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Enhancing Students' Mathematical Communication through Deep Learning-Based Course Review Horay in the Society 5.0 Era

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ABSTRACT

In the Society 5.0 era, students are expected to not only solve mathematical problems but also articulate their reasoning clearly. However, many students struggle with mathematical communication, especially in expressing, justifying, and representing their thinking. This study investigates the effectiveness of the Deep Learning-Based Course Review Horay (CRH) model in enhancing students' mathematical communication skills through an interactive and technology-supported approach. A sequential explanatory mixed-methods design was employed involving 15 eighth-grade students at MTs. Nurul Hidayah, Sumenep. The intervention integrated Course Review Horay—a collaborative, game-based strategy—with deep learning analytics that provided automated, personalized feedback on students' written responses. Quantitative data were collected using a validated Mathematical Communication Test (pre- and post-intervention), while qualitative insights were drawn from classroom observations and student interviews. Findings revealed a significant improvement in mathematical communication scores, from a pretest mean of 42.87 to a posttest mean of 78.93, $t(14) = 4.38$, $p < 0.001$, with a large effect size (Cohen's $d = 1.13$). Thematic analysis showed increased participation, clearer expression of reasoning, and enhanced student confidence supported by real-time feedback. The Deep Learning-Based CRH model effectively fostered cognitive and communicative growth by combining active learning and intelligent feedback. It supported students in verbalizing, representing, and justifying mathematical ideas in a low-anxiety, reflective environment. This model presents a scalable, student-centered approach aligned with the goals of Society 5.0 and 21st-century education.

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1. INTRODUCTION

Education in the Society 5.0 era requires a fundamental shift from knowledge acquisition toward developing higher-order thinking, communication, and digital literacy skills (Suharti et al., 2024).

Within this human-centered technological paradigm, learners are expected not only to understand disciplinary content but also to articulate, reason, and collaborate through multiple modes of communication (Ma et al., 2025). Mathematics—long perceived as an abstract and symbolic domain—demands particular attention because success in this subject increasingly depends on how well students can communicate mathematical ideas clearly, logically, and creatively rather than merely perform procedural computations (Muchyidin & Priatna, 2024).

Recent curriculum transformations worldwide, including in Indonesia, have emphasized twenty-first-century competencies such as critical thinking, collaboration, creativity, and communication. Among these competencies, mathematical communication stands out as a cornerstone that connects conceptual understanding with problem-solving and reasoning (Prayitno, 2021). Yet despite curricular reform, evidence from schools shows that many students still struggle to express their mathematical thinking, especially in verbal and written forms. This persistent gap calls for innovative pedagogical approaches that are both interactive and technology-supported.

Mathematical communication is a fundamental competency that enables learners to express, explain, and justify their mathematical ideas using appropriate language, symbols, representations, and reasoning (Lubis et al., 2024). It extends far beyond the ability to compute or manipulate formulas; it encompasses the capacity to organize thought processes, articulate conceptual relationships, and engage in meaningful dialogue about mathematical phenomena. Through communication, students make their reasoning visible, allowing both peers and teachers to identify misconceptions and deepen conceptual understanding. Wu, (2024) emphasize that thinking in mathematics is inherently communicative—individual cognition develops through social interaction and discourse. When learners are encouraged to verbalize, write, and visualize their ideas, they construct richer cognitive connections between abstract concepts and real-world applications. Moreover, mathematical communication fosters metacognitive awareness, confidence, and collaborative problem-solving—skills that are indispensable in twenty-first-century learning environments. Conversely, weak communication abilities often result in superficial comprehension, procedural dependence, and disengagement from the learning process. Empirical studies by Resnick & Collins, (2023) reveal that many students struggle to translate symbolic representations into coherent verbal or written explanations, indicating the need for pedagogical innovations that explicitly cultivate communicative competence. Therefore, strengthening mathematical communication is not an auxiliary objective but a central mission in mathematics education, particularly within the human-centered, technology-driven context of the Society 5.0 era.

Despite policy emphasis on student-centered learning, classroom practices remain largely teacher-dominated. Many mathematics lessons still follow a transmission model where teachers explain, and students listen, limiting opportunities for peer dialogue or self-expression. Observations at MTs Nurul Hidayah and similar schools reveal that students often remain passive, reluctant to articulate reasoning for fear of making mistakes. Such conditions hinder the development of communicative competence and critical thinking. Another challenge lies in the limited use of technology for formative feedback. Teachers frequently lack tools to analyze students' written or oral responses efficiently, making it difficult to provide personalized feedback. Consequently, misconceptions persist unnoticed. The emergence of deep learning technologies offers new possibilities to address these issues by enabling automated, adaptive, and data-driven insights into students' learning processes.

