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iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 20 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i20.44215

PAPER

Correlation Between Cognitive Levels of Teachers' Questions and Response Enthusiasm of Students

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ABSTRACT

Teachers' questions and students' responses are important interactive links in the educational process. In recent years, with the deepening of research on educational psychology, more and more studies have begun to pay attention to the influence of cognitive levels of teachers' questions on students' responses. However, although some studies have shown that the way teachers ask questions has a significant impact on the learning outcomes of students, there is no clear answer to the precise relationship between cognitive levels of teachers' questions and response enthusiasm of students. In addition, existing research methods often rely too much on descriptive statistics and lack a deep understanding and exploration of correlation. This study aimed to explore the correlation between cognitive levels of teachers' questions and response enthusiasm of students. A new method was first introduced to measure the response enthusiasm of students. Taking English teaching as an example, an evaluation model was constructed through factor analysis, and the evaluation results were analyzed through Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity. Then grey relational analysis was used to measure the correlation between cognitive levels of teachers' questions and response enthusiasm of students. The results revealed that cognitive levels had a significant impact on the response enthusiasm. The findings of this study not only provide teachers with an effective strategy to enhance the learning participation of students, but also bring new theoretical knowledge and practical experience to the field of educational psychology.

KEYWORDS

teachers' questions, cognitive levels, response enthusiasm of students, factor analysis, grey relational analysis

1 INTRODUCTION

In today's educational practice, teachers' questions and students' positive responses are considered to be important links in the learning process. In theory and practice, whether cognitive levels of teachers' questions affect the response

Yang, N. (2023). Correlation Between Cognitive Levels of Teachers' Questions and Response Enthusiasm of Students. *International Journal of Emerging Technologies in Learning (iJET)*, 18(20), pp. 219–233. https://doi.org/10.3991/ijet.v18i20.44215

Article submitted 2023-06-18. Revision uploaded 2023-08-14. Final acceptance 2023-08-21.

enthusiasm of students has always been a hot issue concerned in education [1–4]. Previous studies have revealed that the way teachers ask questions has a direct impact on the learning outcomes of students [5–7]. However, there is no clear answer to the exact relationship between cognitive levels of teachers' questions and response enthusiasm of students.

To have a deeper understanding of the interaction mechanism between teachers' questions and students' responses, this study aimed to explore the correlation between cognitive levels of teachers' questions and response enthusiasm of students [8–10], providing teachers with an effective strategy to enhance the participation and enthusiasm of students, thereby improving the teaching effect [11–14]. In addition, the research on this issue can improve the understanding of learning motivation, participation, cognitive development, and other fields.

Although a certain correlation between teachers' questions and students' responses has been recognized in previous studies, current research methods have some obvious limitations [15–19]. For example, most studies focus on the quantity of questions and responses, but do not consider the quality aspect, which cannot fully grasp their depth and complexity. In addition, current research methods often rely too much on descriptive statistics and lack a deep understanding and exploration of correlation.

This study constructed and validated a new research model to deepen the understanding of the correlation between cognitive levels of teachers' questions and response enthusiasm of students, thereby attempting to overcome these shortcomings. The main research content is divided into two parts. First, the measure of students' response enthusiasm, including description of measure variables, construction of an evaluation model based on factor analysis, and the analysis of evaluation results composed of Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity, with English teaching as an example. Second, the correlation measure of cognitive levels of teachers' questions and response enthusiasm of students based on grey relational analysis. The value of this study is that it not only provides educators with a more scientific and accurate tool to evaluate and enhance students' learning enthusiasm, but also adds new theoretical knowledge and practical experience to the field of educational psychology.

2 MEASURE OF STUDENTS' RESPONSE ENTHUSIASM

2.1 Description of variables

Taking English teaching as an example, this study constructed an evaluation index system of students' response enthusiasm consisting of five first-level indexes. The indexes were described in detail as follows:

i) Learning participation, a basic index to measure the response enthusiasm of students, mainly examining their interactive behaviors in class. The following four second-level indexes were set:
   - Active speaking, representing active participation of students in discussions in class, which was used to measure the frequency and quality of their speech.
   - Classroom interactions, representing students' interactions with teachers and other students, which was used to measure the quality and frequency of their interactions.

