A Teaching Method Based on In-Class Error Analysis for Instructional Improvement

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***Abstract*—In engineering education, students often carry misconceptions that stay hidden during regular classroom teaching. These wrong ideas can stop them from fully understanding new concepts. This paper presents a simple, teacher-led method called in-class error analysis to help identify and correct such misconceptions. The method was used in a Computer Networks course, where students answered multiple-choice questions (MCQs) after each lesson. The teacher studied the wrong answers to find patterns of misunderstanding and then adjusted the next class accordingly. Educational metrics like accuracy, difficulty index, discrimination index, and normalized learning gain were used to study student performance and the impact of re-teaching. The results showed clear improvements, especially in tricky topics like TCP vs UDP and OSI vs TCP/IP layer mapping. By treating mistakes as useful feedback instead of failures, this approach helps teachers improve their teaching and support better student learning. It also works well without needing any advanced technology, making it suitable for many classrooms.**

***Keywords*—Error-analysis, Classroom teaching, Learning analytics, Misconception, Formative Assessment.**

***ICTIEE* Track—Assessment, Feedback, and Learning Outcomes)**
ICTIEE Sub-Track—Learning Analytics for Evaluation and Improvement

I. INTRODUCTION

ADAPTIVE teaching has emerged as a critical component in modern engineering education, where diverse learner backgrounds and varying levels of prior knowledge make uniform instructional strategies less effective. The dynamic nature of engineering subjects—particularly those involving abstract concepts, complex problem-solving, and layered prerequisite knowledge—demands teaching approaches that can respond to student understanding in real time. Traditional lecture-based instruction, though efficient for content delivery, often overlooks the individual learning needs of students and fails to promptly identify and address conceptual misunderstandings.

One of the persistent challenges in undergraduate engineering education is the presence of misconceptions that students carry from earlier learning experiences or form during initial exposure to new concepts. These misconceptions, if uncorrected, can hinder deeper learning and cause long-term difficulties in mastering more advanced topics. In standard classroom settings, such errors often go undetected, especially when students do not voluntarily express confusion or provide incorrect answers due to a lack of confidence or fear of judgment. Consequently, educators may proceed under the false assumption that all students have understood the material, leading to a widening gap between instruction and comprehension. To address this issue, this study proposes a teaching method centered on *in-class error analysis*. The approach involves posing diagnostic or conceptual questions during the lecture, actively engaging students to respond, and closely observing the incorrect responses. Rather than dismissing wrong answers, the instructor treats them as valuable insights into student thinking. Each incorrect response is analyzed to identify underlying causes—be it is a fundamental misunderstanding, a misapplied concept, or a gap in prerequisite knowledge. The insights gained from this analysis are then used to reflectively plan the subsequent class session, revisiting difficult topics, reinforcing key ideas, or modifying the instructional sequence to address observed learning gaps.

This method transforms student mistakes from being merely signs of failure into meaningful data points for instructional refinement. By continuously adapting lessons based on real-time feedback derived from student errors, educators can create a more responsive and personalized learning environment.

The objective of this paper is to evaluate the effectiveness of this teaching method in improving classroom instruction and student learning outcomes. The study focuses on the practical implementation of in-class error analysis in an undergraduate engineering course, examining the types of errors encountered, how these informed instructional changes, and the impact of this reflective practice on student engagement and conceptual understanding. This study is guided by the following research questions:

RQ1: What types of misconceptions are most common in foundational networking concepts?

RQ2: How effectively does reflective error analysis improve conceptual understanding, based on metrics such as difficulty index, discrimination index, and normalized learning gain?

RQ3: Can clusters of student errors reveal deeper conceptual

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gaps?

II. Related Work

Many studies have highlighted the importance of using student responses — especially wrong ones — to improve teaching. This approach is part of what's called formative assessment, where teachers use feedback during the lesson to make teaching more effective. The foundational work by (Black & Wiliam, 1998) showed that when teachers adjust instruction based on student understanding, learning improves.

A key part of formative assessment is examining student mistakes. (Shute, 2008) emphasized that feedback should not only give correct answers but also help students understand why their thinking was wrong. (Chi, 2005) argued that when students hold strong but incorrect beliefs (called misconceptions), they need targeted teaching to change those ideas.

