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Design of an AI-Driven Collaborative Learning Model for Enhancing Peer Interactions and Knowledge Sharing in Online Education

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Abstract

Online collaborative learning communities are susceptible to the problems of lack of peer interaction, skewed participation, and poor knowledge sharing, which adversely affect learning outcomes. The recent developments in artificial intelligence (AI) provide the opportunity to solve these problems with the help of adaptive learning analytics and intelligent collaboration support. The paper suggests an AI-based Collaborative Learning Model (AI-CLM) that is aimed at improving peer interactions and sharing of knowledge during an online study. The suggested model combines the analysis of the interaction of the learners, peer grouping using AI, adaptive feedback, and knowledge recommendation in one framework. It utilizes a systematic algorithm and mathematically formulated evaluation measures to guarantee reproducibility and stringent evaluation. An online collaborative learning course of eight weeks has been evaluated using an experimental mode and showed that the proposed AI-CLM not only performs significantly higher than the traditional collaborative learning methods. Precisely, the degrees of participation boosted since the Peer Interaction Index grew by 12.4 to 21.8, the Knowledge Sharing Score rose by 68.2 to

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84.6, and the Participation Balance Index rose by 0.54 to 0.81, which is more equitable learner participation. Moreover, the average learning performance increased to 85.3 percent as compared to 72.5 percent, and the Collaboration Effectiveness Score also increased to 0.86 compared to 0.63. These findings can be used to conclude that AI-based adaptive collaboration support can significantly enhance social interaction and academic performance during online learning. These results can be relevant to the development of scalable, smart online learning systems that facilitate efficient collaboration and interaction with a learner.

Keywords: Artificial Intelligence, Collaborative Learning, Online Education, Peer Interaction, Knowledge Sharing, Learning Analytics.

1 Introduction

The high rate of expansion of online learning has transformed higher learning by facilitating flexible, scalable, and technology-mediated learning opportunities. Nonetheless, online learning environments still experience the same issues of low levels of interaction with peers, unequal participation, and poor knowledge sharing despite their wide adoption. These problems usually decrease the attention of learners and adversely impact the performance of learning (Ezeanya et al., 2024; Wu et al., 2024). The collaboration in learning has been generally considered as a powerful pedagogical tool to deal with these challenges by fostering social interactions, shared regulations, and building knowledge (Strielkowski et al., 2025). However, the conventional models of online collaborative learning are often based on fixed group-based and facilitated by instructors, which is inadequate to support dynamic behavior and in large-scale online learning environments (Sundaresan & Zhang, 2022; Zamiri & Esmaeili, 2024). The recent developments in the field of artificial intelligence (AI) enabled new opportunities to improve collaborative learning by means of adaptive learning analytics, intelligent feedback, and personal recommendations. Artificial intelligence systems can continuously process the data on the interaction of learners and offer real-time assistance to enhance the quality of collaboration and learning performance (Zheng et al., 2025; Soy, 2025). The systematic reviews provide an increasing number of studies demonstrating that AI-based collaborative learning has the potential to enhance engagement, cooperation, and the quality of learning in higher education (Msambwa et al., 2025; Cai et al., 2025). Even with these developments, the current AI-assisted collaborative learning solutions tend to target single elements, including analytics dashboards, assessment support, or recommendation systems, and provide a more integrated end-to-end collaborative learning solution (Mahamad et al., 2025). Besides, a vast amount of research does not include a formal mathematical formulation of metrics of collaboration and has only limited quantitative validation on various dimensions of collaboration and learning performance (Ouyang et al., 2023; Ouyang et al., 2023). Due to these shortcomings, the current paper offers a solution in the form of an AI-Driven Collaborative Learning Model (AI-CLM) that would help to improve peer engagement and knowledge exchange in online learning (Amer-Yahia, 2022; Sun, 2025). The suggested model will combine the analysis of interaction with learners, AI-based decision making, adaptive collaboration support, and the evaluation of the outcome in one framework. Systematic algorithm and mathematically determined measures of evaluation are proposed to guarantee reproducibility and rigorous evaluation.