- Learning engagement, representing the concentration level of students in classroom activities, which was used to measure their concentration and participation.
- Practical actions, representing the degree to which students applied the knowledge learned in class to practical actions.

ii) Knowledge understanding, an important index to measure students' understanding of teaching content, mainly focusing on their mastery and understanding of classroom knowledge. The four second-level indexes were as follows:

- Mastery of key concepts, representing students' understanding and mastery of key concepts in English classes.
- Comprehensive understanding, representing students' understanding of the whole teaching content.
- Critical thinking, representing the critical thinking ability of students in the understanding process.
- Deep understanding, representing students' deep understanding and thinking of teaching content.

iii) Learning motivation, an important index to measure the learning motivation of students, focusing on their motivation and goals for learning. The four second-level indexes were as follows:

- Intrinsic motivation, representing the intrinsic driving force of students in learning English, such as their interest and curiosity in learning.
- Extrinsic motivation, representing the external driving force of students in learning English, such as the rewards they expected to obtain and the punishments to avoid.
- Goal orientation, representing the degree to which students set and pursued learning goals.
- Self-efficacy, representing students' confidence and sense of ability to complete learning tasks.

iv) Feedback application, an important index to measure how students applied feedback to learning adjustment. The four second-level indexes were as follows:

- Feedback acceptability, representing students' acceptance and attitudes towards the feedback of teachers or classmates.
- Feedback processing, representing the degree to which students understood and analyzed the feedback received.
- Feedback integration, representing how students integrated feedback into their own learning process.
- Feedback application, representing the actual actions and adjustments of students targeted at the feedback.

v) Self-directed learning, an important index to measure the self-driven, self-adjusted and self-guided learning of students. The four second-level indexes were as follows:

- Self-regulation, representing students' ability to control and adjust their learning process.
- Self-evaluation, representing students' ability to evaluate and reflect on their own learning outcomes.
- Self-guidance, representing students' ability to dominate and guide their own learning process.
- Self-learning strategies, representing the strategies and methods applied by students in the process of self-directed learning.

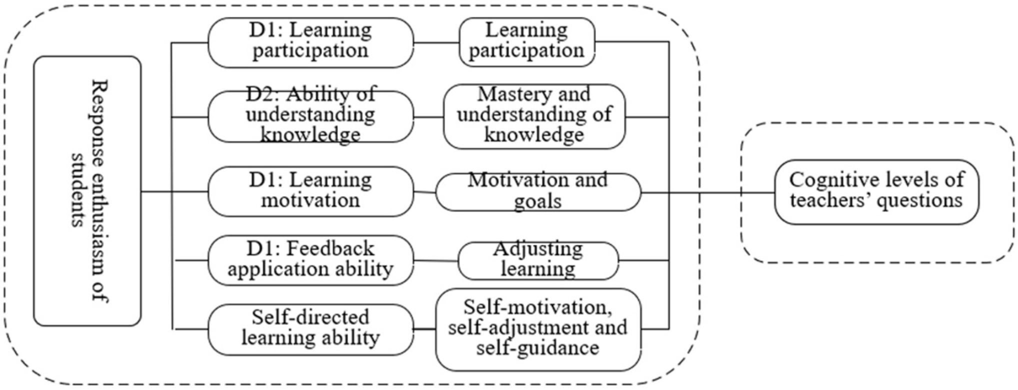

Fig. 1. Correlation mechanism between cognitive levels of teachers' questions and response enthusiasm of students

2.2 Construction of an evaluation model

Factor analysis is a statistical method, which mainly aims to explain most of the variance of the observed variables using a small number of implicit factors. In factor analysis, each observed variable is considered to be represented by a weighted linear sum of one or more common factors and one specific factor. The common factor describes the potential influence factors shared by all observed variables, while the specific factor describes the individual differences in observed variables.

In the evaluation study of students' response enthusiasm, each observed variable corresponded to the above evaluation index. First, after determining the common factors through factor analysis, the factor loading of each observed variable in each common factor was calculated. Then a specific factor and error term were added to obtain the model representation of each observed variable, which helped reduce the number of variables to be considered while revealing the relationship between the observed variables. Figure 1 shows the correlation mechanism between cognitive levels of teachers' questions and response enthusiasm evaluation indexes of students.