The term deep learning has been used across different disciplines with overlapping yet distinct meanings, leading to frequent conceptual ambiguity in educational research (Velázquez & Méndez, 2021). In pedagogy, deep learning refers to a meaningful learning approach that emphasizes conceptual understanding, reflection, and knowledge transfer rather than surface memorization (Xu & Ouyang, 2022). It encourages students to engage cognitively and metacognitively with content, linking new information to prior knowledge through reasoning, inquiry, and problem solving. In contrast, within the field of artificial intelligence (AI), deep learning denotes a subset of machine-learning algorithms that utilize multi-layered neural networks to recognize complex patterns in large datasets (Long et al., 2025). These algorithms enable systems to analyze linguistic, visual, or behavioral data to generate adaptive feedback and predictive insights. In contemporary education, both interpretations increasingly converge: pedagogical deep learning seeks to cultivate intellectual depth in human learners, while technological deep learning provides the analytical infrastructure to support individualized and data-driven instruction (J. Kim & Han, 2022). In this study, the term "deep learning" is employed in an integrated sense—representing a pedagogical approach enhanced by AI-powered analytical tools. The aim is to promote deeper cognitive engagement among students while leveraging technology to deliver timely, personalized feedback. Thus, deep learning in education is not only about machines learning from data but also about enabling students to learn deeply through interaction, reflection, and intelligent technological mediation within a constructivist learning environment.

The Course Review Horay (CRH) model is an active-learning strategy developed to make classroom review sessions interactive and enjoyable. In CRH, students work individually or collaboratively to answer questions displayed by the teacher. Each correct response allows them to mark boxes on a worksheet, often accompanied by cheerful exclamations ("Horay!"), creating a lively and competitive atmosphere (Teng, 2024). CRH promotes motivation, participation, and immediate feedback—three elements crucial for engagement. However, its traditional form relies on manual checking and subjective teacher evaluation. Integrating CRH with deep-learning-based analytics can transform it into a data-informed system where students' written or spoken answers are analyzed automatically to detect conceptual understanding and communication patterns. This combination aligns with constructivist principles, allowing students to learn through social interaction, reflection, and technology-mediated feedback.

Integrating deep learning with CRH addresses both motivational and diagnostic dimensions of learning. From the motivational side, CRH's game-like structure lowers anxiety and encourages active participation. From the diagnostic side, deep learning algorithms can capture linguistic, symbolic, or semantic patterns in students' responses, providing real-time feedback that supports mathematical communication. Prior research in related domains has shown encouraging results. Liu et al., (2023) developed an AI-based essay-scoring system that improved students' writing in mathematics education. Atay et al., (2025) employed deep learning to predict students' learning difficulties by analyzing response times and patterns, allowing teachers to intervene early. Braun & Clarke, (2019) demonstrated that digital technologies enhance deep learning when they promote reflection and interaction rather than passive consumption. However, few empirical studies have examined how such integration can specifically foster mathematical communication in secondary-level classrooms. Most existing studies either focus on motivation or cognitive achievement, overlooking communication as a mediating outcome.

Although a growing body of research highlights the potential of artificial intelligence and active-learning models in education, several critical gaps remain unaddressed in the current literature. First, most studies examining the application of deep learning in education focus primarily on technological innovation rather than pedagogical transformation. The use of AI tools is often confined to laboratory or pilot settings, leaving limited empirical evidence on how such tools perform in authentic, low-resource classrooms typical of many developing regions. Second, previous research tends to emphasize academic achievement or cognitive gains, overlooking mathematical communication as a distinct yet crucial outcome that bridges conceptual understanding and expressive ability. Third, few studies employ mixed-methods approaches that capture both quantitative improvements and qualitative shifts in students' communicative behavior. This methodological imbalance restricts our understanding of how learners experience technology-enhanced learning beyond statistical measures. Finally, conceptual ambiguity persists in defining "deep learning," as some researchers equate it solely with AI algorithms, while others refer to it as a cognitive process of meaningful learning. These theoretical inconsistencies necessitate a clearer, integrated framework that unites pedagogical depth with technological intelligence.