Four of the most important contributions of this work are presented. To begin with, a collateral AI-supported collaborative learning framework is suggested that will be dynamically increasing the level of interaction and knowledge sharing among peers in online learning (Rimada & KL Mrinh, 2025). Second, an orchestrated algorithmic workflow that provides clear parameterization is created in order to aid adaptive cooperation. Third, an all-encompassing mathematical model is structured to determine the interaction level, knowledge sharing, the balance of participation, and learning performance quantitatively. Lastly, in terms of outcomes of experiments, it is proven that the suggested AI-CLM performs much better than conventional collaborative learning methods in a variety of quantitative metrics.

The remainder of this paper is organized as follows. Section 2 presents a review of related work on AI-supported collaborative learning and identifies key research gaps. Section 3 describes the proposed AI-Driven Collaborative Learning Model, including its architecture, algorithm, and mathematical evaluation metrics. Section 4 reports the experimental results and performance analysis. Section 5 concludes the paper by summarizing numerical findings, discussing limitations, and outlining directions for future research.

2 Literature Review

The recent studies on AI-driven collaborative learning emphasize the rise of AI usage in online learning environments to monitor, assist, and control learners in their interactions. Reviews point out that collaborative learning with AI has also developed in the last ten years, and the results are positive in terms of engagement, the quality of collaboration, and the outcomes of learning (Kovari, 2025; Ouyang & Zhang, 2024). Algorithms based on AI learning analytics have been researched as a common tool to capture and analyze patterns in interactions, behavioral cues, and collaboration patterns. Previously, it has been proven that the AI-based analytics can detect the imbalance in participation, engagement patterns, and cooperative problem-solving patterns. Nonetheless, most analytics-oriented strategies are rather observation and diagnosis-based than adaptive intervention to enhance collaboration in real time (Annadurai, 2024). The AI-enabled evaluation and feedback processes to improve team learning have been explored in several studies. Individual feedback and recommendation systems have been found to increase learner involvement and the effectiveness of a team (Jony & Hamim, 2024). However, these practices tend to be isolated entities and no longer integrated with peer grouping and collaboration control processes (Kim et al., 2022). AI-empowered tools and recommendation technologies have also been used to investigate knowledge sharing in learning communities. The studies point out that AI has the potential to promote access to the necessary resources and peer contributions, which will enhance the construction of knowledge (Cao & Yu, 2023). Nevertheless, current literature often concentrates on an organizational or social aspect of sharing knowledge and does not connect them to any quantifiable changes in the learning performance (Anaya Menon & Srinivas, 2023; Kalaivanai, 2026). Recent articles affirm the significant role of human-AI cooperation and socially distributed control of learning, and AI is employed to facilitate the process instead of substituting human interaction (Edwards et al., 2025; Krishnamoorthy, 2026). Although the studies are insightful in terms of conceptualization, there is a lack of empirical support through the implementation of the broad-based quantitative measures (Jun et al., 2026). Overall, three major gaps are found in the literature. First, there exists no unified AI-based collaborative learning system where analytics, adaptive collaboration support, and outcome evaluation are combined. Second, mathematical modeling of collaboration effectiveness is, in many cases, formal, which hinders reproducibility and comparative analysis. Third, most studies partially or contextually validate with no quantitative analysis of interaction, knowledge sharing, and learning performance dimensions. To fill in these gaps, the current paper suggests an all-inclusive AI-Driven Collaborative Learning Model that integrates learning analytics, AI-driven adaptive collaboration processes, and stringent mathematical analysis, thus building on existing research into the AI-assisted collaborative learning in online learning.

3 Methodology

The section presents the proposed AI-Driven Collaborative Learning Model (AI-CLM), its conceptual architecture, algorithmic workflow, and mathematical formulation of evaluation measures that will be used to measure the interactivity with peers and knowledge sharing in online learning.

Conceptual Framework

The proposed AI-CLM will be developed to improve collaborative learning through combining data on interaction between learners, learning analytics, and AI-based adaptive support systems. The model is a closed loop whereby the actions of learners are analyzed and applied to plan strategies for optimizing collaboration.

