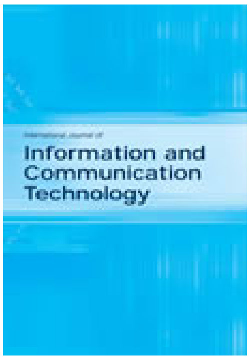

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Monitoring and optimisation of interactive classroom teaching effects empowered by the internet of things

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Abstract: Based on internet of things (IoT) technology, this study constructed a monitoring and optimisation model for the interactive effect of classroom teaching. Centring on indicators such as the effective response rate, the level of follow-up inquiries, the ratio of teacher-student interaction pairs, and the number of group interaction rounds, a data mapping scheme and evaluation framework were designed. Through an empirical analysis of the classroom data of 162 undergraduate courses in a certain university, it was found that although the interaction frequency was high, the structure was unbalanced and student participation was uneven. After the introduction of the optimisation strategy, all four interaction quality indicators significantly improved, verifying the practical effectiveness of internet of things empowerment in enhancing the depth of classroom interaction and student participation. The research provides feasible paths and evaluation tool support for universities to promote data-driven teaching reform.

Keywords: internet of things; IoT; classroom interaction; data-driven; teaching optimisation.

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1 Introduction

With the rapid development of information technology, the application of internet of things (IoT) technology in the field of education is changing the interactive methods of traditional classrooms. In college classrooms, problems such as uneven student participation, low interaction efficiency and lagging feedback mechanisms exist, which affect teaching effectiveness and learning quality. How to use technological means to truly record and dynamically analyse classroom interactions is the current direction of educational research. IoT devices feature real-time perception, automatic recording, and precise identification, capturing the subtle changes in the interaction between teachers and students in the classroom and providing the possibility for an objective assessment of the interaction effect. This study focuses on the classroom teaching scenarios in colleges and universities. By leveraging IoT enabling technologies, it builds a research framework for monitoring and optimising classroom interaction effects. Through the collection and analysis of multi-dimensional data, it reveals the structure and patterns of interaction behaviours and proposes feasible optimisation strategies. The implementation of this research promotes the scientific application of teaching data, enhances the accuracy of teaching quality control, and also provides theoretical support and practical reference for universities to build an intelligent teaching environment. This research has positive significance in promoting educational equity, enhancing students' sense of participation in the classroom, and supporting teachers' teaching improvement. It responds to the current practical demands of 'promoting teaching with data' and 'empowering the classroom with technology' in the process of educational digital transformation.

In this study, 'interaction effectiveness' is defined as the degree to which classroom interactions promote timely, reciprocal, and cognitively meaningful exchanges between teachers and students. Operationally, it is assessed through quantifiable indicators such as the effective response rate, the average level of follow-up questioning, the balance of interaction roles, and group participation depth. Under the current background of the continuous advancement of educational informatisation, IoT technology serves as a supporting means for educational digitalisation. It has been introduced into classroom teaching management and learning behaviour analysis, and is a path to enhance the quality of classroom interaction. Relevant research focuses on how to leverage the IoT to achieve precise perception and dynamic feedback on students' behaviours, teachers' activities, and classroom environments, thereby addressing issues such as lagging interactive feedback and uneven student participation in traditional classrooms. Lu et al. (2022) proposed an English classroom teaching model based on wireless communication technology of the IoT, emphasising that real-time data collection is conducive to forming a multi-directional interactive structure. Qiu and Feng (2022) combined the IoT with blended teaching and verified the positive effect of information synchronisation ability on students' classroom response. Liu and Yang (2021) and Li and Han (2023) respectively conducted research in the fields of intelligent classroom systems and audio recognition technology, pointing out that real-time tracking of speakers and identification of behaviour categories through sensor networks can effectively enhance the visibility and controllability of the interaction process. The art classroom system designed by Guo et al. (2022) has achieved multi-terminal collaboration, demonstrating the application potential of cross-modal data fusion in classroom behaviour analysis. Rui (2024) has constructed a virtual teaching experience platform based on the IoT, which has a positive impact on enhancing students' willingness to participate independently. Hu (2023) introduced the fuzzy control algorithm to model unstructured interactions in the classroom, which is conducive to the recognition and interpretation of complex behavioural patterns. Luo (2021) and Zhang and Li (2021) respectively started from the cloud platform and the terminal system, proposed the intelligent path of teaching management, and strengthened the cross-temporal and spatial integration ability of interactive data. Yu and Mi (2023) then, starting from the teaching feedback mechanism, verified the feasibility of the collaborative improvement of classroom response efficiency by artificial intelligence and

IoT technology. The research results have laid a methodological foundation for building a classroom teaching interaction monitoring and optimisation system supported by the IoT. Current research still mainly focuses on system design or platform development. The measurement framework, behavioural indicator construction and strategy optimisation path for 'interactive effects' themselves are still weak. There is still a lack of systematic monitoring research and empirical verification based on real classroom data, which needs to be refined and deeply integrated with teaching practice. In recent years, the educational landscape has shifted with the rise of the so-called 'smart classroom' – a digitally enriched environment where IoT sensors, AI analytics, and interactive platforms converge to support active learning and teacher-student interaction (Kaur et al., 2022). By locating the present study within this broader trend of intelligent educational systems, the monitoring and optimisation of classroom interaction empowered by IoT becomes part of a global effort to enhance pedagogical outcomes.

Globally, there has been a surge in interest around classroom digitalisation, with educational systems increasingly adopting smart environments, sensor-based learning, and real-time analytics to improve teaching effectiveness. This shift reflects a broader commitment to evidence-based, technology-enhanced instruction across diverse educational contexts. Within this global movement, IoT technologies offer distinct advantages in resolution, immediacy, and contextual richness, positioning them as key enablers of the next generation of interactive classroom design. Compared to traditional educational data collection methods – such as manual observation, post-class surveys, or platform log analysis – IoT-based monitoring provides real-time, continuous, and multi-modal data streams. This enables dynamic tracking of classroom behaviours, capturing interactional subtleties and environmental changes that are often missed by static or retrospective approaches. The integration of voice, motion, and contextual sensing empowers more granular and immediate assessments of teaching and learning processes, laying a robust foundation for data-informed pedagogical optimisation.