In response to these gaps, the present study aims to investigate the effectiveness of a Deep Learning-Based Course Review Horay (CRH) model in enhancing students' mathematical communication within the context of Society 5.0 education. The integration of CRH and deep learning is designed to foster an interactive, enjoyable, and data-informed learning environment. CRH's collaborative and game-like features are expected to motivate students and stimulate verbal and written expression, while deep learning analytics provide automated and personalized feedback that helps teachers identify learning difficulties more precisely. By combining human-centered pedagogy with AI-assisted feedback, this research seeks to demonstrate that technology can serve not as a replacement for teachers but as an intelligent partner that amplifies communication and understanding in mathematics classrooms. Methodologically, the study employs a mixed-methods design involving quantitative measurement of pre-test and post-test performance and qualitative analysis of students' communicative behaviors during classroom implementation. This dual approach allows for a comprehensive assessment of both statistical improvement and experiential transformation.

Guided by this rationale, the study addresses two core research questions: (1) Does the integration of deep learning into the Course Review Horay model significantly improve students' mathematical communication skills? and (2) What qualitative changes occur in students' expression of mathematical ideas when learning through the Deep Learning-Based Course Review Horay model? These questions aim to capture not only measurable improvement but also the nuanced ways in which students' engagement, confidence, and communicative competence evolve during the intervention.

The anticipated contributions of this study are threefold. Theoretically, it clarifies the dual meaning of deep learning in educational discourse and proposes an integrated model that connects AI-based analytics with constructivist, student-centered learning. Practically, it offers empirical evidence of how the Deep Learning-Based CRH approach can strengthen mathematical communication in real classroom contexts, demonstrating a feasible and low-cost strategy for teachers to cultivate 21st-century skills. From a policy perspective, this research aligns with the vision of Society 5.0, emphasizing technology that enhances human capability rather than diminishes it. The findings are expected to inform curriculum designers, teacher educators, and educational policymakers about the potential of AI-supported pedagogies to create more engaging, communicative, and future-oriented learning ecosystems.

2. METHODS

This study adopted a sequential explanatory mixed-methods design, integrating quantitative and qualitative approaches to obtain a comprehensive understanding of the effectiveness of the Deep Learning-Based Course Review Horay (CRH) model in enhancing students' mathematical communication. The sequential explanatory design was chosen because it allows the quantitative results (pretest–posttest scores) to be supported and further interpreted through qualitative findings (observations and interviews). This design structure provides both statistical evidence of improvement and rich contextual insights into how and why those changes occurred.

The quantitative component employed a one-group pretest–posttest design, where participants' mathematical communication skills were measured before and after the intervention. This design was considered appropriate for an exploratory classroom study in which the primary aim was to assess feasibility and potential effectiveness rather than to make causal generalizations. The one-group approach was selected due to limited class size and institutional constraints that prevented random assignment or the inclusion of a control group. However, this limitation is acknowledged: without a control group, alternative explanations such as maturation or testing effects cannot be completely ruled out. Despite this, the design remains valuable for providing preliminary evidence to inform future quasi-experimental replications with larger samples.

The qualitative phase followed the quantitative analysis to explore participants' perceptions, behavioral changes, and experiences during the implementation of the Deep Learning-Based CRH model. Data were collected through classroom observations and semi-structured interviews with both students and the teacher. The triangulation of quantitative and qualitative data strengthened the validity of interpretations by cross-verifying outcomes from different methodological perspectives.

The participants consisted of 15 students enrolled in the eighth grade at MTs. Nurul Hidayah, Sumenep, Indonesia. The class was selected through purposive sampling based on accessibility and the teacher's willingness to implement the technology-enhanced learning model. The small class size reflected the natural composition of the participating school, where mathematics classes typically range between 12 and 20 students. This exploratory sample size is consistent with pilot-scale mixed-methods research aimed at testing pedagogical innovations before large-scale implementation. Demographically, the group included 9 female and 6 male students aged between 13 and 14 years. Based on prior academic records, their average mathematics performance was categorized as medium, with pre-intervention mean scores between 40 and 60 on a 100-point scale. None of the students had prior experience with the Course Review Horay model or deep learning-based instructional feedback. Ethical clearance was obtained from the school administration, and both students and parents provided informed consent to participate voluntarily. All data were anonymized using coded identifiers (e.g., S1–S15) to protect participant confidentiality.