Let z_u be the original variable (observed variable), u be the serial number of each evaluation index, X_u be the standardized variable of the original variable, D_1, D_2, D_3,... D_l be the common factors, k be the serial number of the factor, with $k = 1, 2,..., l(l \leq o)$, γ_u be the specific factor, coefficient s_u be the specific factor loading, s_{uk} be the coefficient of the u-th variable in the k-th common factor, and $S = [s_{uk}]$ be the factor loading matrix. The expression of the model was given as follows:

$$X_u = s_{u1}D_1 + s_{u2}D_2 + s_{u3}D_3 + \ldots\ldots + s_{ul}D_l + s_u\gamma_u \tag{1}$$

$$u = 1,2,\ldots,o \tag{2}$$

2.3 Analysis of evaluation results

i) KMO test and Bartlett's Test of Sphericity

For the evaluation of students' response enthusiasm, several indexes should be examined, such as students' understanding of class content, participation, and their interactions with teachers, which may influence each other. Therefore, KMO test and Bartlett's Test of Sphericity should be used to confirm that the dataset of this study was suitable for factor analysis.

In this study, the KMO value was used to measure whether there was sufficient correlation between the indexes, thereby grouping them into a common factor. Therefore, the skewness between each pair of indexes should be calculated, and then compared with the measure with each index. If the KMO value was greater than 0.7, it was considered that sufficient correlation existed between the indexes, and factor analysis was feasible. If the KMO value was too low, it may mean that the indexes needed to be re-examined, and some indexes may not have strong correlation with other ones, or more indexes needed to be added.

After passing the KMO test, Bartlett's Test of Sphericity was required to confirm that the correlation matrix was not an identity matrix. In this study, the identity matrix meant that all indexes had no correlation, which was not expected, because this study aimed to find out the common factors that affected the response enthusiasm of students. If the *p* value was less than 0.05, it meant that the null hypothesis was rejected, and the correlation matrix was not the identity matrix. Therefore, the collected index dataset was suitable for factor analysis.

After completing the two tests, factors were extracted to determine the common factors that affected students' response enthusiasm. Then factor rotation and score estimation were carried out, which obtained the comprehensive evaluation value of students' response enthusiasm.

ii) Extracting common factors and determining their number

After determining that factor analysis was suitable, the next important step was to extract common factors and determine their number, which aimed to extract some basic, common and underlying structures from the multiple observed variables. Those structures were factors, which explained the correlation or variance of the main part of original data.

In this study, principal component analysis (PCA) was used to extract common factors, which reduced a large variable set into a few key and independent factors. These factors were linear combinations based on original variables, which helped understand the relationship between original variables and reduced the data complexity.

Many ways are used to determine the number of common factors, and a common method is based on the eigenvalue size, which is also known as the "criterion for eigenvalue greater than 1" or the "Kaiser criterion". According to this criterion, only those factors whose eigenvalues are greater than 1 are retained. In this study, the eigenvalue was used to explain the factor's contribution to the variance of original data. The larger the eigenvalue, the more information the factor had, providing an approximate number of factors, which was further fine-tuned based on expertise or parallel analysis.

The following gave the calculation formula of the sum of the squares of each row of elements in the factor loading matrix, that is, the common factor variance:

$$g_{2u} = s_{u1}^2 + s_{u2}^2 + \cdots\cdots + s_{ul}^2 \tag{3}$$

In the evaluation of students' response enthusiasm, this step was to extract several major factors, which represented their response enthusiasm, from all the first- and second-level indexes, such as students' participation in class, understanding ability, feedback quality, etc. Then the number of these factors was determined to facilitate the solution of the factor model, rotate the initial factor loading matrix, and estimate the factor scores, thereby finally obtaining the comprehensive evaluation value.

iii) Solving the factor model

After extracting the common factors and determining their number, the next step was to solve the factor model. At this stage, this study used the common factors, which had been extracted, to represent each variable.

Solving the factor model involved two important matrices: factor loading matrix and specific factor variance matrix. The former described the relationship between each original variable and each factor. Each original variable was considered as the linear combination of one or more shared factors and specific factors. Each element of the factor loading matrix represented the correlation coefficient between the corresponding original variable and the factor.