This research focuses on the monitoring and optimisation of classroom teaching interaction effects empowered by the IoT, concentrating on the multi-dimensional behavioural data of teacher-student interaction in real teaching scenarios in colleges and universities. It attempts to develop a systematic framework for measuring and analysing classroom interaction effects and proposes targeted optimisation strategies. The research will take the undergraduate classroom of a certain university as a sample and collect multi-source data related to teaching interaction in the classroom through IoT devices, including dimensions such as the number of questions raised by teachers and students, response delay, discussion participation and behaviour coverage. Combined with behaviour recognition and coding methods, an interaction evaluation index system based on frequency, depth, fairness, and responsiveness will be established. Through data mapping and statistical analysis methods, the overall characteristics and patterns of classroom interaction are presented, providing quantitative support for the subsequent optimisation path.

Unlike existing studies that mainly focus on the construction of teaching systems and platform design, this study emphasises starting from the interactive process, paying attention to the structural and dynamic characteristics of teaching behaviours themselves, and emphasising precise diagnosis and hierarchical improvement based on data feedback. The research designed a set of evaluation frameworks, combined with the interactive performance in the actual classroom operation, proposed multiple optimisation ideas such as frequency adjustment, teacher-student participation distribution and feedback mechanism improvement, and verified the effect based on empirical data. This study innovatively proposed an interactive effect construction idea oriented towards ‘monitorability, explainability and optimisability’ at the theoretical level, expanding the index system and logical framework of classroom interaction research. Introduce a monitoring model that combines IoT technology with behavioural data analysis at the methodological level to achieve real-time acquisition and in-depth analysis of classroom interaction status. At the practical level, based on empirical results, feasible improvement strategies are proposed, providing theoretical support and practical solutions for enhancing classroom teaching interaction in colleges and universities and promoting the application of digital education.

While previous studies have primarily focused on system construction or technological capabilities, they often overlook how such systems translate into measurable interaction improvements. This study extends the literature by linking IoT-based behavioural data collection to an integrated evaluation and optimisation framework. By emphasising process-level indicators such as response effectiveness and interaction structure, this work bridges the gap between technical implementation and pedagogical impact, offering a novel pathway for empirical classroom optimisation.

2 Materials and methods

2.1 Data collection and sample selection

2.1.1 Research object and research scenario

This study takes three undergraduate courses of a comprehensive university as the research objects, which respectively include liberal arts, science and engineering, and public basic courses. The course types include lecture-based, discussion-based and blended teaching, ensuring the diversity and representativeness of the data samples. A total of nine teaching classes were selected for the study, involving nine teachers and a total of 482 students. All the participating teachers have more than five years of teaching experience, and the students are from the first to the third year of college. The research scenario is set in the teaching building of the school where the smart classroom system has been completed. Each classroom is equipped with high-definition cameras, audio collection devices, intelligent voice recognition systems, and environmental perception terminals and other IoT basic equipment, achieving real-time monitoring and data collection of the entire classroom process. During the teaching process, behaviours such as teachers’ lectures, students’ raising of hands to speak, group discussions, and interactions between teachers and students are recorded simultaneously. At the same time, auxiliary data such as volume, movement frequency, and position changes are automatically generated. This study does not interfere with the classroom teaching content. It only collects objective data from teaching activities to ensure the naturalness and authenticity of interactive behaviours (Liu et al., 2021). All research subjects signed informed consent forms, and the data collection process strictly adhered to privacy protection principles and ethical norms. This behaviour capture method in a real classroom environment can provide stable and complete data support for the subsequent analysis of interactive effects, and is also closer to the actual operation status of the current IoT teaching scenarios in colleges and universities.

2.1.2 Data types and indicator systems

The data types include behavioural data, environmental data and auxiliary audio and video data of the interaction between teachers and students during the classroom teaching process, all of which are automatically collected and synchronously stored through IoT devices. Behavioural data includes the number of times teachers ask questions, the number of times students respond, the number of times they raise their hands, the frequency of group discussions, and the number of rounds of classroom speeches, which are used to reflect the frequency and breadth of interaction. Environmental data such as noise levels, light changes, temperature and humidity, are used to analyse whether external conditions for teaching interaction affect the participation status. After the audio and video data undergo speech recognition and behaviour recognition processing, effective behaviour segments are extracted and time series encoded (Gao et al., 2022).

Table 1 Evaluation index system for classroom teaching interaction effect

Dimension	*Indicator name*	*Data source*	*Indicator type*
Interaction frequency	Number of teacher questions	Behaviour recognition data	Continuous
	Number of student responses	Behaviour recognition data	Continuous
Interaction breadth	Student participation coverage rate	Facial recognition statistics	Percentage
Interaction depth	Consecutive follow-up rounds	Audio semantic analysis	Count
	Proportion of higher-order questions	Question text analysis	Percentage
Participation equity	Gender participation difference	Student information matching	Difference value
Response timeliness	Average student response latency	Timestamp calculation	Seconds

As shown in Table 1, to evaluate the interaction effect, this study constructed an interaction evaluation index system based on five dimensions, namely interaction frequency, interaction breadth, interaction depth, participation fairness and response timeliness, with several quantifiable indicators under each dimension. The frequency of interaction includes the number of speeches, the number of questions. The breadth of interaction focuses on the coverage rate of participating students. The depth of interaction is reflected through the follow-up chain, the proportion of high-level questions. Fairness reflects the balance of participation among different student groups. The timeliness of response focuses on the time interval between the interaction between teachers and students. This indicator system provides clear operational standards and data basis for subsequent monitoring and analysis, and comprehensively presents the characteristics and changing trends of classroom interaction empowered by the IoT (Hu et al., 2024).

2.1.3 Data collection

This study employs multi-source IoT devices to collect data throughout the entire classroom teaching process, including four types of data channels: behaviour, voice, image and environment. High-definition cameras and infrared sensors installed in the classroom are used to capture behavioural information such as students raising their hands, speaking, standing and group interactions. Microphone arrays and voice recognition systems are used to extract voice content from teachers' lectures, students' responses, and questions, while recording variables such as voice length and response time. Environmental sensors synchronously record noise levels, light intensity, and temperature and humidity data (Liu and He, 2025). The data collection cycle is six consecutive weeks. Each course is collected three times a week, with 45 minutes of complete data recorded for each class. In total, 162 classes have their data collected. All original data are uniformly summarised to the teaching data middle platform and numbered, classified and backed up in accordance with a unified format. To ensure data integrity and accuracy, this study established a data quality inspection mechanism to evaluate the rate of missing values, recognition error rate and equipment stability. In this study, the average response time of students in each class was calculated as shown in formula (1):

$$\text{ART} = \frac{1}{n}\sum_{i=1}^{n}\left(T_{si} - T_{ti}\right) \tag{1}$$

Here, T_{si} represents the timestamp when the i^{th} student starts to speak, T_{ti} represents the timestamp when the teacher raises a question, and n is the number of times the teacher asks questions in this class.