The Mathematical Communication Test (MCT) served as the primary quantitative instrument to measure students' ability to express and reason through mathematical ideas. Designed specifically for this study, the test comprised five open-ended questions aligned with three key indicators of mathematical communication: (1) verbal expression, which assesses how students articulate their reasoning and problem-solving processes using clear written language; (2) symbolic representation, which evaluates their capacity to employ mathematical symbols, diagrams, or graphs appropriately to support explanations; and (3) logical argumentation, which measures their ability to justify solutions coherently and defend conclusions using mathematical reasoning. Each item required students not only to compute results but also to communicate the conceptual basis behind their answers. For instance, one question asked students to explain in their own words why the area of a triangle is equal to one-half of the product of its base and height, while another required them to interpret a classmate's misconception about decimal values and provide a corrective explanation. Responses were scored using a four-point rubric ranging from 1 (very weak communication) to 4 (excellent communication), focusing on clarity, coherence, and conceptual accuracy. The test was designed to capture both linguistic and representational dimensions of mathematical communication, enabling researchers to evaluate improvements in students' ability to express mathematical reasoning comprehensively after the implementation of the Deep Learning-Based Course Review Horay model.

Table 1. Sample Items from the Mathematical Communication Test

Indicator	Sample Item	Expected Student Response
Verbal Expression	"Explain in your own words why the area of a triangle is ½ × base × height."	Students describe the relationship between the base, height, and the rectangular area they derive from.
Symbolic Representation	"Draw and label a diagram to represent the relationship between the radius and diameter of a circle."	Students correctly illustrate and label the relationship as D = 2r.
Logical Argumentation	"A student claims that 0.5 is larger than 0.05 because 5 is greater than 0. Explain whether this is correct and why."	Students reason that place value affects magnitude; 0.5 > 0.05 due to tenths vs. hundredths.

The content validity of the test was established through expert review by three mathematics education specialists from Universitas PGRI Sumenep. Each expert evaluated the items based on clarity, relevance, and alignment with communication indicators using a 4-point relevance scale (1 = not relevant to 4 = highly relevant). The Content Validity Index (CVI) for individual items ranged from 0.83 to 1.00, with an average Scale-CVI (S-CVI) of 0.94, exceeding the acceptable threshold of 0.80 (Liang et al., 2025). A pilot test with 20 non-participating students from the same grade level yielded a Cronbach's alpha coefficient of 0.87, indicating high internal consistency. Construct validity was also supported through expert judgment, ensuring that the test captured both linguistic and symbolic aspects of mathematical communication.

Qualitative data were collected using structured observation checklists and semi-structured interview protocols. The observation sheet focused on student engagement, verbal participation, and collaborative interaction during CRH sessions. The interview protocol explored students' perceptions of how the learning model affected their confidence, understanding, and ability to communicate mathematical ideas. Interviews were conducted individually in Indonesian, lasting approximately 15–20 minutes each, and later transcribed for analysis.

The implementation of the study followed a carefully structured sequence conducted over four weeks, consisting of eight 80-minute sessions integrated into the regular mathematics curriculum. Before data collection, the teacher received a comprehensive orientation on the principles of the Course Review Horay (CRH) model and on the use of deep learning technology to analyze students' responses. The procedure began with the pretest phase, during which all participants completed the Mathematical Communication Test (MCT) to establish baseline performance and identify initial strengths and weaknesses in their ability to communicate mathematical ideas. This was followed by the intervention phase, where the Deep Learning-Based Course Review Horay model was implemented in every lesson. The teacher introduced mathematical topics through collaborative and game-like review activities that encouraged students to discuss, explain, and justify their answers aloud. Each student's written responses during the CRH sessions were recorded and then analyzed using a deep learning algorithm capable of recognizing mathematical expressions and evaluating the clarity and logic of explanations. The teacher used the technology-generated feedback to provide individualized guidance in subsequent sessions. After completing the instructional sequence, the posttest phase was administered using the same MCT to measure changes in students' mathematical communication performance. To complement the quantitative data, qualitative observations and interviews were conducted to explore students' behavioral and perceptual modifications throughout the process. This systematic procedure ensured that both the cognitive and experiential aspects of learning were captured comprehensively.

Quantitative data from the pretest and posttest were analyzed using SPSS version 26. Before applying inferential tests, assumptions of normality and homogeneity of variance were verified. The Shapiro–Wilk and Kolmogorov–Smirnov tests indicated that both pretest and posttest scores were normally distributed ($p > 0.05$). Levene's test confirmed the equality of variances across measurements. Given the small sample size ($n = 15$) but confirmed normal distribution, a paired-samples t-test was deemed appropriate to compare the mean pretest and posttest scores. The t-test's robustness to minor deviations from normality and its efficiency for within-subject designs justified its use (Field, 2018). The analysis produced the mean difference, standard deviation, t-value, and significance level ($\alpha = 0.05$). Additionally, the effect size (Cohen's d) was calculated to determine the magnitude of improvement, interpreted using standard benchmarks (small = 0.2, medium = 0.5, large = 0.8).