The factor model was solved using the following formula:

$$\begin{pmatrix} X_1 \\ X_2 \\ \cdots \\ X_o \end{pmatrix} = S \times \begin{pmatrix} D_1 \\ D_2 \\ \cdots \\ D_o \end{pmatrix} \tag{4}$$

The following formula was solved to normalize the eigenvector I_{uk}:

$$Y_{uk} = \frac{1}{|I_{uk}|} * I_{uk} \tag{5}$$

The solution of the above formula was multiplied by $(\eta_u)^{1/2}$, which obtained the initial factor loading matrix *S*, i.e.

$$S_{uk} = Y_{uk} * \sqrt{\eta_u} \tag{6}$$

For the evaluation of students' response enthusiasm, the process of solving the factor model was to map all the first- and second-level indexes to the extracted shared factors, and then evaluate the correlation degree between each index and these shared factors. The extent to which each index was influenced by its own special nature (i.e. specific factor) should also be evaluated, thereby clearly seeing which factors were the most important ones affecting students' response enthusiasm, and how much influence each factor had.

iv) Rotating the initial factor loading matrix

In factor analysis, the initial factor loading matrix solved may lead to a certain degree of correlation between each factor and most variables, which made the specific meaning of these factors difficult to explain. Therefore, this study performed factor rotation in order to better explain and understand each factor.

Factor rotation is to change the factor loading matrix while keeping the original total variance of data unchanged, which makes the loading of each factor in most variables close to 0, and the loading in a few variables as large as possible, thereby obtaining a clearer and more understandable explanation of each factor. Factor rotation can be divided into orthogonal and oblique rotations. The factors are independent of each other after orthogonal rotation, while the factors may be correlated after oblique rotation.

In the evaluation of students' response enthusiasm in this study, a factor "classroom activity level" may exist, which may have higher factor loading with the first-level indexes, such as "students' participation" and "response enthusiasm", and lower factor loading with other first-level indexes. However, the "classroom activity level" may have a certain correlation degree with all the first-level indexes in the original factor loading matrix, which made the specific meaning of "classroom activity level" difficult to understand. Factor rotation processing made the loading of "classroom activity level" as large as possible in variables, such as "students' participation" and "response enthusiasm", while the loading in other variables close to 0, thereby more accurately understanding the meaning of "classroom activity level" and better explaining its impact on students' response enthusiasm.

v) Estimating factor scores

After factor analysis was completed, the factor loading matrix was obtained, which was the loading of each variable in each factor. However, the scores of each student evaluated in each factor should also be estimated, and this process was to estimate the factor scores. There are many common methods to estimate the factor scores, including Thompson factor score method and least square estimation.

Thompson factor score method is a standardized process that takes into account the loading of each individual being studied in each factor and the variance of each factor. The advantage of this method is that it ensures the independence of factor scores, but it may lose some information. Thompson assumed that the factors were used for regression of *o* evaluation indexes, then there were:

$$D_k = n_{k0} + n_{k1}z_1 + n_{k2}z_2 + \cdots\cdots + n_{ko}z_o \tag{7}$$

The least square estimation solves factor scores by minimizing the sum of squares of their prediction error. The advantage of this method is that there is less information loss, but it may lead to some correlation between factor scores. Let E be the correlation coefficient matrix of original variables, and S' be the transposition of the factor loading matrix S after factor orthogonal rotation. In this study, the factor score coefficient matrix was obtained based on least square estimation as follows:

$$N = S'E^{-1} \tag{8}$$

Let matrix N be the factor score coefficient, and matrix X be the standardized original observed variables, then the factor score estimation formula was given as follows:

$$D_k = N * X \tag{9}$$

In the evaluation of students' response enthusiasm, the scores of each student being studied in each factor should be estimated. For example, the scores of each student in the "classroom activity level" factor may need to be estimated, which may be based on the performance of their first-level indexes, such as "students' participation", "response enthusiasm", etc. By estimating factor scores, the performance of each student in each factor was known, which better understood their response enthusiasm, thereby providing a basis for subsequent teaching strategies.

vi) Solving the comprehensive evaluation F value

The last step of factor analysis was to solve the comprehensive evaluation value, which obtained the final evaluation results through factor scores. This step was mainly achieved through the appropriate weighted sum of all factor scores, by generally selecting the variance contribution rate of each factor (i.e. the eigenvalue/total eigenvalue) as the weighting coefficient. The weight of each factor should be determined first, by usually selecting the weight as the variance contribution rate of the factor. After multiplying the scores of each student in each factor by the corresponding weight, they were summed up to obtain the comprehensive evaluation value of each student, i.e.