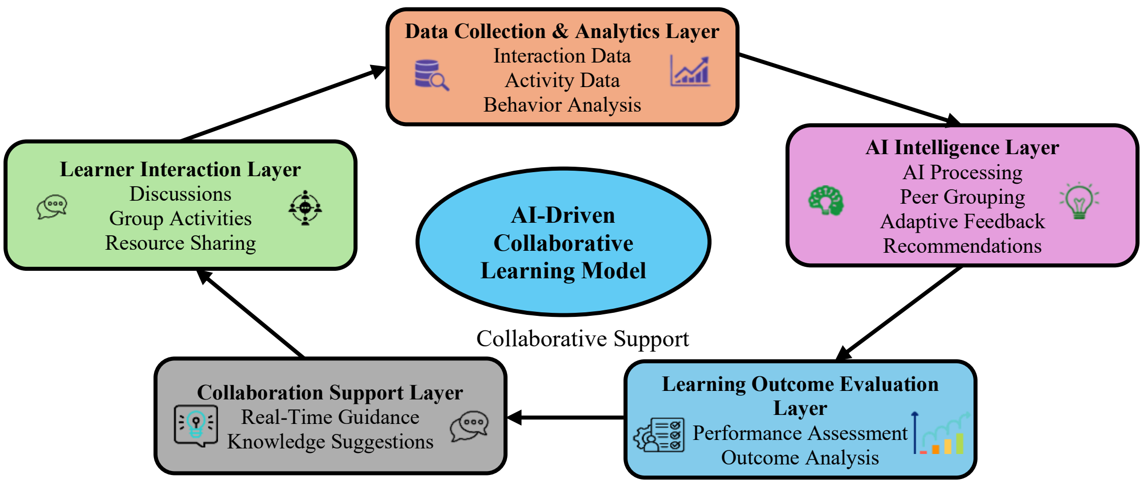

Figure 1: Conceptual framework of AI-driven collaborative learning model

The proposed model has a conceptual architecture as demonstrated in figure 1, which comprises five interrelated layers: Learner Interaction, Data Collection and Analytics, AI Intelligence, Collaboration Support, and Learning Outcome Evaluation.

Model Architecture

The model is composed of interrelated functional layers, which support collaborative learning collectively. Interaction among learners is the input of the system, and learning analytics and AI processing become possible to make adaptive decisions. The AI part is tasked with peer grouping, creation of feedback, and recommendations, and provides services to learners via collaborative assistance systems. The evaluation of learning outcomes is done on a periodic basis, and the results are incorporated back into the system to enhance further collaborative cycles.

Algorithmic Workflow

The operational workflow of the AI-CLM follows an iterative process. Initially, the profiling of learners based on their previous knowledge, level of engagement, and frequency of activities is done at the start of the learning session. The data of interaction are constantly gathered and evaluated during the collaborative activities to calculate collaboration indicators. The AI module is based on these indicators. proactively responds to peer grouping and provides adaptive feedback and knowledge recommendations.

The results of the learning are measured at specific intervals, and the learner profiles are updated as well to facilitate the continuous adaptation of the system.

AI-Driven Collaborative Learning Algorithm

Algorithm 1: AI-Driven Collaborative Learning Algorithm (AI-CLM)

Input: Learner set $L = \{l_1, l_2, \ldots, l_N\}$, learning resources R, collaboration threshold θ

Output: Optimized peer groups, adaptive feedback, collaboration performance metrics

1. Initialize learner profiles $P_i = \{k_i, e_i, a_i\}$for each learner $l_i \in L$
2. Set initial collaboration intensity $CI_i = 0$and metric weights w_1, w_2, w_3, w_4
3. For each learning session t, collect interaction data D_t
4. Compute collaboration intensity scores using interaction indicators
5. Apply AI-based peer grouping based on CI_i, k_i, and e_i
6. Generate adaptive feedback and knowledge recommendations
7. Evaluate collaboration and learning performance
8. Update learner profiles and collaboration parameters
9. Repeat until course completion

The proposed AI-CLM has a step-by-step procedure, which is outlined in Algorithm 1. The algorithm starts with the initiation of the learner profiles with the help of initial knowledge, level of engagement, and frequency of activities. The strengths of collaboration are initialized to a value of zero, and their metric weights are allocated to weight the effect of interaction, knowledge sharing, participation balance, and learning performance. The interaction data (posts, replies, shared resources) during every learning session are gathered and utilized to calculate the scores of collaboration intensity. The scores will be used to drive the peer grouping process of the AI, and they will be balanced and effective. Based on the adaptive feedback, knowledge recommendations are then provided to the learners to enhance their participation and the quality of interaction. The assessment of the learning outcomes is done occasionally, and the profiles of learners are revised to incorporate the new behavior trends, which allows for constant optimization of the process of collaborative learning.

