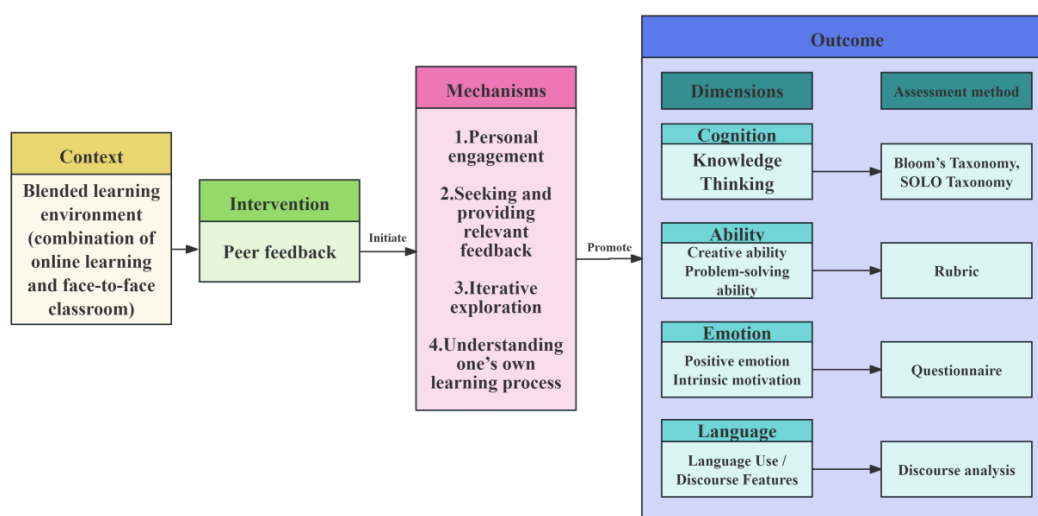


Figure 2. CIMO-logic Framework.

This framework makes two key contributions. Theoretically, it opens the “black box” of peer assessment by articulating how interventions trigger mechanisms that lead to outcomes, rather than merely reporting outcome gains. Practically, it provides educators with a guide for designing peer assessment that is structured, linguistically sensitive, and oriented toward iterative learning. As Wu and Zhao^[8] argue, future feedback research should increasingly incorporate multimodal and AI-supported tools, and the present framework offers a foundation for adapting peer assessment to these evolving contexts.

6. Conclusions

This study demonstrated that peer assessment in

a blended teaching environment significantly enhanced students’ deep learning outcomes across cognition, ability, and emotion. Cognitive development was evidenced by higher-order thinking behaviors and SOLO taxonomy levels, ability development was confirmed through significant improvements in instructional design and classroom teaching, and emotional engagement was revealed through positive correlations between motivation and performance. In addition, the discourse analysis of 312 peer comments showed that metalinguistic explanations, elicitation questions, and praise directly mediated deep learning processes. To consolidate these findings, a CIMO-logic framework was constructed, clarifying how context and intervention trigger mechanisms that lead to measurable learning outcomes.

Several limitations should be acknowledged. First, the study's scope was confined to a single course with a specific cohort of students, which may limit the generalizability of findings across different disciplines or cultural contexts. Second, the linguistic analysis was restricted to textual peer comments, without exploring multimodal feedback (e.g., audio or video), which has been shown to affect engagement and personalization^[56]. Third, while the CIMO-logic framework offers theoretical insights, its mechanisms were inferred from one-time data rather than tested longitudinally.

Future research should move in several promising directions. First, longitudinal designs are required to evaluate whether the effects of peer assessment endure across semesters and transfer to future academic or professional tasks^[57]. Second, multimodal approaches should be explored, incorporating audio, video, or annotated screen-casts, as they may enhance both the cognitive and emotional dimensions of peer learning^[56,58]. Third, the integration of AI into peer feedback ecosystems offers strong potential: AI can support real-time quality checks of feedback, scaffold learners in using effective discourse moves, and combine with peer and teacher feedback in hybrid models^[59,60]. Fourth, refining the CIMO-logic framework through systematic testing in varied contexts (e.g., anonymous vs. identified feedback, different disciplines) will strengthen its explanatory and predictive power^[8,61]. Taken together, these directions can address current gaps and extend the theoretical and practical contributions of peer assessment in blended learning environments.

Author Contributions

Conceptualization, R.S.; methodology, R.S.; software, R.S.; validation, R.S.; formal analysis, R.S.; investigation, R.S.; data curation, R.S.; writing—original draft preparation, R.S.; writing—review and editing, A.A. and K.A.B.J.; supervision, A.A. and K.A.B.J.. All authors have read and agreed to the published version of the manuscript.

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Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The datasets generated and/or analyzed during the current research are not publicly available due to the need to utilize the data for the writing of a doctoral thesis. The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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