2.1.4 Data cleaning and preprocessing

After completing the collection of the original data, to ensure the accuracy and scientific nature of the subsequent analysis results, this study carried out systematic data cleaning and preprocessing on the collected multi-source data. Screen and handle the missing values, duplicate records and recognition errors existing in the behaviour recognition data. Missing value processing adopts temporal interpolation and adjacent behaviour filling strategies. For missing values caused by camera occlusion or recognition failure, reasonable completion is carried out by referring to the behaviour states in the upper and lower time slices (Eich et al., 2025). For duplicate records, thresholds are set based on the timestamp and behaviour type for deduplication processing to ensure that each behaviour is counted only once. Perform text transcription and context annotation on the voice data, and eliminate invalid noise segments and non-classroom interfering sentences. The image data is used to remove the failed recognition segments through the face recognition algorithm and rebind the behaviour labels. Extreme outliers in environmental data are judged and eliminated using the 3σ criterion (Pabba and Kumar, 2022). For continuous variables, this study uniformly carried out standardisation processing to ensure that different indicators have the same dimension. The standardisation formula is shown in formula (2):

$$Z_i = \frac{X_i - \mu}{\sigma} \tag{2}$$

Among them, X_i is the original value, μ is the sample mean of this indicator, σ is the standard deviation, and Z_i is the standardised value. The cleaned behaviour, voice, image and environmental data are synchronously integrated according to the timestamp to form a unified structured data table, and an analysis sub-database is established by class. The completion of cleaning and preprocessing work has effectively improved the quality and consistency of data, providing a reliable data foundation for the monitoring and modelling of classroom teaching interaction effects.

2.2 Monitoring of classroom teaching interaction effects

2.2.1 Interactive behaviour recognition

Under the support of the IoT environment, the way to recognise classroom teaching interaction behaviours uses the joint look at different kinds of data, like video images, voice audio, and where people are in the room (Younger and Warrington, 2022). This study uses a behaviour recognition model and sensor fusion method to find and sort the interaction behaviours between teachers and students in the classroom. The main behaviours found include teachers asking questions, students raising hands, students speaking, students responding, teacher-student talking, and starting or ending group discussions. Each behaviour is marked with time and the person's ID. Behaviour recognition uses a way based on convolutional neural networks and dynamic time window matching. It combines picture frames from the camera and voice from the microphone, then matches and sorts them using the behaviour label set. For example, to find when a student raises a hand, the system looks at how the arm moves. If the hand moves up from a still position for more than 15 frames and goes above the shoulder, it counts as raising a hand. How often and how long the behaviour happens are also used to make the result more certain. To make sure the system is right, this study uses a cross-checking method and checks how well each kind of behaviour is found. The way to calculate accuracy is in formula (3) (Yu and Bai, 2021):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Among them, TP represents the number of behaviours that are recognised as interactive but actually interactive, TN represents the number of behaviours that are recognised as non-interactive but actually non-interactive, FP and FN respectively represent the number of misjudgements and missed judgements. In this way, the interactive behaviour recognition system can achieve efficient, continuous and automatic recognition of diverse interactive behaviours within the classroom, providing a solid foundation for subsequent coding and monitoring analysis.

2.2.2 Interactive behaviour coding methods

To make classroom interaction behaviours easier to measure and compare, this study finished behaviour recognition first, then setup one standard coding system. This turns complex classroom behaviours into a clear data format. The coding uses 'time-behaviour type-participant-behaviour direction' as the main parts. This helps make sure each interaction behaviour has a clear ID in the database. The coding follows an event sequence rule. Each real interaction behaviour gets one coding unit. It records the time it happened, what the behaviour was, who did it, what kind it was, and which round it was in. The behaviour types are split into five groups: teacher starts the interaction, student speaks first, students interact with each other, group work led by teachers, and behaviours that are not interactions.

As shown in Table 2, it is the coding rule table for classroom interaction behaviours designed in this study, which clearly defines the coding logic and representation methods of various interaction behaviours. For example, the code 'T-Q-S1' indicates that the teacher asks a question to student 1, 'S2-R-T' indicates that student 2 responds to the teacher's question, and 'S3-D-G1' indicates that student 3 participates in the discussion within group 1. To ensure the consistency of the encoding, three rounds of trial marking and adjustment were conducted before the official encoding. Finally, the encoding dictionary was determined, and the batch encoding of classroom behaviours was completed through a dual mechanism of manual review and automatic matching. This approach provides a standardised data foundation for subsequent statistics on interaction frequency, in-depth analysis, and quality assessment, enhancing the accuracy and stability of classroom interaction research in the IoT environment.

Table 2 Coding rules table for classroom interaction behaviours

Code format	*Meaning description*	*Actor*	*Target*	*Interaction type*
T-Q-S1	Teacher asks a question to student 1	Teacher	Student 1	Questioning
S2-R-T	Student 2 responds to the teacher	Student 2	Teacher	Responding
S3-D-G1	Student 3 participates in group 1 discussion	Student 3	Group 1	Peer interaction
T-GD-All	Teacher guides a whole-class discussion	Teacher	All students	Guided whole-class
S4-NI-Null	Student 4 does not engage in any interaction	Student 4	None	Non-interactive behaviour