$$D = \gamma_1 D_1 + \gamma_1 D_2 + \cdots \gamma_N D_N \tag{10}$$

3 CORRELATION MEASURE OF COGNITIVE LEVELS OF TEACHERS' QUESTIONS AND RESPONSE ENTHUSIASM OF STUDENTS

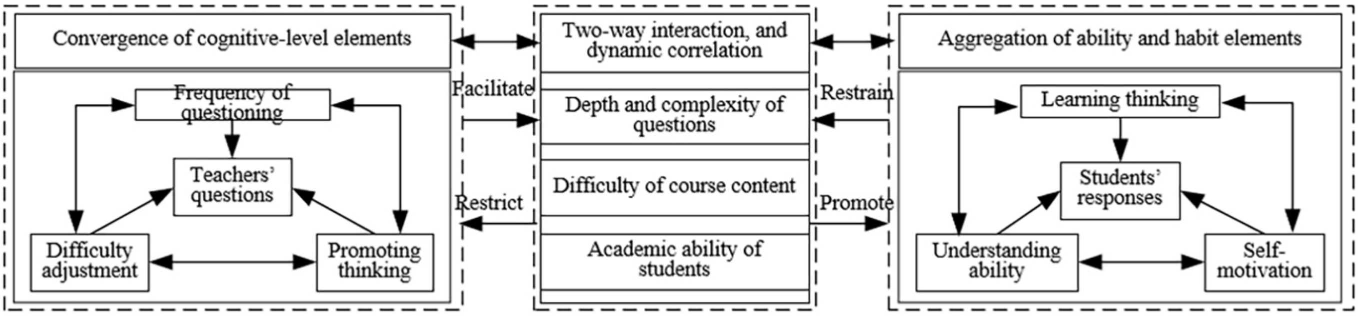

Fig. 2. Interaction between cognitive levels of teachers' questions and response enthusiasm of students

Figure 2 shows the interaction between cognitive levels of teachers' questions and response enthusiasm of students. The correlation factors included three aspects, namely, depth and complexity of questions, difficulty of courses, and academic ability of students. Deeper questions may require students to engage in more complex thinking, which may increase their participation and motivation, but may also confuse or upset them. The complexity of questions may affect students' enthusiasm in answering them. Too complex questions may result in students being unwilling or unable to answer, while the questions with appropriate complexity can increase their participation. Similar to the complexity of questions, the difficulty of course content may affect the response enthusiasm of students. The academic ability of students also affects their responses to questions. Some students may be more active when facing complex problems, while others may be confused or frustrated by them.

This study measured the correlation based on grey relational analysis. The first step was to determine the comparison and reference sequences. In this study, the reference sequence was the evaluation result of students' response enthusiasm, which was derived from the steps of factor analysis in the previous section. The comparison sequence was the cognitive levels of teachers' questions, which may come from different indexes, such as complexity and depth of teachers' questions.

Let $Z_u(j)$ be the comparison sequence, and $Z_0(j)$ be the reference sequence, then the reference sequence was represented as:

$$z_0 = \{z_0(j) \big| j = 1, 2, \ldots\ldots, 16\} \tag{11}$$

After taking five common factors and one comprehensive factor representing students' response enthusiasm as six evaluation items (*D1*, *D2*, *D3*, *D4*, *D5*, and *D*), the correlation (correlation degree) between them and cognitive levels of teachers' questions was studied.

To avoid the impact of index quantization methods, quantization units and data differences by orders of magnitude on the evaluation results, the following standardization processing should be conducted:

$$Z_u(j) = \frac{z_u(j) - MINz_u(j)}{MAXz_u(j) - MINz_u(j)} \tag{12}$$

Then grey relational analysis should be made for the comparison and reference sequences to calculate their correlation coefficient, which aimed to see whether cognitive levels of teachers' questions and response enthusiasm of students were close to each other in the development and change trend. If they were close, it indicated that some correlation may exist between them. Let $\zeta_u(j)$ be the correlation coefficient between the j-th index of the u-th object and the j-th index in the reference sequence, and o be the distinguishing coefficient. The grey relational coefficient value $\zeta_u(j)$ was calculated using the following formula:

$$\zeta_u(j) = \frac{MIN(u)MIN(j)\left|Z_0(j) - Z_u(j)\right| + \vartheta MAX(u)MAX(j)\left|Z_0(j) - Z_u(j)\right|}{\left|Z_0(j) - Z_u(j)\right| + \vartheta MAX(u)MAX(j)\left|Z_0(j) - Z_u(j)\right|} \tag{13}$$

