Analysing AI utilisation in education through learner question types: A constructivist approach

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This study investigated the evolving role of artificial intelligence (AI) in higher education by analysing learner-generated questions through a constructivist framework. Drawing on Piaget and Vygotsky's theories, student inquiries were categorised into three roles: knowledge transmitter, facilitator and co-learner. Data from 11 students across 12 information technology courses yielded 434 authentic questions, expert labelled and augmented to balance class distributions. Several natural language processing models including bidirectional encoder representations from transformers (BERT; baseline and fine-tuned), disentangled attention BERT approach (DeBERTa) and robustly optimised BERT approach (RoBERTa) were evaluated for their ability to classify these questions. Results indicate that while models excel at processing factual (knowledge transmitter) queries, they face challenges distinguishing higher-order facilitator and co-learner questions. Notably, DeBERTa achieved the highest overall accuracy (86.36%) yet struggled with capturing contextual nuances inherent in complex queries. These findings underscore the potential of AI to support personalised learning and adaptive feedback in educational settings while highlighting the indispensable role of human oversight. Implications for integrating such models into learning management systems and avenues for future research including model refinement, cross-disciplinary validation and ethical AI implementation are discussed.

Implications for practice or policy:
- Instructors could enhance learner engagement by integrating AI-based question analysis tools to provide tailored feedback based on inquiry depth.
- Course designers may need to incorporate AI-driven scaffolding strategies to support students' higher-order thinking skills.
- Learning management systems could benefit from embedding automated question categorisation functions to identify students' learning needs more efficiently.
- Educational institutions should consider developing ethical guidelines for the use of AI in formative assessment processes.

Keywords: artificial intelligence (AI) in education, learner-generated questions, natural language processing (NLP), personalised learning, constructivist learning theory, language classification

Introduction

The rapid evolution of artificial intelligence (AI) technologies has significantly transformed higher education. This transformation has redefined learning environments, reshaped student motivations and altered pedagogical practices. Educators are shifting from knowledge transmission to facilitation, while students increasingly learn in autonomous and personalised ways (Lim et al., 2022; Sharif & Atif, 2024). AI-powered systems that dynamically respond to learners' needs have become essential tools in this new paradigm (Kong et al., 2025; Netland et al., 2025; Xu et al., 2024).

While AI's effectiveness in delivering factual knowledge is well studied, less attention has been paid to its potential in supporting higher-order cognitive processes central to constructivist learning, such as scaffolding and critical inquiry. Constructivist theory identifies three educator roles: knowledge transmitter, facilitator and co-learner (Jha & Atif, 2025; Kang et al., 2016; Lee & Kang, 2019; Vygotsky, 1978). As students engage with generative AI tools in the classroom, questions arise about whether these systems can support deeper engagement and knowledge co-construction. Recent studies have highlighted that AI's adaptive and reflective affordances can reinforce constructivist pedagogy by supporting active engagement, metacognitive growth and conceptual change in learner-centred settings (Grubaugh et al., 2023; Yang, 2025). Constructivist theories such as Piaget's (1964) and Vygotsky's (1978) emphasise learning as both cognitive and social. Vygotsky's concept of the zone of proximal development (ZPD) is especially relevant in evaluating AI's ability to scaffold learners towards deeper understanding. In this context, a recent review of AI literacy research (Sharif et al., 2025) suggests that generative AI can act as a co-constructive learning partner. While grounded in constructionist perspectives, these AI-mediated scaffolds can support learners' epistemic practices in ways that align with ZPD-oriented supports when situated within a broader constructivist learning framework (Lin et al., 2025).

This study explored whether AI systems can enact these multifaceted instructional roles by analysing learner-generated questions. For instance, a factual question such as "What is constructivism?" reflects the knowledge transmitter role, while a more exploratory question such as "How can constructivist principles improve online collaboration?" aligns with the facilitator role.

This study was guided by the following research questions:

1. To what extent can AI systems classify learner-generated questions into constructivist roles (knowledge transmitter, facilitator, co-learner)?
2. What challenges do AI models face in interpreting the intent behind learner-generated questions?
3. How can insights from question classification inform the design of AI educational tools that support deeper learning and critical inquiry?

To address these questions, the study aimed to:

- Collect and categorise learner-generated questions using constructivist frameworks.
- Evaluate natural language processing (NLP) models (e.g., bidirectional encoder representations from transformers (BERT)) for their effectiveness in classifying questions according to the identified instructional roles.
- Develop guidelines for designing AI educational tools that foster personalised, critical learning.

Unlike previous studies focused on AI content delivery, this research applied these instructional roles to assess learner interactions with AI, using NLP models such as BERT and generative pre-trained transformer (GPT) to classify student questions. The findings offer insights into learner engagement and support the development of ethically grounded, constructivist-aligned AI tools for education.

Background

Overview of AI in education

Building on the transformative role of AI introduced earlier, this section explores how AI technologies are reshaping contemporary educational practices. Since the COVID-19 pandemic, adoption has accelerated, transforming teaching and learning through tools such as automated essay scoring using generative models, analysing classroom discourse for cognitive and behavioural patterns and organising instructional content based on semantic similarity. Beyond these applications, constructivist perspectives emphasise that AI literacy education also requires learners to engage in epistemic practices and hands-on creation, highlighting AI's potential not only for efficiency but also for deeper student-centred inquiry (Lin et al., 2025; Yang, 2025). These applications improve efficiency and inform pedagogical decisions.

Empirical studies highlight diverse applications. Kong et al. (2025) demonstrated that AI-powered dashboards can classify classroom discussions into behavioural and cognitive dimensions, fostering critical thinking and collaboration. Xu et al. (2024) and Netland et al. (2025) found that AI-generated instructional videos reduced production time substantially while maintaining similar learning outcomes, though human-made videos conveyed stronger social presence. Such findings point to hybrid models that combine AI efficiency with human creativity. In assessment, Yavuz et al. (2024) reported that GPT-4's reliably scored grammar and spelling in English as a foreign language essays but inflated marks for advanced writers, signalling a need for calibration. Li et al. (2024) further showed how AI can integrate text and image vectors to personalise content delivery.