Research consistently shows that examining student errors—rather than just correct answers—can make teaching more effective. This idea fits under the umbrella of formative assessment, where instructors adapt teaching based on ongoing feedback. A comprehensive study by (Qadir et al., 2020) demonstrated how formative assessment and feedback in engineering classrooms helps both students and teachers focus on misunderstandings as they occur. In engineering mathematics(Sikurajapathi et al., 2020) used assessment, where student input was analyzed to detect common mathematical misconceptions. Their system then provided tailored feedback to address those errors promptly. In science education(Lichtenberger et al., 2025) conducted a controlled intervention in physics. They used concept questions during classes to surface and correct misconceptions, resulting in improved conceptual understanding compared to traditional instruction.

(Roselli & Brophy, 2006) highlighted the effectiveness of immediate, in-class polling systems (Classroom Communication Systems) for identifying misconceptions. They found significant improvement in student retention when instructors responded right away to incorrect student answers. (Escalante, 2021) analyzed responses from hundreds of engineering students on the Force Concept Inventory to identify persistent Newtonian misconceptions. Although not directly linked to real-time classroom error analysis, it underscores how common and entrenched student misconceptions are in engineering education. Together, these studies support the idea that actively seeking out and addressing misconceptions can improve student learning. However, most work either relies on digital tools (e-assessments, polling clickers) or large-scale testing instruments. There is surprisingly little research on a simple, human-driven method where instructors collect wrong verbal answers during class, reflect on them, and modify the next lesson accordingly.

In recent years, the integration of learning analytics (LA) into teaching practices has proven highly effective in identifying misconceptions and guiding adaptive instruction. (Elmoazen et al., 2023) demonstrated how error tracking and formative feedback in virtual engineering labs led to clearer concept retention and faster correction of student misunderstandings. Similarly, in a study focused on reducing conceptual learning gaps, Mitigating Conceptual Learning Gaps (Naseer & Khawaja, 2025) reported that students who received analytics-informed feedback showed up to a 28% increase in understanding over those who did not receive targeted interventions.

(Kohnke et al., 2022) emphasized the importance of combining formative assessment with LA to predict student performance and recommend real-time pedagogical actions, which aligns closely with the current study's use of multiple-choice questions and distractor effectiveness metrics. (Sajja et al., 2023) further contributed by using AI-enhanced analytics to identify confusion patterns and adapt teaching in real-time—a technique that mirrors the human-led classroom reflection cycle used in this work. Moreover, (Romero & Ventura, 2020) outlined a comprehensive review of educational data mining and LA techniques, reinforcing the role of metrics like normalized learning gain, discrimination index, and item difficulty in enhancing instruction across STEM disciplines. These contemporary studies support the present paper's claim that real-time error analysis, when combined with robust analytics, serves as a powerful low-tech strategy to improve conceptual understanding in engineering education

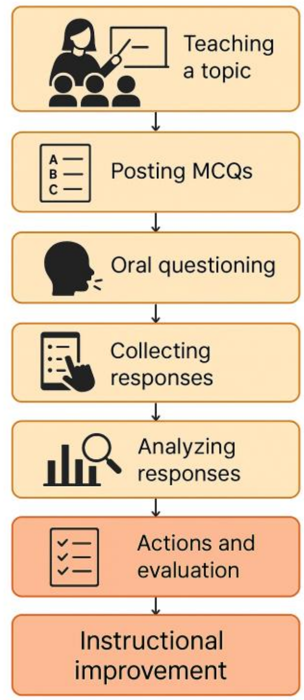

Fig. 1. Instructional Cycle for In-Class Error Analysis-Based Teaching Methodology

Theoretical Foundations of the Error-Analysis Approach:

The use of error analysis in the classroom is strongly supported by contemporary research in metacognition and reflective learning. Recent studies show that when learners are encouraged to think about *why* they made an error, they develop stronger metacognitive awareness and deeper conceptual understanding. For example, Del Valle (2025) found that students in constructivist, reflection-based learning environments demonstrated significantly higher academic success and stronger metacognitive regulation. Similarly, reflective and metacognitive interventions in design and engineering-related courses have been shown to improve students' awareness of their thinking processes and enhance overall performance (Ahmed & Hilal, 2025).