Finally, the correlation degree should be calculated, and the cognitive levels of questions of all teachers should be sorted. The correlation degree is a comprehensive evaluation of the grey relational coefficient, which reflects the overall similarity between response enthusiasm of students and cognitive levels of teachers' questions. By sorting the correlation degree, which types of cognitive levels have the greatest impact on students' response enthusiasm can be found out, thereby providing teachers with strategies and suggestions to improve the response enthusiasm of students. The calculation formula of correlation degree was given as follows:

$$e_u = \frac{1}{b}\sum_{u=1}^{b} \xi_u(j) \tag{14}$$

The greater the correlation degree value e_u, the more consistent the change trend of $Z_u(j)$ and $Z_0(j)$, and the greater the correlation between cognitive levels and response enthusiasm.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. Common factor score ranking of students' response enthusiasm evaluation indexes in different courses

Course Number	*D1*	*D2*	*D3*	*D4*	*D5*	Scores	Ranking
Course 1	0.96158	0.26354	1.01258	0.84851	–0.34169	0.72	1
Course 2	–0.0145	2.17234	–0.8124	1.64423	–0.3146	0.68	2
Course 3	1.65248	0.3618	–0.835	–0.1462	0.53367	0.67	3
Course 4	0.82654	–0.3648	1.76324	0.93265	–0.84101	0.52	4
Course 5	1.67521	–0.3027	–0.7618	0.43262	–1.11232	0.42	5
Course 6	–0.1752	0.57168	0.76852	0.08541	–0.35526	0.31	6
Course 7	0.92518	–0.8512	0.22518	0.56225	0.75474	0.12	7
Course 8	0.44582	–1.1024	0.68192	–0.8563	0.2125	–0.06	8
Course 9	0.0925	–0.3281	–1.421	–1.11124	0.62162	–0.36	9
Course 10	–0.462	–0.4219	–0.2305	–0.31241	–1.459	–0.42	10
Course 11	–0.7152	0.07125	–1.4326	–0.4546	–0.24124	–0.54	11
Course 12	–1.2547	–0.4251	0.83264	0.0722	–1.4127	–0.56	12
Course 13	–1.3217	–0.1726	–0.6524	–0.4754	0.8546	–0.76	13
Course 14	–1.2384	–0.9852	0.63258	–0.0194	2.1621	–0.98	14
Course 15	–0.7326	–0.8619	–0.7516	1.61241	0.3143	–0.81	15

According to Table 1, the common factor scores of students' response enthusiasm evaluation indexes in different courses can be compared and analyzed. In the table, *D1* to *D5* represent five common factors, namely, learning participation (*D1*), knowledge understanding (*D2*), learning motivation (*D3*), feedback application (*D4*), and self-directed learning (*D5*), which measure the performance of students in these aspects.

It can be seen from the table that Course 1 has the highest comprehensive scores (0.72), ranking first, mainly because it has high scores in *D1* (learning participation), *D3* (learning motivation) and *D4* (feedback application), indicating that students have high-level learning participation in the course and a deep understanding of course content, and are able to apply feedback to the learning process. However, the scores of Course 1 in *D5* (self-directed learning) are negative, indicating that the course does not sufficiently encourage students to learn in a self-directed way. Course 14 has the lowest comprehensive scores (–0.98), ranking last, mainly because the course has low scores in *D1* (learning participation), *D2* (knowledge understanding) and *D3* (learning motivation), indicating that students have low participation in the course and insufficient learning motivation, and their understanding of course content is not deep. However, Course 14 has the highest scores in *D5* (self-directed learning), because the course design forces students to rely on self-study to improve their understanding and mastery.