Qualitative data from interviews and observations were analyzed through thematic analysis following Braun and Clarke's (2019) six-phase framework: (1) familiarization with the data, (2) generation of initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the report. Coding was conducted manually and cross-checked using NVivo 12 software to ensure systematic organization. Two independent coders analyzed the data, and discrepancies were discussed until interrater agreement reached 0.86 (Cohen's kappa), indicating strong reliability. Themes were derived inductively from recurring patterns in student responses and classroom behaviors. These themes provided interpretive depth to the quantitative results, highlighting how students' communication evolved in quality, confidence, and contextual understanding throughout the intervention.

To ensure methodological rigor, multiple validation strategies were implemented. For the quantitative strand, validity was confirmed through expert review and statistical testing, while reliability was measured via Cronbach's alpha. For the qualitative strand, triangulation across data sources (interviews, observations, and quantitative outcomes) enhanced credibility. Member checking was performed by sharing summary interpretations with participants to verify accuracy. Thick description of classroom context and learning interactions ensured transferability, while a clear audit trail documented every stage of data collection and analysis to maintain dependability and confirmability.

Ethical approval was granted by the institutional review board of Universitas PGRI Sumenep. Participation was voluntary, with informed consent obtained from students and their parents. All data were treated confidentially and used solely for research purposes. Students' identities were coded (S1–S15), and no personally identifiable information was disclosed in publications or reports.

3. FINDINGS AND DISCUSSION

The quantitative analysis examined whether the implementation of the Deep Learning-Based Course Review Horay (CRH) model significantly improved students' mathematical communication skills. Pretest and posttest data from 15 students were analyzed using a paired-samples *t*-test after confirming normality through the Shapiro–Wilk test ($p > 0.05$). The results indicated a substantial increase in the mean scores, suggesting that the intervention had a positive effect on students' ability to articulate mathematical reasoning.

Table 2. Descriptive Statistics of Pretest and Posttest Mathematical Communication Scores

Statistic	Pretest	Posttest	Mean Gain	% Increase
Mean	42.87	78.93	+36.06	84.1 %
Median	43.00	80.00	—	—
Standard Deviation (SD)	8.39	7.63	—	—
Minimum Score	30	65	—	—
Maximum Score	58	90	—	—
Range	28	25	—	—
Standard Error of Mean	2.17	1.97	—	—
Skewness	0.11	−0.32	—	—
Kurtosis	−0.65	−0.41	—	—

The descriptive results in Table 2 show a clear upward shift in students' mathematical-communication performance after exposure to the Deep Learning-Based Course Review Horay (CRH) model. The mean score increased from 42.87 (SD = 8.39) on the pretest to 78.93 (SD = 7.63) on the posttest, representing a mean gain of 36.06 points or an 84 % relative improvement from baseline. The narrowing of the standard deviation (from 8.39 to 7.63) indicates that post-intervention scores became more homogeneous, suggesting that weaker students improved substantially, and overall group variance decreased. The near-symmetrical distribution (skewness ≈ 0) and low kurtosis values confirm that the data are approximately normal, meeting the assumption required for parametric analysis. These descriptive trends were subsequently confirmed by the paired-samples *t*-test (see Table 2 in the Results section), which revealed a statistically significant difference between pre- and posttest means, $t(14) = 4.38$, $p < 0.001$, with a large effect size (Cohen's $d = 1.13$). This magnitude of effect exceeds the conventional threshold for strong educational impact ($d \geq 0.80$), indicating that the learning intervention had a substantively meaningful influence on students' mathematical-communication abilities.

Table 3. Paired-Samples t-Test Results for Mathematical Communication Skills

Comparison	$t(14)$	p-value	Cohen's d	Interpretation
Pretest – Posttest	4.38	< 0.001	1.13	Large effect

As shown in Table 2, the difference between pretest and posttest scores was statistically significant ($t(14) = 4.38$, $p < 0.001$), with a large effect size (Cohen's $d = 1.13$). This indicates that the Deep Learning-Based CRH model produced a strong practical improvement in students' mathematical communication performance. The mean gain of 36 points represents an 84% relative increase from baseline. These findings suggest that when mathematical learning is delivered through active, technology-supported approaches, students not only retain information but also become better at articulating mathematical ideas clearly and confidently. The integration of deep learning analytics appears to have enabled the teacher to provide more targeted feedback, supporting the refinement of students' written and verbal reasoning.