These findings reinforce the idea that learning becomes more meaningful when students actively analyze and reconstruct their understanding rather than passively receiving information. By prompting learners to revisit their misconceptions and compare them with correct reasoning, our error-analysis approach aligns with this modern, learner-centered pedagogical perspective. Furthermore, recent large-scale work on metacognition confirms that students who monitor and reflect on their learning are more engaged and demonstrate better long-term retention (Zhang et al., 2024). Thus, the mechanism underlying our approach is grounded in strong theoretical and empirical support from contemporary education research.

III. Methodology

The process begins with the teacher delivering a topic from the Computer Networks curriculum. This can be through lectures, presentations, whiteboard discussions, or demonstrations. The objective is to cover the concept clearly and thoroughly so that all students have a fair chance of understanding the topic. After the topic delivery, the teacher engages students through oral questioning or live polls to check immediate understanding. This helps break the monotony and encourages attentiveness. Students respond verbally or by raising hands, and this quick check gives the teacher a sense of the class's grasp of the concept. The next step is to post 10 well-designed MCQ questions related to the topic. These questions are hosted digitally (via Google Forms). Each student submits their answers. The aim is to capture individual understanding anonymously and objectively. The system collects 60 responses, 600 sample answers per session, giving a clear picture of student comprehension. The data includes right/wrong answers, option choices, and timestamps. Once the responses are in, error analysis is performed. The incorrect responses are examined for patterns — for example, are many students choosing the same wrong option? This might indicate a common misconception or a tricky distractor. Metrics like difficulty index, discrimination index, and option effectiveness are calculated. Based on the analysis, common student errors are grouped into misconception clusters. These clusters help the teacher understand why the errors occurred — e.g., conceptual confusion, misreading the question, or flawed logic. Clustering may also identify specific students who consistently show similar misunderstandings.

To understand the nature of students' errors more meaningfully, we categorized the misconceptions observed in their responses into four broad groups. This helped us interpret the patterns behind incorrect choices rather than treating them as isolated mistakes.

1. *Terminology-based misconceptions* These occurred when students misunderstood or confused fundamental definitions, such as the roles of OSI layers or basic networking terms.
2. *Conceptual-process misconceptions* These reflected gaps in understanding how a process unfolds, for example in connection establishment, flow control, or data transfer sequences.
3. *Application-level misconceptions* These appeared when students struggled to apply conceptual knowledge to situational or scenario-based questions, often leading to incorrect reasoning about what a protocol would do in each context.
4. *Distractor-driven misconceptions* These arose when students consistently selected distractors that seemed intuitively correct but were based on common misunderstandings. The patterns in these choices revealed deeper misconceptions that were not immediately visible through scores alone.

By organizing misconceptions in this way, we were able to provide targeted feedback during classroom discussions and address not just *what* students got wrong, but *why* they were thinking in that direction. This structured approach made the error-analysis exercise more actionable and pedagogically meaningful.

The teacher then designs the targeted interventions such as:

1. Clarifying concepts in the next class
2. Revisiting foundational topics
3. Providing analogies or visual aids
4. Assigning personalized remedial work

Ethical Considerations: The study was carried out in alignment with the institution's ethical guidelines throughout the process of data collection and analysis. Students participated voluntarily, and their privacy was carefully protected by assigning unique anonymized codes known only to them. No marks, grades, or academic rewards were tied to their responses, ensuring that they could answer freely without any performance-related pressure.

Since the activity formed part of regular classroom practice aimed at improving teaching and learning, it qualified for an exemption from formal institutional review. All collected data were used solely for educational improvement and research purposes and were handled responsibly to maintain confidentiality and uphold ethical standards.

IV. Learning Analytics for Conceptual Improvement

To assess student understanding and improve instruction in a Computer Networks class, we implemented a real-time error analysis framework using 10 multiple-choice questions (MCQs) based on the TCP/IP protocol suite (for Questionnaire visit the link given in APPENDIX). These questions were administered to 60 students, and their 600 responses were analyzed using key educational metrics. This classroom-driven analysis provides targeted feedback, highlights learning gaps, and supports evidence-based teaching improvement.