2.2.3 Statistics of monitoring data

2.2.3.1 Descriptive statistics

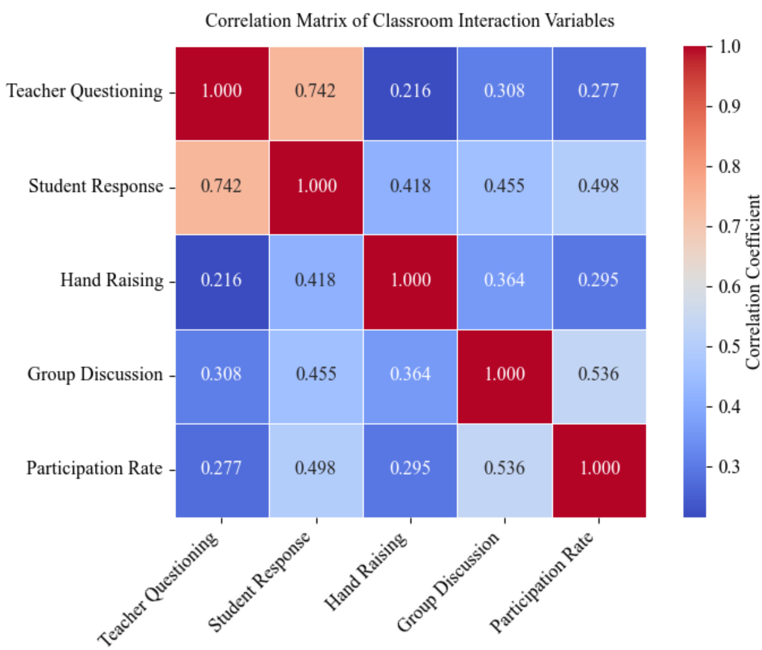
This study conducted descriptive statistical analysis on classroom teaching interaction data, presenting the basic characteristics and distribution patterns of interaction behaviours. The statistical content includes indicators such as the total number of interactive behaviours, the frequency distribution of different behaviour types, the average duration of each behaviour, the proportion of student participants, and the interaction level under different course types.

As shown in Table 3, the data of 162 classes in nine teaching classes were summarised and calculated. The research found that the proportion of teacher-initiated interaction in the total interaction volume was relatively high, while the number of students' active speeches was relatively low. The frequency of group discussion-based interaction in liberal arts courses was significantly higher than that in science and engineering courses. During the statistical process, all variables were grouped and processed by course type. Basic statistics such as mean, standard deviation, minimum and maximum values were used for analysis to reflect the fluctuation range and central tendency of interactive behaviours in different teaching scenarios. Taking the variable of 'the number of teachers' questions' in the classroom as an example, the average is 8.27 times in lecture-based courses with a standard deviation of 2.41, while it rises to 12.63 times in discussion-based courses with a standard deviation of 3.02, indicating that the type of course has a significant impact on the frequency of interaction.

Table 3 Descriptive statistics of classroom interaction behaviours (per lesson)

Variable	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Number of teacher questions	10.45	3.12	5	17
Number of student responses	6.87	2.94	2	14
Total number of hand-raising acts	4.22	2.31	0	11
Frequency of group discussion initiation	2.34	1.09	1	5
Student participation coverage (%)	43.68	11.45	21.5	68.2

Figure 1 Correlation coefficient matrix of teaching interaction variables (see online version for colours)



2.2.3.2 Correlation analysis

In this study, the Pearson correlation coefficient was used to test the linear relationship between each pair of variables, and the significance levels were set at 0.05 and 0.01. The main variables examined include the number of times teachers ask questions, the number of times students respond, the total number of times they raise their hands, the frequency of group discussions, and the coverage rate of student participation.

As shown in Figure 1, the correlation coefficient matrix of the interactive behaviour variables in this study is given. It helps to see how the variables change together. There is a strong positive link between the number of teachers' questions and the number of students' responses, r = 0.742. This means when teachers ask more questions, students respond more. The coverage rate of student participation also has a positive link with the frequency of group discussions, r = 0.536. This means group discussions help more students take part. There is a middle level positive link between the total number of hand-raising behaviours and the number of students' responses, r = 0.418. But there is no strong link with the number of teachers' questions. This means some students raise their hands but may not get the chance to speak.

2.2.3.3 Regression analysis

This study employs a multiple linear regression model to explore the impact of various classroom interaction behaviour variables on 'student participation coverage', identify the influencing factors, and determine the direction and intensity of their effects. Taking the student participation coverage rate as the factor (Y), and the number of teachers' questions (X_1), the number of students' responses (X_2), the number of raising hands (X_3), and the frequency of group discussions (X_4) as independent variables, a regression model was constructed. The form of the regression equation is shown in formula (4):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \varepsilon \tag{4}$$

Among them, Y represents the standardised student participation coverage rate, β_0 is the constant term, $\beta_1 \sim \beta_4$ is the regression coefficient of each predictor variable, and ε is the error term. The model adopts the stepwise regression method for variable screening, controls the multicollinearity problem, and tests the explanatory power and goodness of fit of the model.

Table 4 Regression analysis results

Independent variable	*Regression coefficient (β)*	*Standard error*	*t-value*	*Significance (p)*
Number of teacher questions (X_1)	0.094	0.063	1.49	0.139
Number of student responses (X_2)	0.317	0.072	4.4	0
Number of hand-raising acts (X_3)	0.106	0.069	1.54	0.126
Frequency of group discussions (X_4)	0.429	0.058	7.39	0
Constant term (β_0)	0.002	0.048	0.04	0.964
R^2		0.462		
Adjusted R^2		0.448		
F-value		33.75		
p		< 0.001		

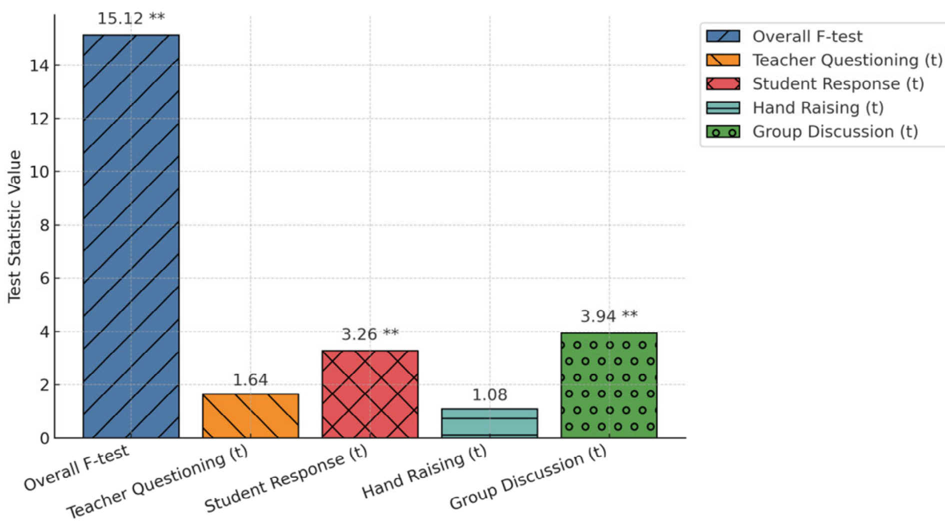
As shown in Table 4, the number of student responses and the frequency of group discussions have a significant positive impact on student participation coverage. Although the regression coefficient of the number of teacher questions is positive, it does not reach the statistical significance level, while the influence of the number of hand raises is relatively weak.