To complement the statistical results, qualitative data from classroom observations and semi-structured interviews were analyzed thematically using NVivo 12 software. Three major themes emerged: (1) increased participation and engagement, (2) improvement in expressing mathematical ideas, and (3) the use of technology as a tool for learning and communication. Representative excerpts from student and teacher interviews are provided to illustrate each theme. Observation notes revealed that the CRH format, which incorporated competitive quiz-style activities and cheerful exclamations, created a dynamic and enjoyable classroom atmosphere. Students were noticeably more willing to volunteer answers and discuss ideas than in previous lessons. The teacher commented: "Before this activity, only a few students dared to speak up in math class. But during the Horay sessions, almost everyone wanted to answer because they saw it as a fun challenge." (Teacher Interview, T01) Students echoed this sense of enthusiasm, with one participant noting: "I used to feel nervous when asked to explain in front of the class, but now it feels easier because we do it together and it's like a game." (Student S07). This shift in participation supports the quantitative improvement observed, as active engagement is often a precursor to better communication and understanding.

The second theme captured how students developed greater fluency in verbalizing and justifying their mathematical reasoning. Interviews and written work showed increased use of complete sentences, proper terminology, and coherent logical arguments. One student remarked: "Now I try to explain step by step, not just write numbers. When I can say it in words, I understand it better." (Student S03). Another explained how visual tools enhanced expression: "When I draw diagrams or use symbols, it's easier to show what I mean instead of only speaking." (Student S11). Teachers also observed this progress: "Their answers are not only correct but also more complete—they can explain why and how, not just what." (Teacher Interview, T02) These qualitative insights illustrate that the Deep Learning-Based CRH model encouraged students to externalize their thought processes, bridging the gap between internal reasoning and outward communication.

The third theme focused on how deep learning technology supported both teaching and learning. The AI system automatically analyzed students' written responses, identifying common errors and providing immediate feedback. Students reported that they appreciated receiving personalized comments: "The computer told me which part of my explanation was unclear. It felt like the teacher could see my mistake faster." (Student S09). Teachers highlighted that the data analytics feature made feedback more efficient and precise: "Usually, checking all the students' written answers takes time. But the system grouped their errors so I could discuss them collectively." (Teacher Interview, T01). However, minor technical challenges such as internet instability and unfamiliarity with the system were noted, particularly during the first sessions. Despite this, both students and the teacher agreed that the technology-enhanced classroom interaction, rather than replacing it, emphasized its role as a facilitative communication tool.

The integration of quantitative and qualitative results provides a more holistic understanding of how the Deep Learning-Based CRH model enhanced mathematical communication. Quantitatively, the significant rise in test scores and large effect size demonstrate measurable learning gains. Qualitatively, these improvements were reflected in students' behavioral and attitudinal changes—greater participation, clearer articulation, and increased confidence. The mixed-method triangulation confirms that the improvement in mathematical communication was not merely statistical but experiential.

Students learned not only what to communicate but also how to communicate more effectively. The interactive nature of CRH promoted peer dialogue, while the deep learning analytics facilitated individualized feedback loops. Figure 1 illustrates this integrated mechanism.

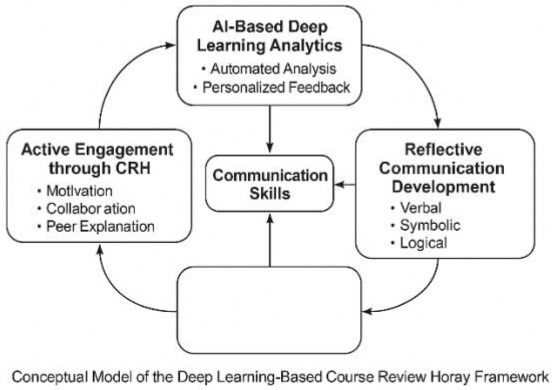

Figure 1. Conceptual Model of the Deep Learning-Based Course Review Horay Framework

Figure 1 illustrates how the Deep Learning-Based Course Review Horay (CRH) model works as an integrated system to improve students' mathematical communication. The diagram shows three main components—Active Engagement through CRH, AI-Based Deep Learning Analytics, and Reflective Communication Development—that interact dynamically to strengthen communication skills. Through the CRH model, students participate actively in fun, collaborative, and competitive learning activities that motivate them to share ideas and explain reasoning. This active engagement stimulates verbal participation and builds confidence in expressing mathematical concepts. The deep learning analytics component provides automated analysis and personalized feedback, allowing teachers to identify students' misconceptions and offer targeted support quickly. In turn, students receive immediate, specific feedback that helps them refine their explanations. The reflective communication process then emerges as students learn to express ideas more clearly—verbally, symbolically, and logically—while connecting mathematics with real-world understanding. These three elements form a continuous feedback cycle: engagement encourages participation, technology strengthens feedback, and reflection deepens understanding, which in turn increases engagement again. Overall, Figure 1 emphasizes that effective mathematical communication can be achieved when active learning, artificial intelligence, and reflective thinking work together in a balanced, human-centered learning system aligned with the vision of Society 5.0.