Table 2. Descriptive statistics of teachers' questions at different cognitive levels

Cognitive Levels	*N*	Minimum	Maximum	Mean	Standard Deviation
Understanding level	15	1782	5218	3715.25	1215.28
Application level	15	945	6126	4075.26	1652.24
Analysis, evaluation and innovation level	15	86	485	271.36	132.25
Memory level	15	54	374	167.16	91.25

Based on Bloom's classification method of cognitive objectives, this study divided the cognitive levels of teachers' questions into the following four levels:

1. Memory level: Questions at this level mainly focused on students' memory and understanding of knowledge, which were usually direct and specific, and required them to recall information they had learned. For example, "Tell me what is the first law of thermodynamics?"
2. Understanding level: Questions at this level focused more on students' understanding of knowledge, which required them to explain, generalize, or interpret information. For example, "Can you explain the meaning of the first law of thermodynamics?"
3. Application level: Questions at this level required students to apply what they had learned to new situations. For example, "Please use the first law of thermodynamics to explain why the car engine is hot."
4. Analysis, evaluation and innovation level: Questions at this level required students to think deeply, such as analyzing, evaluating or creating new theories and ideas.

Table 2 shows the descriptive statistics of teachers' questions at different cognitive levels. In terms of mean values, the application level has the highest mean value

(4075.26), indicating that teachers ask application-level questions with the highest frequency in the statistical samples, because questions at this level help students better understand and master knowledge and apply what they have learned to practical problems. The mean value of the understanding level is 3715.25, which is also relatively high, because questions at this level help students understand and digest knowledge more deeply, which is also a common way for teachers to ask questions in the teaching process. The mean value of the analysis, evaluation and innovation level is 271.36, which is significantly lower than that of the understanding and application levels, because questions at this level are more difficult and require students to have high thinking and innovation ability. Therefore, teachers rarely raise questions at this level in the actual teaching process. The memory level has the lowest mean value of 167.16, because questions at this level mainly depend on students' memory, and are not helpful to their deep learning and understanding, leading to their less use by teachers in actual teaching.

In terms of standard deviation, the application level has the largest standard deviation, indicating that the frequency of asking questions at this level has the largest difference in different samples. The memory level has the smallest standard deviation, indicating that the frequency of asking questions at this level has the smallest difference.

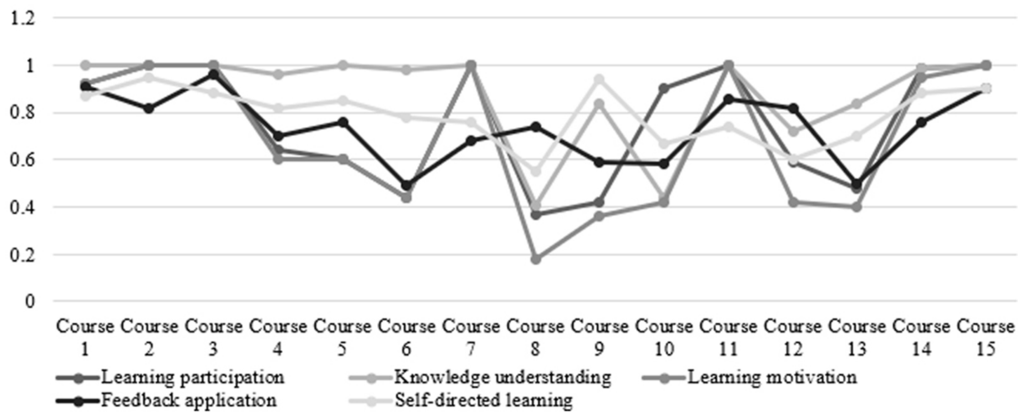

Fig. 3. Measure value of students' response enthusiasm

Figure 3 lists the measured values of five first-level indexes, namely, learning participation, knowledge understanding, learning motivation, feedback application, self-directed learning, in 15 courses. The index value of each course is between 0 and 1. The closer the value is to 1, the better the performance of the course in this index. In terms of learning participation, the scores of Courses 2, 3, 7, 10, 11 and 15 all reach 1, indicating that students have very high participation in the learning process of these courses. Course 8 has low participation with scores of 0.37. In terms of knowledge understanding, the scores of Courses 1, 2, 3, 5, 7, 11 and 15 are all 1, indicating that students perform very well in understanding the knowledge of these courses. Course 10 has the lowest scores of 0.44. In terms of learning motivation, Courses 2, 3, 7, 14 and 15 have the highest learning motivation scores of 1. In contrast, Course 8 has the lowest scores of 0.18. In terms of the feedback application index, Course 3 has the highest scores of 0.96, indicating that students have the best performance in applying feedback to this course. Course 9 has the lowest scores of 0.59. In terms of self-directed learning, Courses 2 and 15 have the highest scores of 0.95, and Course 8 has the lowest scores of 0.55.