Conversational tools are also reshaping collaboration and writing. Hu et al. (2025) found that CollaBot enhanced cognitive engagement and Weber et al. (2024) observed that LegalWriter improved argumentative clarity. However, research still prioritises system performance over learner agency. Constructivist studies argue that meaningful AI integration must engage ethical and reflective dimensions of learning (Dai, 2025), attending to how students use AI for inquiry and exploration (Bakhtin, 1981; Darvishi et al., 2024; Freire, 1993). Addressing this gap, the present study seeks a more holistic understanding of AI's evolving role in educational contexts.

Importance of questions in learning

In constructivist learning theory, questions are fundamental tools that empower learners to actively construct knowledge by connecting new information with their prior experiences. This active engagement not only deepens understanding and retention but also transforms learners from passive recipients into active participants (McLeod, 2024; Vygotsky, 1978; Zajda, 2021). Constructivist approaches emphasise that meaningful learning emerges through exploration, inquiry and reflection – processes that are often initiated and sustained through the act of questioning (McLeod, 2024; Zajda, 2021). As per related studies, we highlighted that AI can amplify these constructivist processes by fostering metacognition and conceptual change when integrated into inquiry-driven learning environments (Grubaugh et al., 2023; Yang, 2025).

Reflective and open-ended questions play a critical role in fostering higher-order thinking. Lunenburg (2011) emphasises that such questions stimulate learners to evaluate, analyse and synthesise knowledge. These types of questions help transform the classroom into an interactive space where knowledge is not merely delivered but co-constructed. By modelling effective questioning techniques, educators cultivate a culture of curiosity, critical thinking and dialogic engagement (Freire, 1993; Lee & Kang, 2019; Piaget, 1964; Vygotsky, 1978).

Theoretical frameworks from dialogic pedagogy further highlight the centrality of questions in learning. Bakhtin's (1981) dialogic theory posits that genuine dialogue, marked by open-ended questioning and exchange of diverse perspective supports the co-construction of knowledge. Similarly, Freire's (1993) dialogic pedagogy challenges the banking model of education by advocating for a problem-posing approach in which dialogue between learners and educators fosters critical consciousness, reflection and agency. In both models, questions function as catalysts for deeper reflection, collaborative learning and transformative educational experiences (Larochelle et al., 1998; Zajda, 2021).

Beyond fostering critical thinking, questioning also enhances metacognition, enabling learners to evaluate their own understanding, recognise gaps and take ownership of their learning (Larochelle et al., 1998). In social and collaborative settings, questions also serve as bridges between individuals, supporting the construction of shared understanding and knowledge. Vygotsky (1978) and Bakhtin (1981) both emphasised the importance of social interaction in learning, where questioning plays a central role in facilitating cognitive development within the ZPD.

The integration of AI in educational settings adds a new dimension to the role of questions. AI-driven tools now enable interactive, personalised learning environments that respond dynamically to student inquiries. A recent systematic review of AI literacy research further suggests that generative AI can function as a collaborative learning partner, enabling students to develop epistemic practices and critically engage with knowledge construction (Lin et al., 2025). These systems offer adaptive feedback and real-time support, enhancing inquiry-based learning and expanding opportunities for metacognitive development (Darvishi et al., 2024; Hu et al., 2025). For instance, in science, technology, engineering and mathematics education, AI tools such as ChatGPT facilitate guided inquiry by providing tailored responses to conceptual questions. This not only supports problem-solving but also deepens conceptual clarity (Darvishi et al., 2024; Steffe & Gale, 1995). Additionally, as Kubalkova et al. (1998) argue, questions can challenge dominant narratives and promote deeper intellectual engagement. Whether used to test understanding, provoke discussion or stimulate reflection, questions serve as powerful instruments for personalising learning, encouraging dialogue and fostering critical inquiry.

Constructivist roles: Knowledge transmitter, facilitator and co-learner

Recent advancements in generative AI have prompted a re-evaluation of instructional roles traditionally held by educators. In constructivist pedagogy, teachers are often viewed as knowledge transmitters, facilitators of inquiry and co-learners (Kang et al., 2007; Piaget, 1964; Vygotsky, 1978). As AI tools become more capable and accessible, learners increasingly rely on them not just for factual information, but also for feedback, suggestions and reflective prompts. This trend raises key questions: can AI genuinely fulfil these multifaceted pedagogical roles, or does it merely imitate surface-level features of human instruction? Lin et al. (2025) argue that while AI can support facilitation and collaboration, its effectiveness in sustaining deeper epistemic practices and dialogic inquiry remains limited (Lin et al., 2025).

The knowledge transmitter is the most readily fulfilled by AI, particularly when responding to factual queries. In such cases, AI serves as an efficient information source, similar to teacher-centred models where knowledge flows from expert to novice (McLeod, 2024; Zajda, 2021). For instance, when asked "What is constructivism?", AI may return a standard explanation such as "Constructivism is a learning theory that posits learners actively construct knowledge based on their experiences." While accurate, these responses often lack the contextual nuance or dialogic depth needed for meaningful learning. Vygotsky (1978) emphasises that true learning is socially mediated, not merely the transfer of information.

The facilitator role demands more from AI, prompting learners to think critically and apply knowledge in practical contexts. For example, in response to "How can constructivist principles be applied in classroom teaching?", an AI might suggest strategies such as collaborative learning or inquiry-based discussion and even pose follow-up questions. These features reflect the guiding functions of educators (Bakhtin, 1981; Freire, 1993). However, AI still struggles to provide context-sensitive support or adapt dynamically to learners' evolving needs (Zajda, 2021).

The co-learner role is the most complex. It involves reflective dialogue, challenging assumptions and collaboratively constructing knowledge. A question such as "What are the challenges of applying constructivist methods in diverse classrooms and how can they be addressed?" requires the AI to analyse multiple perspectives and support deeper inquiry. This aligns with Vygotsky's (1978) ZPD and Freire's (1993) dialogic education model. While AI lacks consciousness and lived experience, early research suggests it can still foster metacognitive reflection by encouraging learners to articulate their thinking (Kong et al., 2025).