Mathematical Modeling of Evaluation Metrics

In order to measure the AI-Driven Collaborative Learning Model (AI-CLM) quantitatively, various metrics will be established to represent various features of collaborative learning, such as peer interaction, knowledge sharing, participation balance, and improvement in learning outcomes.

The level of learner interaction is first quantified using the Peer Interaction Index (PII), which measures the average number of interactions per learner. It is defined in equation (1):

$$PII = \frac{1}{N} \sum_{i=1}^{N} (p_i + r_i) \tag{1}$$

Where Ndenotes the total number of learners, p_i represents the number of discussion posts contributed by learner l_i, and $r_i$denotes the number of replies received by learner l_i. This metric is used in the Results section to compare interaction intensity across learning models. To assess the extent of knowledge exchange among learners, the Knowledge Sharing Score (KSS) is introduced. As shown in equation (2), this metric normalizes the amount of shared knowledge by total learning activity:

$$KSS = \frac{\sum_{i=1}^{N} s_i}{\sum_{i=1}^{N} a_i} \times 100 \tag{2}$$

Where s_i denotes the number of learning resources or knowledge artifacts shared by learner l_i, and a_i represents the total learning activities performed by the learner. Equation (2) is employed to evaluate improvements in collaborative knowledge construction.

Participation equity is measured using the Participation Balance Index (PBI). To compute this metric, the collaboration intensity score for each learner is first calculated as given in equation (3):

$$CI_i = \alpha p_i + \beta r_i + \gamma s_i \tag{3}$$

Where α, β, and γ are weighting coefficients that control the relative influence of posting, replying, and resource sharing behaviors. These coefficients satisfy the condition $\alpha + \beta + \gamma = 1$.

Using the collaboration intensity scores obtained from equation (3), the Participation Balance Index is then defined in equation (4):

$$PBI = 1 - \frac{\sigma(CI)}{\mu(CI)} \tag{4}$$

Where $\sigma(CI)$ and $\mu(CI)$ represent the standard deviation and mean of the collaboration intensity values across all learners, respectively, this formulation ensures that higher values of PBI correspond to more balanced participation.

Learning gains resulting from collaborative activities are measured using the Learning Performance Improvement (LPI) metric. As defined in equation (5), this metric captures relative improvement between pre- and post-assessment scores:

$$LPI = \frac{S_{post} - S_{pre}}{S_{pre}} \times 100 \tag{5}$$

Where S_{pre} and S_{post} denote the average pre-test and post-test scores, respectively. Equation (5) is used to evaluate the impact of AI-supported collaboration on learning outcomes.

Finally, an overall measure of collaboration quality is computed using the Collaboration Effectiveness Score (CES). This composite metric integrates the previously defined measures, as shown in equation (6):

$$CES = w_1 \cdot PII + w_2 \cdot KSS + w_3 \cdot PBI + w_4 \cdot LPI \tag{6}$$

Where w_1, w_2, w_3, and w_4 are non-negative weighting coefficients representing the relative importance of each metric. These weights satisfy the normalization constraint given in equation (7):

$$\sum_{j=1}^{4} w_j = 1 \tag{7}$$

The metrics specified in equations (1) to (7) are calculated at a regular frequency in the course of learning and are employed to produce the quantitative results that take place in the Results and Discussion section.

4 Results

This part provides the results of the experiment that has been conducted with the help of the proposed AI-Driven Collaborative Learning Model (AI-CLM). Peer interaction, knowledge sharing, balance of participation, and learning performance are considered in the evaluation with the help of quantitative measures. The results are contrasted with a traditional online collaborative learning model in order to prove the efficiency of the offered approach.

Experimental Evaluation Overview

The Python language was used to implement the proposed AI-Driven Collaborative Learning Model (AI-CLM). The processing of learner interaction data and computing of metrics was done using common scientific libraries, such as NumPy and Pandas. Scikit-learn was used to perform AI-based analysis and peer grouping, and Matplotlib was used to perform result visualization. Experiments were carried out in a standard software platform so that they can be repeated. The experiment assessment happened during an eight-week online course of collaborative learning. The continuous data of learner interaction and assessment scores were collected during the course of learning. All the reported results are average values calculated between learners and learning sessions, so that they are robust and consistent.

Collaborative Learning Performance Analysis

Table 1 summarizes the comparative performance of the traditional collaborative learning model and the proposed AI-CLM in terms of interaction and collaboration effectiveness.