Discussion

The findings of this study demonstrate that the integration of the Deep Learning-Based Course Review Horay (CRH) model significantly enhanced students' mathematical communication skills. Quantitative analysis revealed a large effect size, confirming a meaningful difference between pretest and posttest results. Qualitatively, students displayed greater engagement, clearer reasoning, and improved verbal and written articulation of mathematical ideas. These results collectively suggest that the combined pedagogical and technological innovation succeeded in addressing one of the persistent challenges in mathematics education—students' difficulty in expressing and justifying mathematical reasoning. The success of this approach reflects the synergy between active learning, intelligent feedback, and reflective communication, forming a dynamic system that fosters both motivation and understanding.

The effectiveness of the model can be explained through the lens of constructivist and sociocultural learning theories (Gashaj et al., 2025). Constructivism posits that learners build knowledge actively through interaction and reflection. The Course Review Horay model provides precisely this environment: it transforms learning from a passive reception of knowledge into an active process of dialogue, play, and peer collaboration. The integration of deep learning technology complements this approach by enabling personalized and data-driven feedback—an essential condition for meaningful reflection. In this study, students who received automated feedback on their written responses showed more awareness of their reasoning errors, supporting the idea that reflection supported by feedback deepens conceptual understanding. This dual-layered design—social learning through CRH and individualized reflection through AI feedback—embodies Vygotsky's concept of the Zone of Proximal Development (ZPD), where learning occurs most effectively when scaffolded by social and technological mediators. The teacher's role as facilitator, supported by real-time analytics, strengthened this scaffolding process by ensuring that each learner received timely and targeted support.

The outcomes align with previous empirical studies that have emphasized the role of technology in supporting deep learning. Deci & Ryan, (2020) found that digital tools enhance reflective engagement when used interactively rather than passively, while Zamrudah, (2024) demonstrated that AI-based automatic scoring systems improved students' writing and explanation skills in mathematics. Similarly, Ricita et al., (2025) revealed that deep learning technologies promote emotional and cognitive engagement through personalized feedback. The present study extends these findings by embedding AI feedback mechanisms within a low-cost, gamified model like CRH, showing that advanced technology can be adapted to everyday classrooms without requiring sophisticated infrastructure.

Moreover, the current results corroborate Perales & González, (2025) theoretical positions that mathematical understanding emerges through communication. The observed growth in students' verbal and symbolic expressions validates the argument that mathematical thinking is essentially communicative: students learn by explaining, defending, and negotiating meaning. The CRH environment encouraged exactly this type of social discourse, while the deep learning analytics ensured that the dialogue was accurate and conceptually grounded. This interplay between social construction and technological precision explains the robust improvement observed in mathematical communication skills.

The combination of CRH and deep learning appears effective for several interrelated reasons. First, active engagement in the CRH model transforms learning into an enjoyable, low-anxiety experience. The inclusion of collaborative competition motivates students to participate and take intellectual risks, aligning with self-determination theory (Chen et al., 2023), which identifies autonomy, competence, and relatedness as key drivers of motivation. Students' comments—such as "It feels easier to explain because we do it together and it's fun"—illustrate this motivational impact.

Second, deep learning analytics enhance feedback quality and immediacy. In traditional classrooms, feedback is often delayed or generic, but AI-driven systems provide instant, individualized analysis of student explanations. This immediacy supports cognitive load theory (Ogunniyi & Jita, 2025), as it allows students to focus cognitive resources on problem solving and reasoning rather than waiting for evaluation. The teacher in this study reported that technology-assisted feedback simplified the diagnostic process, allowing for more targeted discussion and collective problem resolution.

Third, the model cultivates reflective communication, where students learn not only to solve problems but also to evaluate the clarity of their reasoning. This reflection process is consistent with metacognitive theory, which emphasizes awareness and regulation of one's thinking as a predictor of deeper learning. Through continuous feedback and social interaction, students developed the habit of revising their explanations, gradually internalizing higher standards of precision and coherence.