These roles are grounded in core constructivist theories. Piaget's (1964) cognitive constructivism emphasises individual schema building, while, Vygotsky's (1978) social constructivism and Freire's (1993) dialogic pedagogy highlight interactive and co-constructive aspects of learning. These frameworks inform the typology used in this study and provide criteria for evaluating AI's instructional potential.

Research significance and contributions

This study offers a new perspective on the pedagogical potential of AI by analysing learner-generated questions. Rather than treating AI solely as a tool for content delivery, the research reframes it as a possible instructional agent, capable of supporting different levels of cognitive engagement. Prior studies have already suggested that AI can reinforce constructivist pedagogy and foster student agency, particularly in literacy and inquiry-focused contexts (Dai, 2025; Grubaugh et al., 2023; Lin et al., 2025). This study extends this line of work by examining learner-generated questions as a lens for analysing engagement in higher education. Through the typology of knowledge transmitter, facilitator and co-learner, this study provides a structured framework for examining how students interact with AI in diverse learning contexts. This framework has practical implications for AI-enhanced learning environments. For instance, an AI-integrated learning management system (LMS) could classify learner questions in real time, helping educators identify conceptual gaps or support needs. A learner frequently asking basic factual questions might benefit from prompts encouraging deeper inquiry, while higher-level questions could trigger adaptive responses that foster metacognition. Aggregated data could also inform curriculum design and instructional strategies at an institutional level.

Importantly, the study highlights the need for ethical guidelines in implementing such systems. As AI increasingly shapes educational interactions, institutions must ensure transparency, prevent misuse of data and support educators in interpreting AI feedback meaningfully. While AI can simulate some instructional behaviours, it cannot replace the relational and contextual awareness of human educators.

By shifting analytical focus from AI outputs to learner engagement, this study contributes to a deeper understanding of how AI can support constructivist learning, laying the groundwork for more pedagogically informed and responsible AI applications in education.

Methodology

Data collection

Data for this study were collected from student-generated questions submitted as appendices to assignments in 12 undergraduate and graduate-level information technology (IT) courses at a university in Australia. These courses covered a range of subjects including programming, data analytics and software engineering, ensuring a diversity of academic content and student backgrounds. As part of their coursework, students were required to use generative AI tools, such as ChatGPT for various tasks, including brainstorming, refining ideas and verifying solutions. This intentional integration of AI into the curriculum ensured that the collected queries represented authentic and contextually relevant learner interactions with AI tools.

A total of 434 student-generated questions were collected from 11 students enrolled in undergraduate and master's degree programmes in IT, forming the basis for subsequent labelling and analysis. These questions varied widely in structure and intent, ranging from simple informational queries to complex problem-solving prompts. This diversity allowed for a comprehensive analysis of learner-AI interactions, providing a nuanced understanding of how students leverage AI for academic support.

It is important to note that this study focused exclusively on IT-related courses, which may limit the generalisability of findings to other disciplines. IT students may interact with AI tools differently from students in non-technical fields, given their familiarity with technology. Additionally, the data set does not account for potential variations in question types that may arise in disciplines like humanities or social sciences. To address this, future research will aim to collect and analyse data sets from a broader range of subject areas, ensuring a more comprehensive understanding of AI utilisation in education.

Expert-driven question labelling

In this study, three external doctoral-level experts with over 5 years of experience in constructivist educational research participated in the labelling process. A focus group interview with these experts was conducted in three phases. The collected questions were categorised into three constructivist roles: knowledge transmitter, facilitator, and co-learner (Kang et al., 2016; Lee & Kang, 2019). This multiple-stage labelling process included expert consultation to ensure rigorous and reliable categorisation.

In Phase 1, the experts refined definitions for the three roles based on prior research (Kang et al., 2016; Lee & Kang, 2019) and established clear criteria and examples for each.

Phase 2 involved two rounds: in the first, the experts independently labelled 434 questions from 11 students using an Excel sheet with designated columns for each label. Results were then consolidated and discrepancies were resolved during an online meeting. Inter-rater reliability was assessed using Fleiss' (1971) kappa, computed as:

$$\kappa = \frac{(\bar{P} - P_e)}{(1 - P_e)}$$

where $\bar{P}$ is the average observed agreement and P_e is the expected agreement by chance (estimated under the assumption of a uniform distribution across categories). A second round of labelling was then conducted to resolve remaining discrepancies. The experts repeated the labelling process and online discussions until full consensus on the labels were achieved.

Phase 3 involved validating the augmented data set. Initial labelling revealed an imbalance among categories: knowledge transmitter (196), facilitator (135) and co-learner (103). To address this, data augmentation techniques such as back-translation (Shorten et al., 2021) and paraphrasing (Li et al., 2022) were used to generate additional examples for underrepresented categories. This resulted in a balanced data set of 582 questions: 196 knowledge transmitter, 193 facilitator and 192 co-learner. Figure 1 summarises the multi-phase labelling process.

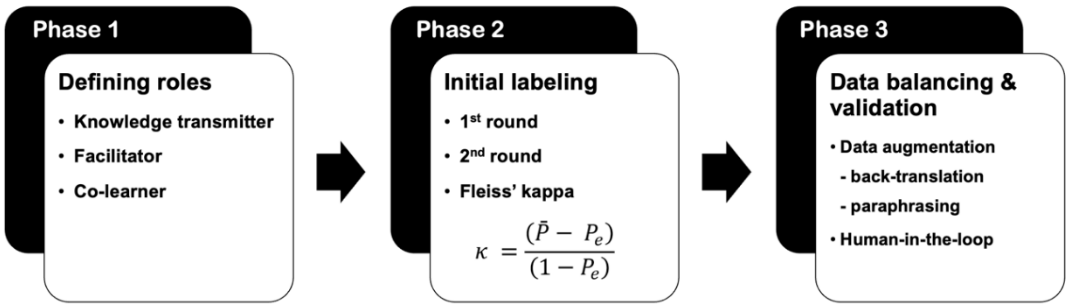

Figure 1. Phases of labelling

This study adopted a human-in-the-loop (HITL) approach to enhance the accuracy and reliability of the NLP model for classifying learner-generated questions. By integrating human expertise into the data labelling, augmentation and model refinement processes, HITL ensured that the data set and model outputs aligned with the nuanced requirements of constructivist educational theory (Mosqueira-Rey et al., 2023). HITL allowed domain experts to iteratively validate and refine question labels during the focus group interview and augmented data review phases, minimising noise and ensuring consistency across the data set.