2.2.3.4 Significance test

This study looks at how important the model is as a whole and how important each variable is. It checks if the model can explain classroom participation in a useful way and finds out which factors affect students' participation the most. The F-test method is used to test the model. It compares the sum of squared regression and the sum of squared residuals in the model to see how well the explanatory variable explains the dependent variable.

As shown in Figure 2, the detailed results of the significance test are listed. These include different statistics and their related significance levels. They are used to check how classroom interaction variables affect teaching improvement. The F-score of the model is 15.12, and the significance level is $p < 0.001$. This means the model has strong explanatory power. For each variable, the t-test method is used. The results show that the number of student responses, $t = 3.26$, $p < 0.01$, and the frequency of group discussions, $t = 3.94$, $p < 0.01$, both pass the 1% level test. This means these two variables clearly affect the student participation coverage rate. The number of teacher questions, $t = 1.64$, $p = 0.104$, and the number of hand raises, $t = 1.08$, $p = 0.283$, do not pass the test. This means their effect is not clear. There might be other factors in the middle that are not included in the model.

Figure 2 Significance test results of teaching interaction variables (see online version for colours)



2.3 Design plan for interactive effects in classroom teaching

2.3.1 Optimisation design of the index system

This study found that the number of students' responses and the frequency of group discussions were significant variables affecting the coverage rate of students' classroom participation, while the number of teachers' questions and the behaviour of raising hands did not show stable statistical effects. In the optimisation design of classroom teaching interaction effects, the original indicator system needs to be adjusted to more accurately reflect the key elements of interaction quality. The optimised indicator system no longer merely focuses on the frequency of behaviour occurrence, but introduces the response structure of behaviour and the characteristics of the interaction chain, emphasising the coherence of interaction and the quality of feedback. Four new variables, namely the effective response rate, the number of rounds of group interaction, the ratio of teacher-student interaction pairs, and the average level of follow-up inquiries, have been added to replace some traditional frequency-related indicators. By optimising the indicators, the depth logic, role distribution and interaction load in the interaction process can be more comprehensively reflected, avoiding the evaluation of classroom participation only based on the frequency of surface behaviours.

As shown in Table 5, it is the optimised index system structure. The effective response rate refers to the proportion of students' responses that are continued or confirmed by teachers, reflecting the bidirectionality of feedback. The number of group interaction rounds is used to measure the number of consecutive speaking rounds among students in each discussion. The proportional representation of teacher-student interaction indicates the proportion of student-initiated interaction in all teacher-student interactions, which is used to reflect whether the structure of the interaction subjects is balanced. The average follow-up level reflects the depth of the interaction and the progress of thinking by analysing the number of consecutive follow-ups in the interaction. The indicators are more in line with the dynamic monitoring and regulation requirements for the quality of teaching interaction in the IoT environment.

Table 5 Optimised indicator system for classroom interaction effectiveness

Optimised dimension	*Indicator name*	*Definition*	*Data source*
Interaction quality	Effective response rate	Proportion of student responses accepted or followed up by the teacher	Audio recognition + coded data
Interaction depth	Average follow-up level	Average number of consecutive follow-up rounds by teachers or students	Behavioural sequence analysis
Participant structure	Teacher-student equality ratio	Number of student-initiated interactions / total teacher-student interactions	Coded interaction logs
Group participation stability	Group interaction rounds	Number of continuous speakers per round × number of discussion rounds	Group discussion records

2.3.2 Data mapping scheme

Based on the multi-source data collected by IoT devices, this study constructs a clear data mapping scheme, and corresponds and calculates each teaching interaction indicator with the observable data field one by one (Silva and Braga, 2020). The mapping process is based on the units of 'behaviour coding + speech recognition + timestamp sequence', and through data logical integration, it realises the structured expression of abstract teaching behaviours. Take the effective response rate as an example. The calculation of this indicator is based on the continuity judgement of the interactive voice between teachers and students. If a teacher provides direct feedback within 30 seconds after a student's response, that response is marked as valid. Let the total number of responses from students be R and the number of valid responses be R_e. Then, the effective response rate is as shown in formula (5):

$$ER = \frac{R_e}{R} \tag{5}$$

For the proportional relationship of teacher-student interaction, the total number of times students actively ask questions and speak up S_a is counted through the behaviour coding log, and then the number of times teachers initiate teacher-student interaction T_i is counted. The proportional relationship is shown in formula (6):

$$B_{st} = \frac{S_a}{S_a + T_i} \tag{6}$$

The closer it is to 0.5, the more balanced the interaction structure is B_{st}. The mapping of the number of group interaction rounds relies on the time chain of speeches within the group and the identification of the speaker's identity. The interval between consecutive speeches must not exceed 10 seconds, and they must come from different students to form one round of interaction. The stability of participation within the group can be obtained by summing up all the interaction rounds within the group.

The average follow-up level is constructed based on the interaction tree model. Each round of follow-up is regarded as one level. Let the total number of follow-up levels be L and the total number of follow-up events be N. Then, the calculation formula of this indicator is shown in formula (7):

$$D = \frac{L}{N}. \tag{7}$$

2.3.3 Evaluation framework formulation

The framework of this research includes evaluation dimensions, grading standards, early warning mechanisms, and improvement suggestions. It follows the closed-loop logic of 'data-driven-behavioural explanation-strategy feedback' as the main idea. The evaluation dimensions are based on four main indicators. They are the effective response rate, the average follow-up level, the ratio of teacher-student interaction pairs, and the number of group interaction rounds. Each indicator is standardised by its distribution in the sample classroom. A three-level evaluation standard is set: excellent (one standard deviation above the average), average (within one standard deviation), and low (one standard deviation below the average). This helps show the classroom interaction effect clearly. The system turns on the evaluation suggestion module when an indicator is lower than the set value. It gives teaching improvement paths like 'improving response quality can be done by giving more waiting time' and 'student leadership can be increased by using group question design strategies'. This framework can be used to give feedback right after each class. It can also help compare results over time. It helps teachers make teaching better using interaction data. It also helps the IoT teaching setup in colleges move from just 'seeing' to also 'changing' and 'improving', making the control of teaching quality stronger.