Table 1: Comparison of collaborative learning performance

Metric	Traditional Model	Proposed AI-CLM
Peer Interaction Index (PII)	12.4	21.8
Knowledge Sharing Score (KSS) (%)	68.2	84.6
Participation Balance Index (PBI)	0.54	0.81
Collaboration Effectiveness Score (CES)	0.63	0.86

The findings suggest that the suggested AI-CLM performs better in terms of peer interaction and sharing knowledge as opposed to the traditional model. The greater Participation Balance Index is evidence that the participation of the learners is more even in the conditions of the application of AI-driven collaboration support. The general Collaboration Effectiveness Score validates the integrated enhancement of all the assessed dimensions.

Learning Performance Evaluation

Table 2 shows the comparison of the results on the performance of learning between the two models in various assessment aspects.

Table 2: Learning performance comparison

Assessment Component	Traditional Model (%)	Proposed AI-CLM (%)
Quiz Performance	72.5	85.3
Group Project Score	74.1	88.7
Final Assessment	70.9	86.2

The findings indicate a steady increase in the performance of learners with the proposed AI-CLM. The increased grades in quizzes, group projects, and final reports serve as a sign that increased cooperation and feedback in the form of specific goals have a beneficial impact on learning processes.

Trend Analysis of Peer Interaction

Figure 2 shows the change in the Peer Interaction Index during the learning period of the two learning models. It demonstrates that the proposed AI-CLM provides the same growth in peer interaction throughout the learning weeks as the traditional model of the collaborative learning.