Overall Accuracy

Overall accuracy (from Eq.1) measures the fraction of correct answers across all questions and all students.

$$\text{Overall Accuracy } = \frac{\sum_{i=1}^{N}\sum_{j=1}^{Q} \text{Correct}_{ij}}{N\times Q} \tag{1}$$

Where, N = Number of students (60), Q = Number of questions (10) and $Correct_{ij}$=1 if student i's answer to question j is correct, else 0.

TABLE I
OVERALL ACCURACY

Metric	Value
Overall Accuracy	71.83%

The overall accuracy of the class was found to be 71.83% (shown in table I), which means that, on average, students answered about 7 out of 10 questions correctly. This indicates a moderate level of understanding of the TCP/IP protocol concepts among the students. While the average performance is acceptable, it also suggests there is room for improvement. Ideally, a well-learned concept should lead to accuracy above 80%. Therefore, this number serves as a baseline for deciding whether to adjust the teaching strategy or reinforce certain topics.

Topic-wise Accuracy

Topic-wise accuracy calculates (from Eq.2) the average correctness for questions belonging to the same topic.

$$\text{Topic Accuracy}_{k} = \frac{\sum_{i=1}^{N} \sum_{j \in T_k} \text{Correct}_{ij}}{N \times |T_k|} \quad (2)$$

Where, T_k= Set of question indices for topic k and $|T_k|$= Number of questions in topic k. The topic-wise accuracy metric breaks down the student performance according to specific subtopics like TCP/IP model, Transport layer, Internet layer, and Application layer. As shown in table II, if the Transport layer questions had an average accuracy of 68%, while the Internet layer had 75%, it suggests that students are more comfortable with the Internet layer concepts.

TABLE II
TOPIC-WISE ACCURACY

Topic	Accuracy (%)
TCP/IP Model	72
Transport	68
Internet	75
Application	70

On the other hand, lower scores in the Transport layer could mean students are unclear about topics like TCP vs. UDP or port addressing. This type of analysis helps pinpoint weak areas, so instructors can plan targeted revision sessions or explanatory examples for those specific topics.

Difficulty Index (Per Question)

The difficulty index (from Eq.3) measures the proportion of students who answered a question correctly (Jaleel, 2012).

$$\text{Difficulty Index}_{j} = \frac{\sum_{i=1}^{N} \text{Correct}_{ij}}{N} \quad (3)$$

Table III shows the obtained difficulty index. The difficulty index tells us how easy or hard each question was for the students. For instance, Q6 and Q8 had high scores (above 80%), meaning most students got this right. These questions were considered easy. In contrast, Q1 and Q2 had scores closer to 65%, suggesting they were moderately difficult. This kind of analysis is useful because it tells instructors which questions challenged students the most and might represent concepts that need to be re-explained. Importantly, none of the questions had very low scores (e.g., below 40%), which means that the test design was reasonably balanced.

TABLE III
DIFFICULTY INDEX (PER QUESTION)

Question	Difficulty Index	Interpretation
Q1	65.00%	Moderate difficulty
Q2	66.67%	Moderate difficulty
Q3	78.33%	Easy
Q4	66.67%	Moderate difficulty
Q5	73.33%	Moderate difficulty
Q6	81.67%	Easy
Q7	66.67%	Moderate difficulty
Q8	80.00%	Easy
Q9	68.33%	Moderate difficulty
Q10	71.67%	Moderate difficulty

Discrimination Index (Per Question)

The discrimination index (from Eq.4) measures how well a question differentiates between high-performing and low-performing students (Jaleel, 2012).

$$\text{Discrimination Index}_{j} = P_{\text{top},j} - P_{\text{bottom},j} \quad (4)$$

Where, $P_{\text{top},j}$= Proportion of correct answers in the top 27% of students for question j and $P_{\text{bottom},j}$ = Proportion of correct answers in the bottom 27% of students for question j.