For example, if the system detects that a large proportion of students' responses are not followed up by the teacher – resulting in a low effective response rate – it automatically flags this indicator and suggests actionable strategies such as increasing wait time or prompting reflective questioning. In a real university pilot, this led to a shift in teacher questioning behaviour within two weeks, raising follow-up levels and improving overall interaction balance. This illustrates how the ‘data-driven-behavioural explanation-strategy feedback’ loop enables responsive instructional improvement in authentic settings.

2.4 Optimisation of interactive effects in classroom teaching empowered by the IoT

2.4.1 Optimisation strategy for interaction frequency

In the IoT environment, raising how often classroom interaction happens needs not just the teacher’s own efforts but also a real-time data system that can track and adjust things as they happen. Based on the earlier statistics and analysis of interaction frequency, this study gives a set of simple strategies to help improve interaction using behaviour feedback. The system checks in real time how often each student raises their hand, speaks, responds, and does other things in class using IoT devices. It then compares these numbers to past averages to find which students interact less. For these students, teachers can help by calling on them, giving them roles, or encouraging them to speak in groups, which can help them want to join more (Kourtiche et al., 2025).

Some classes have too many teacher questions and too few student answers. The system gives a tip to let teachers ask more open-ended questions and add time for students to ask questions. This can help students go from just answering to asking more. The system also tracks the timing of interaction and finds parts of class when not much happens. During these times, teachers can add short tasks like quick Q&A, games, or group talks to raise the overall level of interaction. After class, the system shows a chart of how teacher and student interaction changes over time. This helps teachers see the ups and downs and adjust how fast they teach or when to ask questions. With real-time tracking, clear focus on students, and timing changes, this plan can help make classroom interaction happen more often, help ideas flow between teachers and students, bring more energy to class, and help shift teaching from just ‘giving information’ to ‘sharing ideas actively’.

2.4.2 Paths for improving interaction quality

The quality of interaction looks at not just if a behaviour happens, but also how ideas connect, how deep the thinking is, and how useful the responses are. So, using ‘follow-up level’ and ‘effective response rate’ as key reference variables is important. An IoT system watches in real time how students and teachers talk to each other. It can check if there are many rounds of follow-up or reply behaviours in the talk. It can also remind teachers to ask deeper questions. For example, if a student speaks but the teacher does not ask more questions, the system shows a reminder to the teacher to give more guidance. This helps keep the talk going. When checking if students give good answers, the system uses speech recognition and meaning analysis to mark answers that include things like knowledge points, concepts, ideas, or extended questions as ‘effective responses’. After class, the system shows how many responses were effective so that teachers can change how they teach.

The quality of group talk can also be seen by looking at how well the group talks flow and how often different people speak. If one group keeps showing signs like 'one person talks all the time' or 'same thing repeated', the system tells the teacher to change the group or give out job roles next time. With a system that looks at how the talk flows, what is said, and if it keeps going, a full process from 'seeing what happens' to 'giving quality advice' is built. This gives teachers clear ways to improve and helps move classroom talk from just saying something to really understanding the topic.

2.4.3 Mechanism for balancing teacher leadership and student participation

In classroom teaching using the IoT, the way teachers lead and how students take part affects how fair the interaction is and how well students learn. This study uses the 'teacher-student interaction ratio' to build a dynamic balance system. It watches the behaviour data to manage how teachers and students take turns and helps keep the classroom participation more balanced. The system counts how many times teachers start talking and how often students take part in each class. It then shows a chart to see if the teacher talks too much or if students are not active enough.

If the system finds that the teacher talks too much in many classes in a row, it tells the teacher in the report after class. It suggests using more open teaching ways like group talks, student-led work, and letting students explore topics on their own, so students have more chances to talk. The system also asks teachers to give students clear jobs like asking questions, taking notes, or giving summaries, so students feel more in charge and take part more. When sharing learning resources, teachers can look at how students have talked in the past to match them with the right topics or tasks. Teachers can set goals for how much students should join in before class and then check the results after class. This makes a cycle of 'set goal-do it-check result'. Using this kind of system to guide roles and help students join in more breaks the old way of just 'teachers talk, students listen'. It helps turn the classroom into a space where both sides work and share, making a smart class where everyone takes part fairly.

2.4.4 Data-driven feedback and improvement suggestions

Based on the completion of classroom interaction behaviour identification, index extraction and effect analysis, this study proposes a set of data-driven feedback and improvement suggestion mechanisms to help teachers timely understand interaction problems, clarify improvement directions, and promote the continuous optimisation of teaching strategies. The system automatically generates classroom interaction reports through real-time data collection and multi-dimensional indicator analysis. The report content includes the scores of core interaction indicators, the structure diagram of teacher-student interaction, the hot period of interaction, the distribution of student participation activity, helping teachers quickly grasp the overall trend and key issues of interaction throughout the entire class. The report sets up a 'data early warning module'. If the effective response rate of students is lower than the set threshold, the system will automatically mark it in red and attach improvement suggestions, such as 'increase waiting time' and 'provide discourse framework guidance'.

The system offers a 'group feedback' function, classifying students into three categories based on their interactive performance: high participation, medium participation, and low participation, and pushing teaching suggestions for different student groups to teachers. For instance, for low-participation groups, it is recommended to adopt strategies such as roll call questioning, pre-setting tasks, and group collaborative answering to enhance their participation. For high-participation groups, it is recommended to setup more challenging open-ended questions to enhance the depth of their expression. The system also supports teachers in customising teaching goals, such as enhancing students' ability to follow up or balancing the proportion of speeches within a group. After the teaching session, it provides a matching table of goal achievement rates and optimisation suggestions to help teachers evaluate teaching effectiveness and determine the direction for further adjustments. By deeply integrating IoT technology with the teaching feedback mechanism, this module has achieved a transformation from 'passive observation' to 'active improvement', enhancing the scientific nature of teachers' teaching decisions and the sustainable optimisation ability of classroom interaction quality.