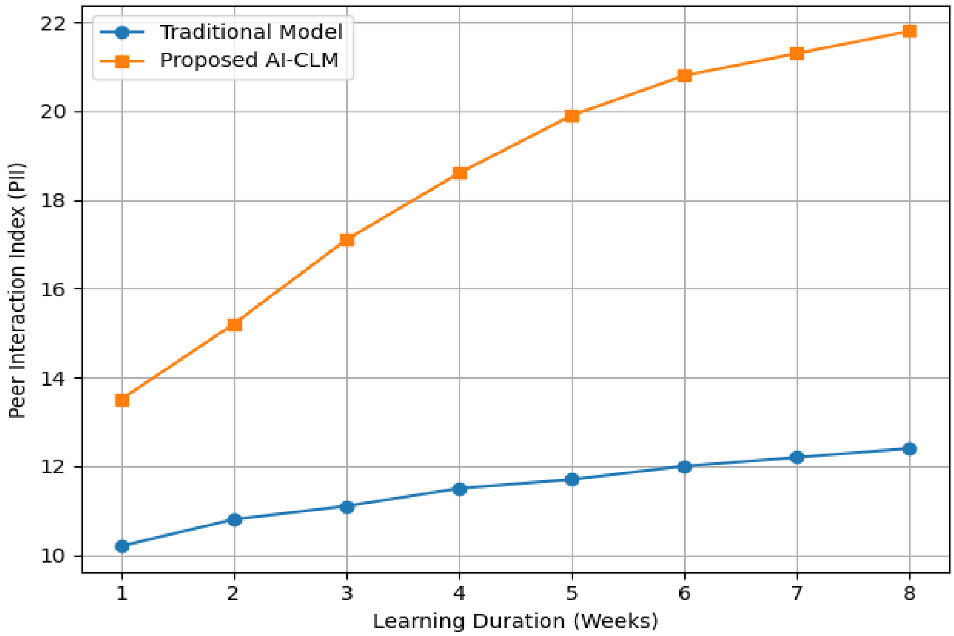

Figure 2: Peer interaction index trends over learning duration

Comparative Analysis of Collaborative Learning Metrics

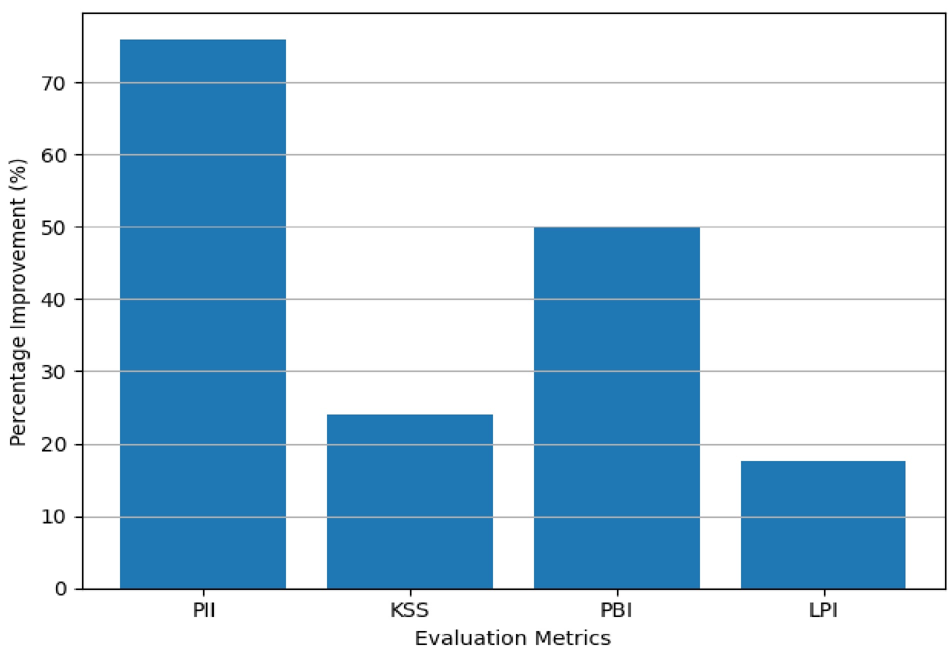

Figure 3: Percentage improvement across collaborative learning performance metrics

Figure 3 shows the percentage change in the proposed AI-CLM as compared to the traditional model in various evaluation metrics. It puts into focus the relative benefits obtained by the proposed AI-CLM in peer interaction, knowledge sharing, balance of participation, and performance in learning. As the experimental findings indicate, the incorporation of AI-enhanced analytics and adaptive support of collaborative learning does result in a quantifiable increase in the effectiveness of collaborative learning. Greater interaction between peers and their equal participation leads to greater knowledge sharing, which in turn increases the performance of learning. The results support the capability of the proposed AI-CLM to solve major limitations of the conventional online collaborative learning environments.

Ablation Analysis

An ablation analysis was performed to assess the contribution of the AI components in the proposed AI-CLM. The baseline model without AI achieved a Peer Interaction Index (PII) of 12.4, Knowledge Sharing Score (KSS) of 68.2%, Participation Balance Index (PBI) of 0.54, and Collaboration Effectiveness Score (CES) of 0.63. When individual AI components were partially enabled, moderate improvements were observed across all metrics. The complete AI-CLM produced the highest results, with PII increasing to 21.8, KSS to 84.6%, PBI to 0.81, and CES to 0.86. These findings confirm that the combined AI mechanisms contribute to the overall improvement in collaborative learning performance.

5 Conclusion and Future Work

The current research suggested an AI-based Collaborative Learning Model (AI-CLM) that would improve the way peers interact and exchange knowledge in online education settings. To facilitate efficient teamwork, the model combines learning analytics and peer grouping based on AI, adaptive feedback, and knowledge recommendation systems. The evaluation was conducted with the help of a structured algorithm and mathematically defined assessment measures to guarantee rigorous and reproducible evaluation. The experimental outcomes show that there are evident quantitative improvements compared to the traditional collaborative learning model. The Peer Interaction Index also rose by 12.4 to 21.8, which showed significantly greater engagement of the learners. The knowledge sharing score increased by 84.6 as compared to the previous 68.2, showing a better exchange of learning resources. There was also an improvement in participation equity, and the Participation Balance Index rose to 0.81, which indicated a decreased level of dominance by a small group of learners. Regarding learning outcomes, the average score in the assessment increased to 85.3% compared to 72.5%, and the total Collaboration Effectiveness Score was also raised to 0.86 compared to 0.63 according to the proposed AI-CLM.

In spite of such encouraging findings, the research has some limitations. The experiment was done in a restricted period of time and only in one online learning environment, which might limit the external validity of the research. Moreover, the existing model is based mainly on interaction and performance data, without referring to either the affective or contextual learner cues. The future of the work will be large-scale and cross-institutional validation of the proposed model, explainable AI techniques integration to enhance transparency and confidence, and incorporation of emotional and social indicators of behavior to enhance further collaborative learning support. Another type of study that will be performed will be longitudinal studies to determine the long-term effects of AI-based collaboration on the engagement of learners, their retention, and future skills.

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