Furthermore, HITL guided the augmentation of underrepresented categories (facilitator and co-learner) through paraphrasing and back-translation and was employed during the evaluation phase to review misclassified examples, enabling expert feedback to fine-tune the model. By leveraging domain expertise, HITL not only improved model accuracy but also ensured that the results were pedagogically meaningful and aligned with the study's educational objectives (Wu et al., 2022).

NLP model development

An NLP model was developed to classify learner-generated questions into three constructivist roles (knowledge transmitter, facilitator and co-learner). Multiple models within the BERT family were selected for comparison due to their strong performance in text classification tasks. Specifically, BERT was chosen for its general-purpose capabilities, while decoding-enhanced BERT with disentangled attention (DeBERTa) and robustly optimised BERT approach (RoBERTa) were included for their enhanced contextual understanding, as demonstrated in a previsous study (He et al., 2020). The augmented data set was stratified into training (70%), validation (15%) and test (15%) sets, with balanced class distributions maintained to prevent bias from class imbalance.

The models were trained using the labelled data set and hyperparameter tuning to optimise performance. Key hyperparameters, including learning rate, batch size, dropout rate and the number of trainable layers, were iteratively adjusted based on validation results. To mitigate overfitting, early stopping (patience = 20 epochs) was applied alongside a ReduceLROnPlateau scheduler, which adjusted the learning rate when model performance plateaued. Model evaluation consisted of accuracy, precision, recall and F1 score (the harmonic mean of precision and recall) to ensure thorough comparisons of classification effectiveness.

Model evaluation and question analysis

Model evaluation involved systematically assessing the performance of NLP models to classify learner-generated questions into the predefined constructivist roles. To achieve this, confusion matrices were utilised to clearly visualise patterns of correct and incorrect classifications. Allowing a structured approach to error analysis (Riehl et al., 2023).

Subsequently, a qualitative analysis was conducted by manually reviewing these misclassified questions. This process focused on identifying recurring misclassification patterns, which were categorised into three main types based on their semantic and structural features. These consisted of firstly, conceptual similarities between question roles, such as when facilitator-type questions resembled knowledge transmitter queries in structure; secondly, ambiguous learner intent, particularly in co-learner questions that overlapped with facilitator prompts; and thirdly, technical complexity, where domain-specific or overly complex phrasing led to incorrect role assignment. These categories provided a structured basis for understanding the limitations of the current NLP models in accurately interpreting nuanced instructional intent.

Ethical compliance and research integrity

This study complied with the university's research ethics and integrity policies. It involved anonymised, non-identifiable student-generated data collected with informed consent. Based on institutional guidance for low-risk research, the study did not require formal ethics review or clearance.

Before data collection, all students were fully briefed on the purpose of the study, the voluntary nature of their participation and the intended use of their contributions, after which informed oral consent was obtained. Participation was not linked to academic assessment and students were assured that their academic progress would not be affected by their decision to participate or decline.

No personal identifiers were collected, and the data set comprised only de-identified textual questions. Given the non-intrusive nature of the study and the absence of sensitive information, the data were securely stored and accessible only to the research team. These measures ensured that participants' rights and privacy were respected and that the research was conducted with transparency, integrity and academic responsibility. Figure 2 illustrates the research workflow.

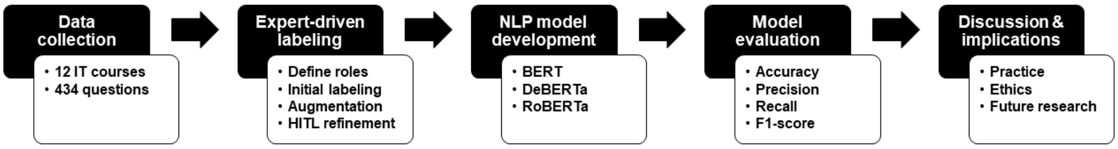

Figure 2. Research process and methodologies

Results

Data set overview and augmentation process

The data collection and labelling process followed a structured approach through multiple focus group interview rounds to ensure the reliability and accuracy of the labelled data set. The process consisted of three key phases, each aimed at refining the data and addressing class imbalance issues.

In Phase 1, the experts refined the definitions of the three constructivist roles based on prior literature. Consensus was reached on the operational definitions and classification criteria, ensuring consistency in the labelling process (see Table 1).

Table 1
Defined question levels and examples

Level	Definition	Example questions
1. Knowledge transmitter	Questions that ask for direct facts, definitions or explanations without requiring deeper thinking Keywords: definition, explanation, meaning, basic fact	"What is AI?" "What is the definition of deep learning?" "Explain the concept of neural networks."
2. Facilitator	Questions that apply knowledge to real-world situations, encouraging deeper thinking and practical use Keywords: application, implementation, integration, practice, contextual	"How does AI personalise learning in educational settings?" "What factors should be considered when applying deep learning in healthcare?" "In what ways can constructivist theories be implemented to improve classroom collaboration?"
3. Co-learner	Questions that reflect, critique or challenge existing ideas, aiming to improve or rethink current knowledge Keywords: critique, limitations, assumptions, alternative, improvement	"What are the ethical concerns in using AI for student assessment and how can they be mitigated?" "How can different deep learning architectures be combined to optimise performance in medical diagnosis?" "What limitations exist in current constructivist approaches and what alternative strategies could address these shortcomings?"

Phase 2 involved the independent labelling of 434 learner-generated questions by the experts. Initial labelling showed moderate inter-rater reliability (Fleiss' kappa = 0.60), with complete agreement on 264 questions, partial agreement on 166 and disagreement on 4 items. Following this, the experts met to resolve disagreements and clarify domain-specific terminology. A second round of labelling was then conducted, resulting in improved reliability (Fleiss' kappa = 0.83), with complete agreement on 361 questions and partial agreement on 73. The final distribution consisted of 196 knowledge transmitter, 135 facilitator and 103 co-learner questions, demonstrating the effectiveness of the iterative focus group interview process in enhancing consistency.