3 Results and discussion

3.1 Results

3.1.1 Monitoring results of sample classroom interaction effects

After completing the optimisation of the indicator system and data mapping, this study systematically monitored and analysed the optimised interaction effect indicators based on 162 sample classroom data collected by the IoT, presenting the performance of four key indicators: effective response rate, average follow-up level, teacher-student interaction ratio, and the number of group interaction rounds. Overall, the optimised indicators can more accurately reflect the structural and quality characteristics of classroom interaction, and discover the deep-seated problems that the original frequency-based indicators are difficult to reveal.

Table 6 Descriptive statistics of optimised interaction effectiveness indicators in sample classrooms ($n = 162$)

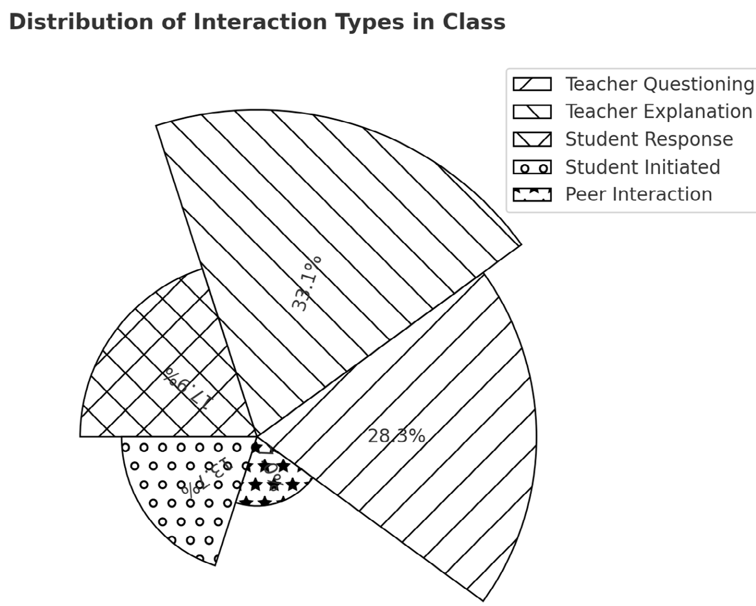
Indicator name	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
Effective response rate	0.562	0.117	0.311	0.802
Average follow-up level	1.72	0.53	1	3.2
Teacher-student equality ratio	0.386	0.109	0.184	0.673
Group interaction rounds	2.45	0.94	1	5

As shown in Table 6, the main interaction indicators after optimisation are listed. This gives a database for later difference analysis and strategy changes. The average effective response rate in all classrooms was 0.562. This means about 56.2% of students' responses could be followed up or confirmed by teachers in time. The effective response rate in discussion-based classrooms was much higher than in lecture-based ones. The average of the questioning levels was 1.72. This means most classroom interactions stayed at the first or second level of questioning and did not go deeper. The student-to-teacher interaction ratio was 0.386. This shows that teacher-led interaction is still the main way in the classroom, and students did not speak actively very often. The average number of group interaction rounds was 2.45. This means that in classrooms with group discussions, most groups could finish 2 to 3 rounds of speaking. But some groups still had only a few students talking while others stayed quiet.

3.1.2 Analysis of interaction behaviour characteristics between teachers and students

Under the optimised indicator system, this study looked at how interaction behaviours between teachers and students were different in the sample classrooms. It focused on the main structure of teacher-student interaction, how students took part, and the types of behaviours shown. The data collected and behaviour coded through the IoT show that most classrooms still follow a one-way structure led by teachers. The number of students who start interactions on their own is still low. This is more common in lecture-based classrooms.

Figure 3 Proportions of classroom interaction types



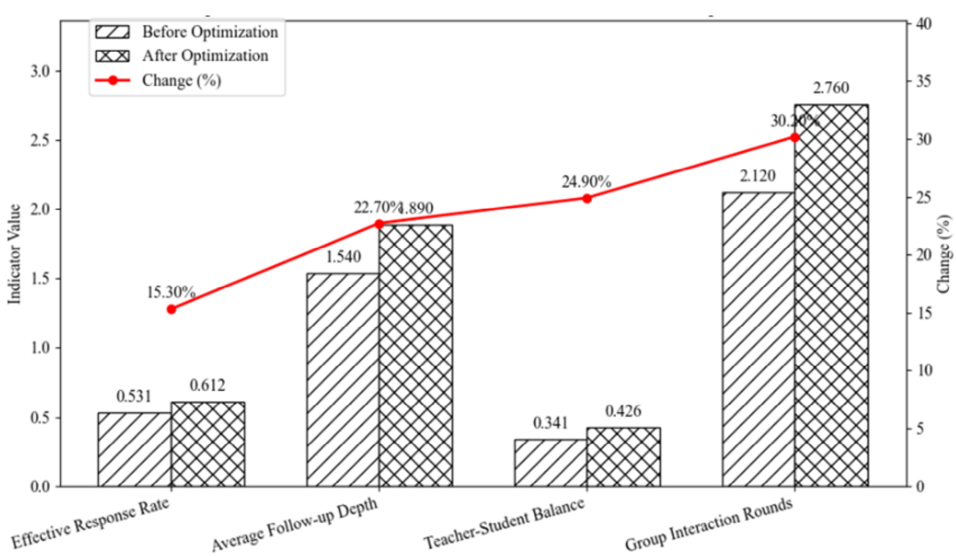
Looking at the ‘one-to-one ratio of teacher-student interaction’, the average value in the sample classrooms is 0.386. This means only 38.6% of the interaction is started by students, and teachers still lead most of the communication. In some courses that focus on discussion, the ratio can go over 0.50. This shows that how the lesson is planned and how the interaction is done can change how much students take part. The data also shows that students who speak up are mostly in the top 20% of the group. Around 35% of the students do not show any active behaviour during the class, which shows there is a clear gap in how much students take part.

As shown in Figure 3, it shows how often each type of interaction happens in the classroom. Teacher questioning and teacher explanation take up more than 60% of all interactive behaviours. Students’ active speaking only takes up 13.7%. Peer interactions like group discussions and questioning together are less than 20%. The data shows that the IoT has helped make interaction easier to notice and give feedback faster. But in real teaching, there still needs to be more open and active tasks so more students can speak up. This can help make the interaction structure better.

3.1.3 Verification of interactive optimisation effects empowered by the IoT

To test how well classroom interaction got better with the IoT, this study looked at 81 classrooms before and after using the new method. It used four indicators: effective response rate, average follow-up level, ratio of teacher-student interaction pairs, and number of group interaction rounds. Then, it compared the results. Before using the new way, teachers followed the usual teaching method. They had no help from data feedback. They mostly used their own judgement to guide interaction. After using the new way, teachers had access to reports from the IoT system. They could change how they asked questions, how groups were made, and how discussions were done based on the feedback after class.