TABLE IV
MOST COMMON MISCONCEPTIONS (PER QUESTION)

Question	Correct Answer	Most Common Wrong Answer	Insight
Q1	C	A	Students confuse the correct layer or protocol
Q2	B	D	Misunderstanding of transport layer responsibilities
Q3	D	B	Confusion between TCP and UDP
Q4	D	C	IP addressing or routing concepts unclear
Q5	C	B	Internet layer protocols mixing

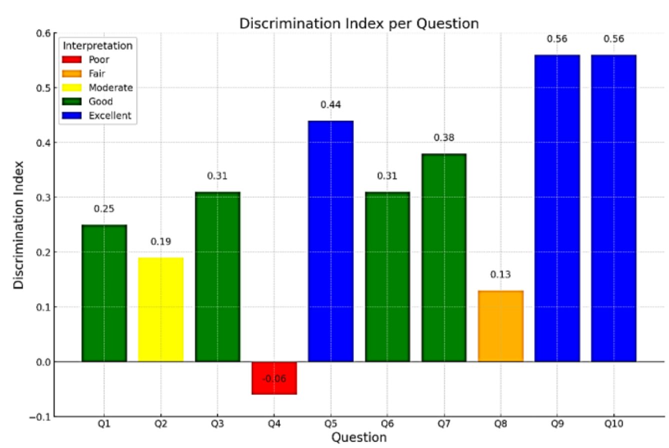

Fig. 2. Discrimination Index (Per Question)

Q6	B	A	Network addressing misconceptions
Q7	B	C	Application layer roles misunderstood
Q8	B	D	UDP vs TCP distinctions unclear
Q9	B	A	Email protocol confusion
Q10	D	A	TCP/IP model layers not well differentiated

The discrimination index (shown in figure 2) is a very important metric for evaluating the quality of the question itself. It tells us how well a question distinguishes between strong and weak students. A higher positive value (e.g., 0.56 for Q9 and Q10) means that high-performing students consistently got it right, and low-performing students got it wrong, which is ideal. However, Q4 had a negative value, which is a red flag. This suggests that low-scoring students got Q4 right more often than high-scoring students, possibly due to guessing, poor question phrasing, or a misunderstanding. Questions like Q4 should be reviewed and possibly rewritten or removed in future tests. The table IV looks at the most frequent wrong answer chosen for each question. For example, for Q1, the correct answer was C, but many students chose A. This implies that students have a specific misunderstanding, not just a random error. These kinds of patterns help instructors understand exactly what students are confusing. For instance, if a majority selected "A" thinking it was the correct layer in the TCP/IP model, that tells the teacher where the misconception lies and allows them to clarify that specific point in the next class. This form of analysis goes beyond just right or wrong and gets into the reason behind the wrong answers, making it highly useful for instructional improvement. A detailed analysis is given in table V. Following the detailed analysis of misconceptions (as shown in Tables IV and 5), we carefully planned targeted instructional interventions aimed at correcting these specific misunderstandings. Rather than repeating the same content, the focus was on conceptual clarification, alternative representations, and active engagement strategies that directly addressed the root causes of the errors. Once the misconception clusters were identified from the MCQ responses, each was reviewed to determine:

1. Whether the confusion was terminological, structural, or functional
2. What prior knowledge was missing or misapplied
3. Whether the error was widespread (high-frequency wrong choice) or isolated

These interventions were implemented during the next class session, typically within 1 or 2 days of the error analysis. This timing ensured that:

TABLE V
DETAILED ANALYSIS OF THE MOST COMMON MISCONCEPTIONS

Q#	Correct Answer	Most Common Wrong Answer	Technical Interpretation
Q1	C (Session is not in TCP/IP model)	A	Many students mistakenly selected A (Application), perhaps due to confusion with the OSI model. The TCP/IP model merges the session, presentation, and application layers into a single application layer, whereas the OSI model treats them separately. Students may not have internalized this abstraction, leading to confusion.
Q2	B (Transport layer provides reliable delivery)	D	The choice of D (Addressing packets with IP addresses) suggests confusion between transport and network layers. IP addressing is the responsibility of the Internet layer, not transport. Students selecting D likely equate "data delivery" with "addressing," showing a partial understanding of protocol responsibilities.
Q3	D (TCP is connection-oriented)	B	Selecting B (ICMP) indicates confusion between control and transport protocols. ICMP is used for diagnostics and error messages, not for data transport. The confusion may stem from the misconception that ICMP somehow establishes connections because it's involved in "testing" (e.g., ping).
Q4	D (IP is unreliable and connectionless)	C	Students choosing C (Reliable and connectionless) misunderstand what "reliability" means in networking. IP is connectionless and does not guarantee delivery, which is the job of TCP. The confusion here may arise from assuming IP being widely used means it must be reliable.
Q5	C (Internet layer handles logical addressing)	B	Selecting B (Transport layer) shows confusion about the layer responsibilities. The transport layer uses port numbers for addressing *within* a host, not between hosts. Logical IP addressing is solely handled by the Internet layer. This suggests a mix-up between host-level and network-level addressing.
Q6	B (IP protocol is in Internet layer)	A	Students choosing A (FTP) may be categorizing protocols based on familiarity, not layer responsibility. FTP is an application layer protocol and operates on top of TCP/IP. The error suggests the need to reinforce the protocol stack layering.
Q7	B (DNS resolves domain names)	C	C (HTTP) is a web application protocol and doesn't resolve domain names. Students may wrongly associate HTTP with DNS because both involve the internet. The misconception may stem from observing domain names in browser URLs and assuming HTTP handles that directly.
Q8	B (TCP provides error recovery, UDP does not)	D	Choosing D (TCP does not use port numbers) is technically incorrect, as both TCP and UDP use ports. The error reveals a lack of clarity in understanding how transport protocols identify applications. Students likely confuse TCP's features (reliability, handshaking) with addressing mechanisms.
Q9	B (SMTP sends email)	A	A (FTP) is commonly known for transferring files, and students may incorrectly associate file attachments with FTP instead of SMTP. The confusion may also be due to SMTP being less familiar or not clearly distinguished from POP/IMAP in instruction.
Q10	D (Network Access = Data Link + Physical)	A	Students choosing A (Network Layer) might be mapping OSI layer concepts directly onto the TCP/IP model. In the TCP/IP model, data link and physical layers are collapsed into the Network Access Layer, not the Network Layer. This reveals confusion in layer mapping between the two models.

1. The misconceptions were still cognitively active in students' minds
2. The intervention could serve as an immediate conceptual correction

Each intervention session included:

1. A brief recap of the key concept
2. A corrective explanation using the new representation
3. A follow-up example or MCQ to apply the corrected understanding

V. Evaluating Instructional Impact

To further substantiate the instructional value of the in-class error analysis approach, we extended our investigation to include additional learning analytics. These metrics provide richer insights into student progress, question design quality, and the effectiveness of targeted interventions. Specifically, we examined three key dimensions: Normalized Learning Gain, Distractor Effectiveness, and Error Persistence. These analytics collectively enhance the robustness of our methodology by moving beyond performance snapshots to a more dynamic understanding of how learning evolves over time.

E. Normalized Learning Gain

The overall and topic-wise accuracy provide a static view of student performance; Normalized Learning Gain (from Eq.5) offers a dynamic measure of how much conceptual understanding has improved because of instructional intervention. This metric is particularly effective in quantifying the impact of re-teaching strategies that were informed by prior error analysis.

The gain is calculated using Hake's normalized formula:

$$g = \frac{\text{Post-test Score} - \text{Pre-test Score}}{100 - \text{Pre-test Score}} \tag{5}$$

In our study, the Transport Layer was identified as a relatively weak area, with an average accuracy of 68% during the initial assessment. Based on the detailed misconception analysis (Table VII), a follow-up session was designed with emphasis on clarifying distinctions between TCP and UDP, reliability, and port addressing. A fresh set of MCQs, aligned with the same conceptual objectives, was administered immediately after the re-teaching.

The average score in this follow-up assessment increased to 81%, leading to a calculated normalized gain:

$$g = \frac{81 - 65}{100 - 65} = \frac{16}{35} \approx 0.46$$

A gain value of 0.46 corresponds to moderate conceptual improvement (as per Hake's scale: low < 0.3, medium 0.3–0.7, high > 0.7). This demonstrates that instructional changes, informed by in-class error data, significantly improved student learning. This evidence supports the use of real-time error feedback as a catalyst for pedagogical refinement.

F. Distractor Effectiveness

The correct answers are an important indicator of understanding, analyzing the behavior of distractors (incorrect options) can provide crucial insights into both student thinking and question quality. A distractor is effective when it successfully attracts students who lack conceptual clarity, but is typically avoided by well-prepared students. This aligns with the pedagogical goal of using multiple-choice questions not just for grading, but as diagnostic tools.