Phase 3 addressed the class imbalance through data augmentation. Back-translation (Shorten et al., 2021) and paraphrasing (Li et al., 2022) were used to increase the number of facilitator and co-learner questions while maintaining semantic integrity. After augmentation, the data set comprised 196 knowledge transmitter, 193 facilitator and 192 co-learner questions. All generated questions were reviewed by the experts to ensure alignment with constructivist role definitions and eliminate ambiguity, resulting in a balanced data set suitable for robust NLP model training (see Table 2).

Table 2
Distribution of questions after augmentation

Category	Original count	Augmented count	Final count
Knowledge transmitter	196	0	196
Facilitator	135	58	193
Co-learner	103	89	192
Total	434	147	582

By adopting this systematic approach, the study ensured a balanced data set that mitigated the risk of biased model predictions and enhanced the representational accuracy of each question type. This refined data set provided a robust foundation for training and evaluating NLP models in subsequent phases.

NLP model training and evaluation

This section outlines the training and evaluation process for four NLP models – BERT (baseline and fine-tuned), DeBERTa and RoBERTa – for classifying student-generated questions. A unified augmented data set was employed to fairly compare each model's capabilities. The models were evaluated using accuracy, precision, recall and F1 score to capture both overall and class-specific performance, particularly important in nuanced classification tasks.

Experiments were conducted using Python 3.8, PyTorch 1.12.0, CUDA 11.2 and Hugging Face Transformers, on an NVIDIA RTX3070 GPU (8GB VRAM). To ensure generalisability, the data set was stratified into training (70%), validation (15%) and testing sets (15%), with balanced class distributions maintained across all splits.

Training procedures differed slightly to highlight each model’s strengths. The baseline BERT model used pre-trained parameters without fine-tuning. The fine-tuned BERT model updated the last three layers to adapt to the educational context. DeBERTa employed advanced contextual representation and the AdamW optimiser, while RoBERTa incorporated a larger pre-training corpus and dynamic masking to improve context sensitivity. All models used the ReduceLROnPlateau scheduler for adaptive learning rate adjustment and early stopping (patience = 20 epochs) to prevent overfitting (see Table 3).

Table 3
Hyperparameter settings

Parameter	BERT (baseline)	BERT (fine-tuned)	DeBERTa	RoBERTa
Max length	128	128	128	128
Batch size	8	8	8	8
Learning rate	2e-5	2e-5	2e-5	2e-5
Optimiser	Adam	Adam	AdamW	AdamW
Dropout rate	0.3	0.6	0.5	0.5
Trainable layers	None	Last 3 layers	Last 3 layers	Last 3 layers
Scheduler	None	ReduceLROnPlateau	ReduceLROnPlateau	ReduceLROnPlateau
Early stopping	N/A	Patience 20	Patience 20	Patience 20

Table 4 presents a summary of the model performance, indicating that DeBERTa achieved the highest accuracy at 86.36%, consistently outperforming other models across all evaluation metrics. Fine-tuned BERT also demonstrated a substantial improvement over its baseline, highlighting the efficacy of fine-tuning for this educational classification task. RoBERTa performed consistently but did not surpass DeBERTa or the fine-tuned BERT model (see Table 4).

Table 4
Comparison of model performance

Model	Test loss	Accuracy	Precision	Recall	F1 score
BERT (baseline)	1.3497	81.82%	82.30%	81.82%	81.95%
BERT (fine-tuned)	0.4367	84.09%	85.09%	84.09%	84.14%
DeBERTa	0.3239	86.36%	87.18%	86.36%	86.52%
RoBERTa	0.4627	82.95%	83.38%	82.95%	83.06%

DeBERTa delivered the highest overall performance, particularly excelling at classifying level 1 (knowledge transmitter) questions with a precision of 96.67%, reflecting its strength in handling factual content. However, it showed inconsistent performance on level 2 (facilitator) questions, demonstrating the difficulty all models faced in identifying application-based, context-sensitive inquiries.

The fine-tuned BERT model performed best on level 3 (co-learner) questions, achieving a high recall of 92.00%. This came at the cost of lower precision, suggesting some ambiguity or semantic overlap within this category. RoBERTa demonstrated balanced performance across all levels, notably achieving an F1 score of 85.71% for co-learner classification. Overall, facilitator-level questions proved the most challenging for all models, likely due to their nuanced nature. This indicates a need for further refinements such as enhanced feature engineering, context-aware embeddings or more targeted training approaches to improve classification accuracy. These results emphasise the importance of aligning NLP model selection and fine-tuning with the cognitive complexity of educational tasks.

Table 5
Model performance by question level

Model	Level	Precision	Recall	F1 score	Sample size
BERT (baseline)	1	90.32%	82.35%	86.15%	34
	2	80.00%	82.76%	81.36%	29
	3	74.07%	80.00%	76.92%	25
BERT (fine-tuned)	1	90.62%	85.29%	87.88%	34
	2	88.00%	75.86%	81.48%	29
	3	74.19%	92.00%	82.14%	25
DeBERTa	1	96.67%	85.29%	90.62%	34
	2	78.79%	89.66%	83.87%	29
	3	84.00%	84.00%	84.00%	25
RoBERTa	1	87.50%	82.35%	84.85%	34
	2	75.00%	82.76%	78.69%	29
	3	87.50%	84.00%	85.71%	25

Error analysis

As mentioned above, despite DeBERTa achieving the highest overall performance across all evaluation metrics, several misclassification patterns were identified. The model frequently misclassified facilitator questions as either knowledge transmitter or co-learner, indicating challenges in distinguishing subtle contextual differences.

Across all confusion matrices, most predictions match the actual labels, indicating that the models generally distinguish the three categories well. However, there is a consistent pattern of misclassifications between the second and third categories, suggesting that questions requiring deeper reasoning or contextual understanding are sometimes confused with either simpler factual tasks or more collaborative problem-solving. While the majority of samples are correctly identified, these overlaps highlight the shared linguistic or conceptual features that the models occasionally struggle to disentangle (see Figure 3).