Figure 4 Comparison of classroom interaction indicators before and after optimisation (see online version for colours)



As shown in Figure 4, the average values of each indicator before and after optimisation are shown. This proves that the optimisation method in this study can be used in real situations. All four indicators got better after optimisation. The effective response rate went up from 0.531 to 0.612, which is a 15.3% rise. The average follow-up level changed from 1.54 to 1.89, which shows that the interaction became deeper. The ratio of teacher-student interaction rose from 0.341 to 0.426, and students talked more on their own. The number of group interaction rounds grew from 2.12 to 2.76, which means students spoke more times in a row during group work. The data shows that with real-time data from the IoT and the use of feedback, teachers can better manage how fast and how they interact. This helps make the classroom more active and improves how students take part and interact.

3.2 Discussion

3.2.1 Problem summary

Based on the earlier research and results, this study shows that IoT technology helps with watching and giving feedback on classroom interaction. But some important problems still exist in university classrooms now. Teachers ask questions often, but not many students answer, and when they do, the talk does not go far or last long. Most of the time, classroom talk stays simple and does not go deeper. Teachers still talk the most, and students do not speak up much, so the talk between them is not balanced. Some students do not join in at all, so not everyone is involved. Group discussions do happen, but there are not many chances to speak, answers sound the same, and the reasons for the talk are not clear, which makes the group work not very useful. From the tech side, the IoT system gives a lot of data on how people act, but some teachers still go with what they feel and do not really use the data to change their teaching. They are not good at reading the reports and using them. So, a full system where data helps change teaching has not been built yet. These problems can be put into four points: talk is not deep enough, students are not active, not everyone joins in, and feedback is not used well. This shows that machines alone cannot make classroom talk better. Teachers need to read the feedback, change how they teach, and make their lessons better. When teachers and technology work well together, the talk in class will get better, and teaching will improve.

3.2.2 Research suggestions

Based on the research results and the problems found, some suggestions are given to make classroom interaction better with the help of IoT. First, teachers need to better understand and use interaction data. They should use the feedback reports from IoT systems and change their teaching in a way that fits their goals. Schools should give training to help teachers learn how to read data and notice patterns in how students act. When making lesson plans, teachers should use different kinds of tasks with clear levels to keep the interaction fresh and clear. They can try student-led parts or switch group roles to let more students take part and be active. Also, IoT systems should have alerts and tips during class. For example, if one interaction number stays low for some time, the system can tell the teacher to ask questions in a different way or change the speed of teaching. It is also a good idea to include interaction data in how student progress is checked, so students are more willing to take part. In the future, research should make the ways of checking interaction better by adding signs like feelings, word use, and how much students take part. These will make the system of judging interaction stronger and help build smart classrooms that give helpful feedback. In the end, using both data from machines and smart teacher choices can keep making classroom interaction better – from just seeing the problems to really fixing them.

4 Conclusions

This study explores the monitoring and optimisation of classroom interaction effects through IoT technologies. Based on real classroom data from a university, an optimised interaction index system was developed, focusing on four key indicators: effective response rate, average follow-up level, teacher-student interaction ratio and group interaction rounds. Leveraging IoT-based data collection and analysis, the study completed the full process of behaviour identification, coding, statistical analysis and evaluation. Empirical results demonstrate that the IoT-supported interaction monitoring system effectively captures diverse classroom behaviours, generates structured interaction profiles, and provides teachers with timely insights into participation levels and interaction dynamics. Prior to optimisation, the classroom exhibited issues such as teacher-dominated interactions, low student engagement, and shallow interaction depth. Following the intervention, all key indicators improved markedly: effective response rate rose by 15.3%, follow-up levels increased by 22.7%, teacher-student interaction ratio improved by 24.9%, and group interaction rounds increased by 30.2%. These findings confirm the practical feasibility of data-driven teaching optimisation strategies. IoT technology enables comprehensive sensing of classroom dynamics and offers data-based feedback, early warnings and visualised structure analysis. However, the success of interaction optimisation hinges not only on technological monitoring, but also on teachers' capacity to interpret data and enact responsive instructional adjustments. Moving forward, the integration of data, pedagogical strategies, and real-time classroom behaviours should be deepened to construct a dynamic, precise, and feedback-driven intelligent interactive teaching ecosystem.

This study holds broader significance in the context of educational digital transformation. As institutions worldwide strive to implement data-driven teaching models and smart learning environments, the proposed IoT-enabled framework offers a concrete, scalable pathway for monitoring and enhancing classroom interaction. It exemplifies how sensor data and behavioural analytics can support pedagogical goals, improve instructional responsiveness, and foster more inclusive learning participation. Positioned within this transformation, the findings contribute not only to interaction design but also to the strategic evolution of digitally empowered teaching ecosystems. Despite the promising findings, certain limitations should be acknowledged. The sample was limited to a single institution, which may affect the generalisability of results. In addition, the current evaluation framework focuses primarily on observable behavioural indicators, potentially overlooking cognitive or affective dimensions of engagement. Future research could expand the model to include cross-institutional datasets, real-time adaptive feedback mechanisms, or integrate AI-driven semantic analysis to capture deeper learning processes. The system benefits teachers in daily instruction by providing immediate, actionable insights into classroom interaction patterns. For example, post-class reports highlight gaps in student participation or missed follow-up opportunities, enabling targeted adjustments in questioning techniques or group facilitation. Over time, these micro-level feedback loops support more balanced, engaging, and adaptive teaching practices. By embedding such mechanisms in everyday teaching workflows, the system shifts data from passive observation to meaningful pedagogical improvement, reinforcing the role of IoT as a real-time instructional aid rather than just a monitoring tool.

This approach can also inform future applications in K-12 and vocational education, where structured interaction monitoring and data-informed feedback could help teachers manage diverse learning groups and adapt instruction more precisely. By demonstrating a scalable IoT-based model, this study provides a framework that educational institutions at different levels can adapt to foster more responsive, evidence-driven teaching ecosystems.

Declarations

Competing interests: All authors declare that they have no conflicts of interest.

Data availability statement: The data used to support the findings of this study are all in the manuscript.

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