Overall, Courses 2, 3, 7, 11 and 15 have high scores in all first-level indexes, indicating that the teaching style and content of these courses motivate students to learn. However, the scores of Courses 8 and 10 are relatively low in multiple first-level indexes, indicating that these courses need to be optimized and improved in the aspects of course design and teaching methods.

Table 3. Correlation coefficient between cognitive levels of teachers' questions and response enthusiasm of students

Course Number	*D1*	*D2*	*D3*	*D4*	*D5*	Ranking of *D* Relational Values
Course 2	0.56	0.498	0.402	0.458	0.413	1
Course 11	0.412	0.574	0.321	0.448	0.355	15
Course 15	0.521	0.486	0.512	0.512	0.547	12
Course 13	0.395	0.612	0.48	0.487	0.425	13
Course 6	0.68	0.885	0.787	0.621	0.775	8
Course 1	0.985	0.64	0.98	0.825	0.912	4
Course 4	0.832	0.562	0.521	0.564	0.557	11
Course 9	0.345	0.626	0.398	0.927	0.338	2
Course 12	0.427	0.582	0.765	0.862	0.716	3
Course 14	0.475	0.524	0.721	0.561	0.742	10
Course 3	0.662	0.635	0.398	0.84	0.317	5
Course 7	0.965	0.425	0.631	0.568	0.619	9
Course 8	1	0.418	0.824	0.745	0.832	6
Course 10	0.461	0.485	0.481	0.45	0.471	14
Course 5	0.632	0.49	0.425	0.695	0.406	7

Table 3 lists the grey relational values of 15 courses in five common factors (i.e. *D1*, *D2*, *D3*, *D4*, and *D5*) and the grey relational value ranking of each course. The grey relational value reflects the correlation between cognitive levels of teachers' questions and response enthusiasm of students. The larger the value, the stronger the correlation. The correlation of Course 2 ranks first in all courses, which indicates that the course has the highest matching degree between the questioning strategies of teachers and the response enthusiasm of students. The correlation coefficients of Courses 9 and 12 rank second and third, respectively, indicating that the questioning strategies of teachers are also very successful in these two courses, which effectively stimulate the response enthusiasm of students. The grey relational coefficients of Courses 11, 13 and 10 rank 5th, 13th and 14th, respectively, indicating that the correlation between cognitive levels of teachers' questions and response enthusiasm of students is relatively weak in these courses. Therefore, the questioning strategies of teachers need to be further optimized to improve the response enthusiasm of students.

5 CONCLUSION

This study aimed to measure the correlation between cognitive levels of teachers' questions and response enthusiasm of students. First of all, this study set the comparison and reference sequences in accordance with the response enthusiasm of students (i.e. learning participation, knowledge understanding, learning motivation, feedback application and self-directed learning) and the cognitive levels of teachers' questions (i.e. memory level, understanding level, application level, as well as analysis, evaluation and innovation level). Then the correlation degree between these two variables was quantified by calculating the grey relational coefficient value. Finally, all evaluation objects were sorted according to the correlation degree.

The following key conclusions have been found through the analysis of experimental results:

1. Cognitive levels of teachers' questions have a significant impact on the learning participation, knowledge understanding and learning motivation of students, indicating that the questioning strategies of teachers greatly affect the learning attitudes and behaviors of students.
2. Learning participation has the highest correlation in all evaluation items, which further emphasizes that cognitive levels of teachers' questions are important to the learning participation of students.
3. Although the correlation between feedback application and self-directed learning is relatively low, this does not mean that these two factors are not important. On the contrary, they play an important role in the learning process of students, and have a certain correlation with the questioning strategies of teachers.

In summary, this study has confirmed the significant correlation between cognitive levels of teachers' questions and response enthusiasm of students, which provides teachers with a new perspective to think about and improve their teaching strategies, thereby improving the learning motivation and effect of students. At the same time, this provides a new analytical and measurement tool for future research to explore various factors in the educational process more deeply.

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