We analyzed distractor effectiveness by comparing the selection rates of wrong options among the top 27% (high performers) and bottom 27% (low performers) of the cohort. Table VI presents a representative sample of this analysis.

Table VI
Distractor Effectiveness in Selected Questions

Question	Distractor (Wrong Option)	% Low Performers Selecting	% High Performers Selecting	Effectiveness
Q1	A	48%	8%	High
Q3	B	35%	20%	Moderate
Q4	C	40%	42%	Poor
Q8	D	30%	12%	Moderate

In Q1, the distractor A ("Application") was selected by nearly half of the low performers but was largely ignored by high performers. This indicates that the distractor is functioning well—it identifies conceptual confusion between the OSI and TCP/IP models. In contrast, Q4 presents a concern. The distractor C ("Reliable and connectionless") was chosen almost equally by both groups. This lack of discrimination, along with Q4's negative discrimination index reported earlier, suggests that the option may be misleading or the question poorly phrased. In such cases, the item should be reviewed and possibly rewritten for clarity.

G. Error Persistence

A critical measure of instructional success is whether previously identified misconceptions are resolved over time. To assess this, we tracked specific error patterns across multiple sessions and analyzed how students responded to similar concepts after intervention. This form of longitudinal error tracking, or error persistence analysis, helps in evaluating the depth and durability of conceptual change. We re-administered questions in later sessions following targeted re-teaching. Fig. 3 summarizes the change in performance for selected misconceptions.

These improvements clearly demonstrate that misconceptions identified via error analysis can be effectively remediated. For example, confusion between TCP and UDP functions was significantly reduced following analogies and visual explanations of reliable vs. unreliable protocols. Similarly, clarification around the OSI and TCP/IP layer mapping helped students overcome persistent structural misunderstandings. The post-intervention gains validate that the method not only detects conceptual gaps but also closes them when followed by deliberate, responsive instruction.

H.Discussion

Learning analytics played a key role in this study by turning student answers into valuable insights for better teaching. After each class, the teacher used tools like Google Forms to collect multiple-choice answers from students. These responses were then analyzed using learning analytics techniques such as overall accuracy, topic-wise accuracy, difficulty index, discrimination index, and distractor analysis. These metrics helped the teacher understand not just which questions were difficult, but why students were making mistakes. For example, the discrimination index showed which questions were good at separating strong students from weak ones, and the distractor analysis revealed which wrong options were tricking confused students. This information helped the teacher identify common misconceptions and redesign the next lesson to directly target those issues. The use of analytics also allowed tracking improvement over time, showing that students scored better after re-teaching, especially in topics like the Transport Layer. Overall, learning analytics made the teaching process more data-driven, responsive, and effective.

I. Limitations of this study

a) The study focused on a single subject with 60 students. Broader application across subjects can further validate the method. Future work will expand the analysis across multiple courses, semesters, and institutions to enhance generalizability.
b) The current approach relies on manual analysis by the teacher. To scale this benefit, integrating digital tools or semi-automated systems in the future could make the process more efficient while preserving its diagnostic value.
c) Learning gains were measured shortly after intervention. Long-term impact remains a promising area for future exploration.

Conclusion

This study shows that in-class error analysis is a helpful and easy way to improve learning in engineering courses. Instead of just teaching and moving on, the teacher looks at where students are going wrong and uses that information to make the next class better. This makes learning more focused and personal for the students. With the help of learning analytics like accuracy rates, misconception patterns, and normalized learning gain, the teacher can clearly see what's working and what needs to change. The method led to better understanding and fewer repeated mistakes, even in difficult topics. The best part is that it does not require any special tools, just careful observation and thoughtful planning by the teacher. This strategy not only helps students learn better but also encourages teachers to keep improving their teaching methods. In the future, this approach can be tried in other engineering subjects or expanded using simple digital tools.

Future Work

This method can be applied to other engineering or technical subjects to test its effectiveness in different areas. Future work could also explore using simple digital tools to help teachers quickly identify common student errors. Additionally, training programs can be developed to help educators use this approach effectively in regular classroom teaching.

Appendix

A Sample Survey Questionnaire used is available at: https://tinyurl.com/2cwda2k9

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