Analysing these misclassification patterns revealed the following key observations. Many facilitator questions exhibit structural similarities to knowledge transmitter questions, where they begin with factual inquiries and gradually extend to application-based queries. The model struggled to discern the nuanced difference between seeking factual information and encouraging deeper engagement. This challenge reflects the inherent difficulty in differentiating between knowledge transmission and facilitation within educational contexts (see Table 6).

Table 6
Confusion due to conceptual similarities

Question	Actual label	Predicted label
What are the benefits of padding in deep learning?	facilitator (2)	knowledge transmitter (1)
How do you map WHO regions to countries in the HALE life expectancy data set?	facilitator (2)	knowledge transmitter (1)

Note. WHO = World Health Organisation; HALE = health-adjusted life expectancy.

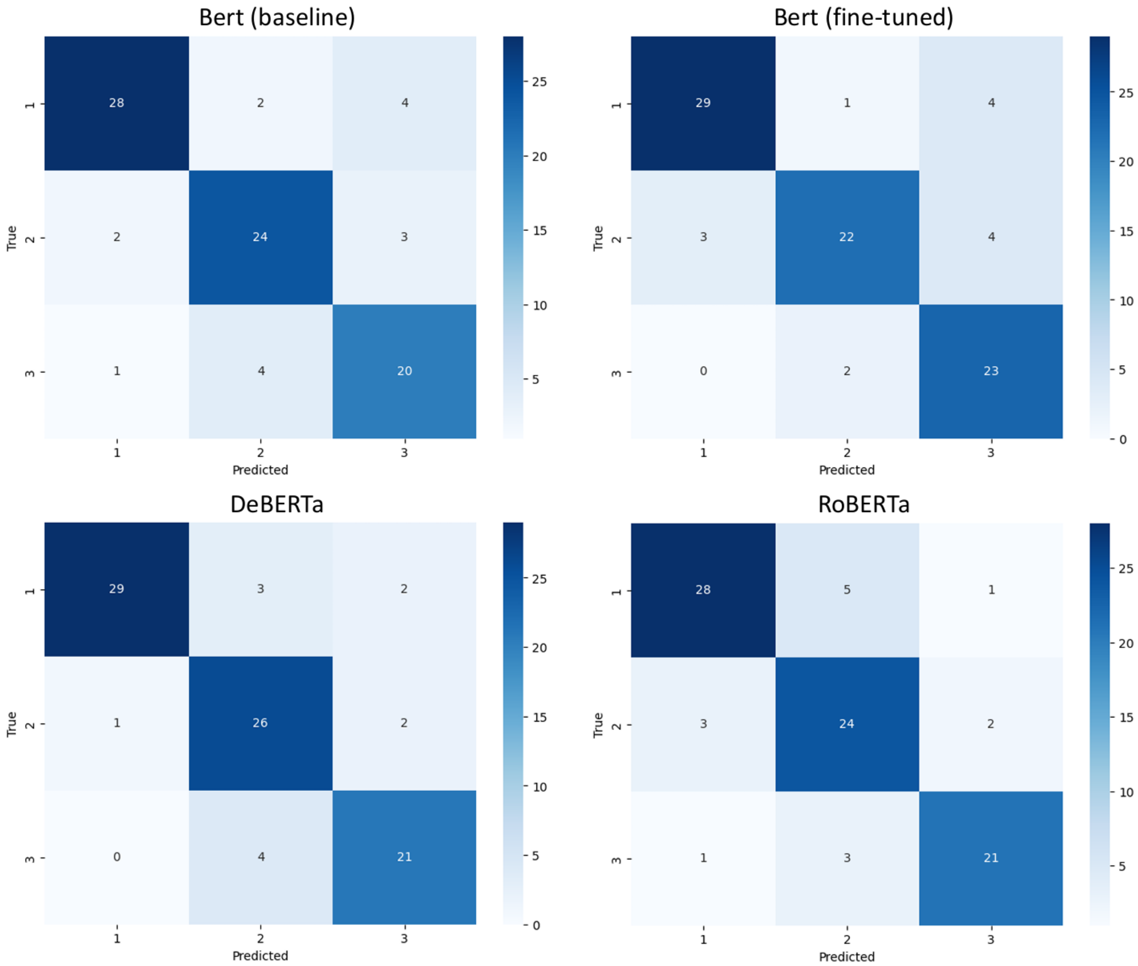

Figure 3. Results of the confusion matrix for the test set

Co-learner questions, which involve open-ended exploration and collaborative problem-solving, were sometimes misclassified as facilitator questions. This suggests that the model found it challenging to capture the implicit intent behind exploratory and solution-oriented queries. Since the intended learning objectives are context-dependent, the model's reliance on textual features alone may not be sufficient for accurate classification. To address this challenge, future work should explore integrating multi-turn dialogue models or context-enhanced attention mechanisms that capture pragmatic cues beyond surface-level textual features (see Table 7).

Table 7
Difficulty in understanding intent

Question	Actual label	Predicted label
What could be the impact of AI-driven collaborative activities on student social skills and engagement?	co-learner (3)	facilitator (2)
How might AI help learners to better articulate and refine their learning goals?	co-learner (3)	facilitator (2)

Questions that include domain-specific terminology or require specialised knowledge were often misclassified as co-learner, even when they were intended to be categorised under facilitator. This indicates that the model may equate complex phrasing with higher cognitive engagement levels, suggesting limitations in its ability to differentiate between linguistic complexity and educational depth (see Table 8).

Table 8
Influence of technical terminology and expression complexity

Question	Actual label	Predicted label
Could you combine this code into a single toggle button to integrate the following functions? 1. VGG16 + Yolov5 mode, 2. Yolov9 mode.	facilitator (2)	knowledge transmitter (1)
I've completed my report. Could you review each section against the rubric criteria and check if it meets them? I'll send it part by part.	facilitator (2)	knowledge transmitter (1)

Overall, the qualitative review indicates that current models handle direct factual queries reliably but struggle to infer intent and epistemic depth in facilitator and co-learner questions, particularly when phrasing is ambiguous or context-dependent. These patterns highlight the need for more context-sensitive modelling and sustained human oversight to ensure pedagogically valid feedback.

