The Mechanism of Teacher Influence on the Learning Engagement of Students

https://doi.org/10.3991/ijet.v17i21.35109

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Abstract—As a non-teaching factor, the influence of teachers can often trigger positive teaching effects and exert impacts on students’ learning engagement. However, few of the existing studies on the online learning engagement of college students have viewed this topic from a quantitative perspective, and few have concerned about the influence mechanism of Teacher Influence (TI). To fill in this research blank, this paper studied the influence mechanism of TI on the learning engagement of students. At first, this paper analyzed the theories related to the said influence mechanism and proposed a TI model for the online teaching environment. Then, after investigating students’ understandings, participation, and questions with the online teaching activities created by teachers, the TI model was built in the paper. In view of the complexity of this TI model, this paper fully considered the meaning of the interactions of teacher and student nodes during the actual online teaching activities, proposed a two-stage TI maximization algorithm based on the learning input responses of the nodes, and realized comprehensive quantification of TI. The effectiveness of the proposed algorithm was verified by experimental results.

Keywords—teacher influence (TI), learning engagement of students, influence mechanism, influence maximization

1 Introduction

Influence is a kind of ability to effectively affect and change the thinking and behavior of other people in a way that they are willing to accept [1–8]. In terms of teacher influence (TI), it refers to the ability of a teacher to demonstrate the correct action orientations for students via their speeches, behaviors, spirits, and sentiments, so as to promote students to achieve their expected learning goals. As a non-teaching factor, usually, TI can trigger positive teaching effects [9–13].

In recent years, the online teaching developed based on Internet technologies and supported by various group learning platforms has been widely applied due to its many merits such as timely feedback, rich resources, and free of geographical restrictions [14–19]. Unobstructed communication between teachers and students in online class can make students feel the teachers’ positive sentiments as they devote themselves in teaching, then a harmonious teaching-student relationship could be formed and it’ll become a pleasant thing for teachers and students to carry out their teaching and learning activities together. The teachers' optimistic mood can affect students and add new vitality to their online learning, in the meantime, students' engagement in learning will be enhanced as well [20–25]. Therefore, it is of practical significance to study the influence mechanism of TI on the learning engagement of students in the online teaching environment.

Liu et al. [26] discussed the relationship between university teacher leadership, teacher-student interaction, and student learning satisfaction, and their research results revealed that the university teacher leadership can significantly and positively affect teacher-student interaction and student learning satisfaction, the teacher-student interaction can significantly and positively affect student learning satisfaction, and the teacher-student interaction acts a mediator between university teacher leadership and student learning satisfaction. Liu et al. [27] introduced the relational embedding theory and adopted descriptive statistics, factor analysis, and correlation analysis to investigate the influence of teacher-student interaction on online learning engagement, and their research results showed that teacher-student interaction can significantly and positively affect learning engagement, and it has a greater impact on behavioral engagement regardless of the interaction patterns; their paper also tells us that the influence of synchronous interaction on engagement is even greater than that of asynchronous interaction, especially on emotional engagement. Hegarty and Thompson [28] adopted a framework based on established factors of student engagement to determine the influence of teachers, their work extended the research of student engagement and paid attention to the importance of teachers in supporting vocational learning in the 21st Century and using mobile technologies to assess ePortfolio. Harisman et al. [29] proposed that teachers' professionalism during learning and problem-solving process can greatly affect students' behaviors in problem-solving, they took three teachers and 18 students as subjects and conducted a survey to figure out the relationship between the teachers' professionalism in solving math problems and the students' behaviors in solving math problems, the study also qualitatively analyzed how each type of teachers and each type of students interact and affect each other. To overcome the low input and poor evaluation effect of distance learning, Zhang and Yang [30] proposed an evaluation method of distance learning input which built a learning behavior input model for the hybrid learning mode of college English course, the paper formulated evaluation standards of learning engagement as comparative references, collected students' learning information during distance English learning, and determined the specific evaluation indexes of learning input.

After carefully reviewing relevant literatures on the online learning engagement of college students, it's found that these studies generally adopt literature research and questionnaire survey methods to qualitatively summarize the influencing factors of online learning engagement based on the theory of learning engagement, and then give some opinions on the improvement of college students' online learning engagement. Few of them have explored this topic quantitatively or discussed the influence mechanism of TI. Therefore, to fill in this research blank, this paper studied the influence mechanism of TI on the learning engagement of students. The second chapter analyzed the theories about this influence mechanism and proposed the TI model in the online teaching environment. The third chapter investigated students' understandings, participation, and questions with the online teaching activities created by teachers, and constructed the TI model. In view of the complexity of this TI model, the fourth chapter fully considered the meaning of the interactions of teacher and student nodes during the actual online teaching activities, proposed a two-stage TI maximization algorithm based on the learning input responses of the nodes, and comprehensive quantified the TI. At last, the effectiveness of the proposed algorithm was verified by experimental results.