From a broader perspective, the Deep Learning-Based CRH model aligns with the educational vision of Society 5.0, which integrates digital technology into human-centered learning ecosystems (Hardiansyah & Wahdian, 2023; B. Kim & Choi, 2022). Society 5.0 promotes technological tools that empower, not replace, human creativity and communication. This study embodies that principle: deep learning served as a facilitator of human dialogue, amplifying teachers' capacity to guide students rather than automating instruction. The observed improvements in communication, collaboration, and confidence demonstrate that technology can coexist harmoniously with humanistic pedagogy.

The model also supports the National Council of Teachers of Mathematics (NCTM, 2020) standards, which emphasize communication as a key dimension of mathematical proficiency. Students in this study progressed from simply computing answers to articulating why their methods were valid—reflecting a shift from procedural to conceptual understanding. This finding echoes the argument of Cinar & Tekkumru-Kisa (2023) that discussion-based, reflective instruction enhances both reasoning and understanding in mathematics classrooms.

While the findings are promising, several limitations must be acknowledged. The study was conducted with a small sample size (n = 15) within a single institution, limiting generalizability. Although the paired-sample t-test and large effect size provide strong evidence of improvement, future studies should include larger samples and a control or comparison group to strengthen causal inference. Additionally, the intervention spanned only four weeks, which may not capture long-term retention or transfer of communication skills. Extended longitudinal research is recommended to evaluate whether these gains persist over time.

Another limitation involves technological and contextual constraints. Implementation required stable internet connectivity and teacher familiarity with AI systems—conditions not uniformly available in all schools. The deep learning model used analyzed primarily text-based data; thus, future iterations could incorporate multimodal analytics, such as speech and gesture recognition, to capture a fuller range of communicative behaviors. Finally, potential biases from teacher involvement in both instruction and evaluation could be mitigated in future studies through external observation or interrater reliability checks.

Despite these limitations, the study offers valuable implications for educational practice and policy. For teachers, the Deep Learning-Based CRH model presents a practical, scalable strategy to promote communication skills without requiring complex hardware. Teachers can adapt their principles—active participation, game-based engagement, and real-time feedback—to various mathematical topics. For curriculum developers, this study provides empirical support for embedding AI-assisted formative assessment within active learning frameworks, helping schools transition toward more personalized and interactive instruction.

For policymakers, the research contributes evidence to the discourse on digital transformation in education. It demonstrates how artificial intelligence can be leveraged to support human-centered pedagogy, consistent with Indonesia's *Merdeka Belajar* vision and global frameworks for 21st-century learning. At a theoretical level, the findings enrich the discussion on AI-supported constructivism, showing that intelligent systems can operationalize feedback loops central to knowledge construction.

This study contributes to educational theory by proposing a model of AI-augmented constructivism, where deep learning analytics and active learning pedagogies operate in tandem. It demonstrates that communication—often viewed as a soft skill—can be systematically cultivated through structured, feedback-driven, and technologically mediated practice. The findings affirm that mathematical communication is both a process and a product of learning, evolving through cycles of participation, reflection, and correction. The Deep Learning-Based CRH framework thus serves as an operational example of how digital technologies can nurture higher-order cognitive and communicative competencies in mathematics.

4. CONCLUSION

This study concludes that the Deep Learning-Based Course Review Horay (CRH) model is an effective pedagogical innovation for enhancing students' mathematical communication skills in the context of the Society 5.0 era. The integration of deep learning analytics into an active, collaborative learning framework resulted in significant improvements in students' ability to express, represent, and justify mathematical ideas both verbally and in writing. Quantitative analysis confirmed a statistically significant increase in students' performance with a large effect size, while qualitative findings revealed higher engagement, confidence, and reflective reasoning. Together, these results demonstrate that when technology is designed to complement human-centered instruction, it can meaningfully support both cognitive and communicative dimensions of learning.

Despite its promising outcomes, this study has several limitations. The small sample size of 15 students, the absence of a control group, and the short intervention period restrict the generalizability and long-term interpretation of results. Additionally, the use of text-based deep learning analytics limits the exploration of multimodal aspects of communication, such as gestures, tone, and collaborative discourse. These constraints highlight the need for further investigation using larger samples, extended time frames, and more advanced multimodal AI tools.

Future research should expand this model across different educational levels and contexts to test its scalability and sustainability. Comparative and longitudinal studies could explore the model's long-term impact on students' reasoning, collaboration, and digital literacy. Moreover, researchers are encouraged to examine how AI-augmented active learning frameworks can be adapted to other disciplines, thereby contributing to the broader goal of creating human-centered, technology-integrated education systems aligned with the ideals of Society 5.0.

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