Future improvements include clearer expert-defined criteria (HITL), intent-sensitive features and domain-informed training.

In summary, the error analysis highlights key challenges in the classification of learner-generated questions, emphasising the need for improved differentiation between question types that share conceptual similarities and intent-driven nuances. Addressing these issues through expert-driven refinements and qualitative insights will further enhance the accuracy and reliability of AI models in educational applications.

Findings and discussion

This study examines how AI models classify learner-generated questions and discusses the pedagogical implications of classification performance across epistemic roles within AI-supported education.

Interpretation of findings

The AI models consistently performed well in classifying factual (knowledge transmitter) questions but struggled with facilitator and co-learner categories that demand deeper reasoning and contextual understanding. From a pedagogical perspective, the significance of these findings lies not in classification accuracy alone, but in demonstrating how learner-generated questions can serve as diagnostic indicators of epistemic engagement in AI-mediated learning environments. By distinguishing between knowledge transmission, facilitation and co-learning-oriented inquiries, the proposed framework provides a basis for aligning AI-supported feedback with constructivist learning goals.

Cognitive load theory (Sweller, 1988) helps explain this gap – AI models handle low-complexity tasks effectively but face difficulty with higher-order thinking. Similarly, Vygotsky's (1978) ZPD highlights that while AI supports learners within their current cognitive range, it struggles to provide the scaffolding required for more complex roles. Data augmentation techniques, including paraphrasing and back-translation, improved model robustness and addressed class imbalances. However, these methods may have introduced biases, leading models to rely on lexical patterns rather than semantic depth. DeBERTa outperformed other models overall, but its misclassifications, particularly of facilitator questions highlight a broader challenge in capturing pragmatic meaning and user intent. Facilitator inquiries often blend factual and application-based elements, which current models interpret inconsistently. These patterns are consistent with reviews indicating that generative AI, while useful for literacy and collaborative tasks, remains constrained in its ability to support deeper epistemic practices and higher-order inquiry (Lin et al., 2025; Yang 2025).

These findings reinforce the continuing need for human instructors in delivering nuanced, context-aware feedback. While AI can support information delivery and basic guidance, complex educational interactions still require human oversight. Future work may incorporate richer contextual signals to improve intent recognition.

Practical implications

Beyond its analytical contribution, this study offers a concrete pedagogical application of AI-driven question classification through the LMS-based feedback framework illustrated in Figure 4. The framework demonstrates how classification outputs can be translated into actionable instructional decisions, supporting a collaborative model in which AI augments, rather than replaces, human pedagogical judgement.

Within this framework, AI-supported evaluation systems embedded in LMS platforms represent a practical application of the proposed question classification approach. By classifying student-generated questions, NLP models can streamline instructor feedback while maintaining academic rigour. The classification framework can also guide students in formulating more complex inquiries. If a learner consistently asks knowledge transmitter questions, the system could prompt deeper, more reflective engagement, encouraging metacognitive development and critical thinking.

Aggregated question data can inform curriculum design. Patterns may reveal areas where students struggle, allowing instructors to adjust content or provide additional support. This dual benefit, individualised feedback and data-driven course refinement demonstrates the value of AI integration. Importantly, a collaborative feedback model that combines AI efficiency with human insight can maximise educational impact. While AI handles initial classification, instructors refine outputs, ensuring pedagogical quality (see Figure 4). This implication is in line with work suggesting that AI can reinforce constructivist pedagogy by enhancing deep inquiry, conceptual change and learner engagement (Grubaugh et al., 2023).

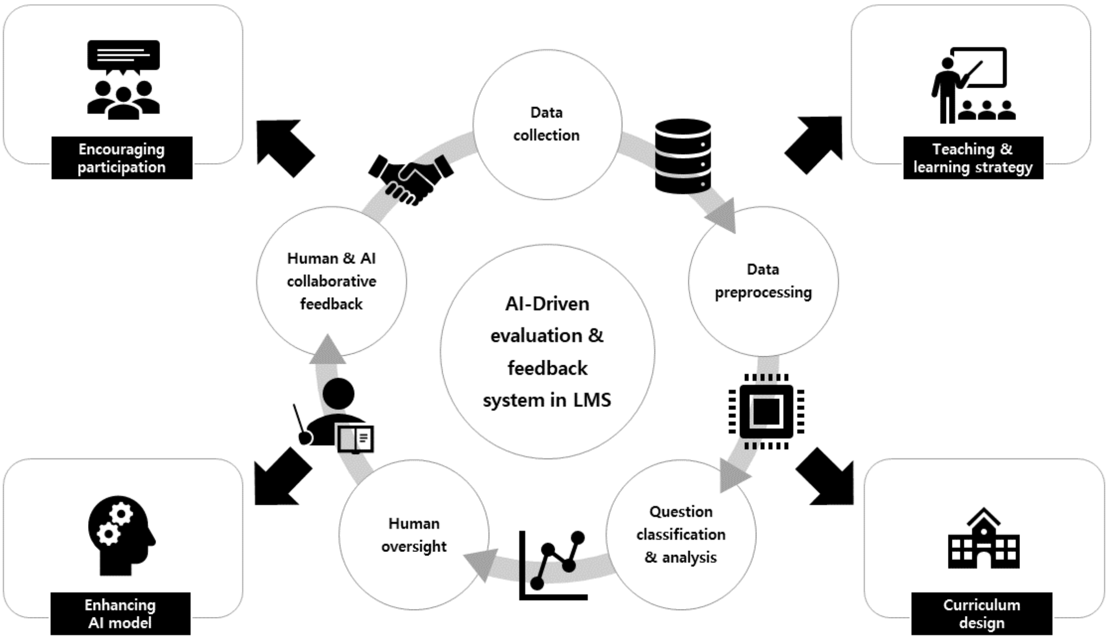

Figure 4. AI-driven evaluation & feedback system in LMS

The system generates significant advantages in four key areas:

- Encouraging participation: Personalised, immediate feedback motivates students to engage more actively in asking questions and participating in learning activities.
- Teaching and learning strategy: Instructors can refine instructional approaches based on insights into question types and difficulty levels.
- Curriculum design: Aggregated question patterns help identify topics needing reinforcement or additional resources, thereby enhancing the curriculum.
- Enhancing the AI model: Corrective feedback from human oversight is incorporated back into the AI model, enabling more accurate and sophisticated feedback over time.

Together, these elements illustrate how AI-supported question classification can support deeper learning and more efficient teaching.

Challenges and limitations

Despite the promising outcomes of this study, several challenges and limitations must be addressed to optimise the integration of AI-driven question classification systems in educational settings.

AI models struggle to accurately interpret the implicit intent behind learner-generated questions – especially distinguishing between facilitator and co-learner questions – due to nuanced linguistic patterns and contextual subtleties. Future work should incorporate context-aware NLP techniques, domain-specific ontologies and continuous HITL feedback to refine intent recognition.

The integration of AI in education raises concerns regarding the transparency of AI-driven feedback, potential algorithmic bias from IT-specific training data and the risk of over-reliance on AI for student evaluation. Additionally, the data set's confinement to IT courses limits the generalisability of the findings across diverse academic disciplines. Addressing these issues requires rigorous bias detection, clear ethical guidelines and cross-disciplinary studies. Such concerns are consistent with arguments that effective AI integration must attend not only to technical performance but also to ethical reflection and holistic learning considerations (Dai, 2025).

While AI-driven question classification offers efficiency and scalability, this study underscores the indispensable role of human oversight. Misclassifications, particularly between facilitator and co-learner questions, demonstrate that current AI models struggle with interpreting complex, context-dependent inquiries. A fully automated system risks propagating errors and providing misleading feedback to students.

A hybrid approach, where AI handles initial categorisation and human educators validate and refine the outputs, presents a balanced solution. This collaborative model leverages the speed and scalability of AI while ensuring that feedback remains pedagogically sound and contextually relevant. Integrating explainable AI techniques could further support educators by providing insights into the model’s decision-making processes, enabling more informed oversight (Ali et al., 2023).

Another challenge pertains to the diversity of learner-generated questions within the data set. Although data augmentation techniques like paraphrasing and back-translation were employed to balance class distributions, the synthesised data may not fully capture the richness and complexity of authentic student inquiries. This could limit the AI model's exposure to diverse linguistic expressions and cognitive patterns.

To address this, future studies should focus on collecting larger and more diverse data sets, representing a wide range of student demographics, academic disciplines and question types. This would improve the model's ability to generalise and adapt to varied educational contexts. These challenges not only underscore the current limitations of AI models but also illuminate promising directions for future research.

Future research directions

A qualitative review of misclassified cases revealed that ambiguous phrasing or context-specific terms often lead the model to default to the knowledge transmitter category, highlighting its difficulty in discerning subtle semantic cues. Building on these challenges, future research should focus on:

- Enhancing model interpretability: Develop explainable AI techniques that provide educators with clear insights into the model’s decision-making processes.
- Cross-disciplinary application: Extend studies to include data from humanities, social sciences and STEM to uncover unique question patterns and refine AI capabilities.
- Longitudinal studies: Examine how learner engagement with AI evolves over time and how continuous AI feedback influences long-term learning outcomes.
- Ethical AI implementation: Establish robust frameworks for data privacy, fairness and transparency to ensure AI benefits are equitably distributed.
- Expanding HITL approaches: Incorporate advanced HITL strategies to continually refine AI outputs and align them with pedagogical goals.

These research directions will help bridge current gaps in AI’s contextual understanding and pave the way for systems that not only perform preliminary question categorisation but also deliver detailed, context-sensitive feedback, ultimately enhancing the overall educational experience.

Conclusion

This study contributes to educational technology research by reframing learner-generated questions as pedagogically actionable signals within AI-mediated learning environments. Rather than treating question classification as a purely technical task, the proposed framework demonstrates how epistemic roles reflected in learner questions can inform feedback design and instructional decision-making aligned with constructivist pedagogy.

The findings indicate that contemporary NLP models can classify learner questions with strong overall performance, yet still struggle to interpret complex, contextually nuanced inquiries. This limitation underscores the continuing necessity of human involvement in validating classifications and ensuring pedagogically sensitive feedback.

Importantly, this research stresses that the role of AI should not be seen as replacing human instructors, but rather as complementing their judgment and instructional support. Integrating the pedagogical expertise and nuanced understanding of experienced educators into AI systems could transform AI from a mere information-delivery tool into a genuinely adaptive educational partner, capable of addressing diverse learner needs effectively. This perspective resonates with prior work emphasising that AI should complement, rather than replace, educators in strengthening constructivist approaches (Grubaugh et al., 2023). It also aligns with reviews highlighting the potential of generative AI to act as a learning partner that cultivates knowledge-building practices (Lin et al., 2025).

From a practical perspective, applying the proposed question categorisation framework within LMS platforms holds significant potential. Such integration would allow AI to automatically analyse students' questions, providing immediate and targeted feedback. Students would benefit from tailored support based on their individual needs. Instructors could quickly identify areas requiring deeper intervention and institutions could utilise aggregated data to inform curriculum enhancements and resource allocation. Therefore, future research should focus on enhancing the interpretability and contextual sensitivity of AI models. Gathering diverse data sets across multiple disciplines and conducting longitudinal studies will be crucial to understanding the broader impact of AI-driven learning interventions over time.

Ultimately, this study emphasises the value of collaborative coexistence between human educators and AI systems. By strategically combining AI's strengths in efficiency and scalability with the nuanced judgment and deeper insights of human teachers, educational institutions can offer more meaningful, personalised learning experiences. It is hoped that the insights and frameworks developed through this research represent a meaningful step towards realising such balanced and productive human-AI partnerships in education.

Author contributions

Hyunmin Lee: Conceptualisation, Investigation, Data curation, Writing – original draft, Writing – review and editing; **Amara Atif:** Investigation, Supervision, Writing – review and editing; **Kyeong Kang:** Investigation, Writing – review and editing.

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