2 Theories about the influence mechanism

In an online teaching environment, TI can affect students' learning engagement from the following aspects:

(1) TI can affect the online learning effect of students. Teachers' positive sentiments as they devote themselves in teaching can make students keep an enjoyable learning mood, promote the interactions between teachers and students and among students during the online learning process. In such a learning environment, students' learning engagement will be higher, which can further promote the online learning effect.
(2) TI can affect the formation of a healthy life outlook and correct values in students. In the aspects of interpersonal relationship, work attitude, and teaching style, TI can affect students' life outlook and values intentionally and unintentionally, and students with a positive attitude towards life generally have a higher degree of engagement in learning.
(3) TI can affect the formation of interpersonal relationships between students. A harmonious teacher-student relationship can not only help teachers build their reputations, but also increase students' interest and enthusiasm for participating in online teaching activities, and students with a harmonious teacher-student relationship generally have a higher degree of engagement in learning.
(4) TI can affect the establishment of optimism in students. Since emotions are highly contagious, teachers' optimistic mood can affect students and add new vitality to their online learning, then the learning resilience and efficiency of the students could be improved, and students with an optimistic attitude generally have a higher degree of engagement in learning.

If a teacher can be the decision maker in achieving the classroom teaching goals, can build a ladder for students to increase their knowledge and enhance their skills, and can accurately control students' learning process with the help of the learning input responses of teaching evaluation, then this teacher can be considered to exert an impact on students' learning engagement via TI. In order to quantitatively analyzed the influence mechanism of TI on students' learning engagement, this paper built a TI model for online teaching environment, and the structure of the model is shown in Figure 1.

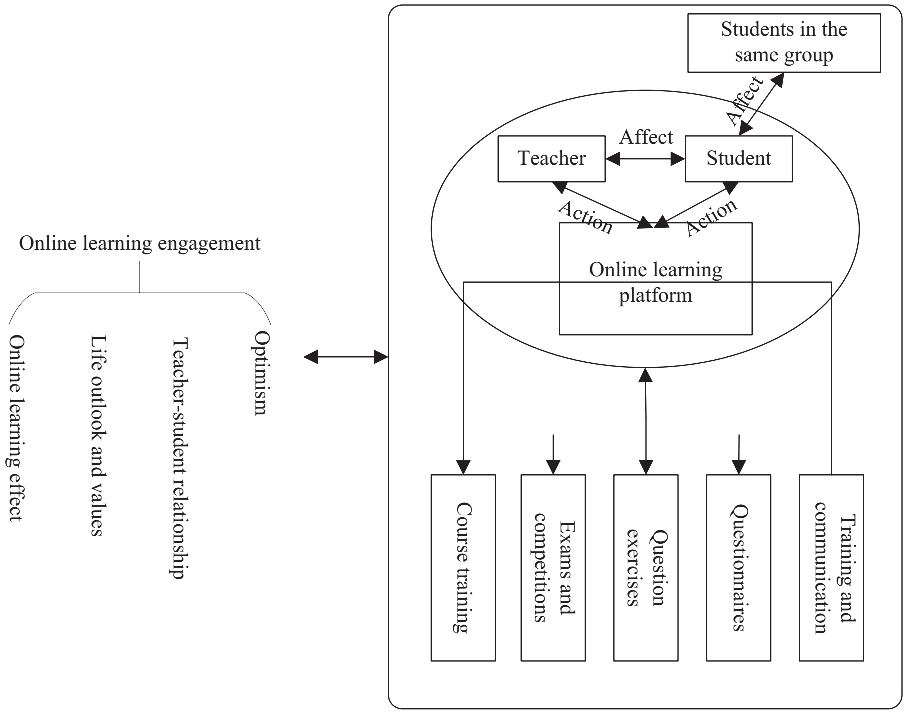

Fig. 1. Structure the model for the influence mechanism of TI on students' learning engagement

3 About the TI model

Assuming: the TI model has m nodes; the nodes represent two types of objects: teachers and students. For the learning input response of each student, in this paper, an m-order matrix can be used to represent the learning input response results of student nodes. Set p = 1 correspond to "understand", p = 2 correspond to "participate", and p = 3 correspond to "raise questions"; for the p-th student, the learning input response of node u_i to node u_j is represented by the element a^p_{ij} in the matrix; if $u_j \in \phi_{ui}$, then let $a^p_{ij} = x^p_{ij}$; if $u_j \notin \phi_{ui}$, then let $a^p_{ij} = 0$. In this way, this paper could attain 3 m-order matrices.

When calculating the learning input responses between nodes, this paper considered students' behaviors (understand, participate, and raise questions) in response to the online teaching activities created by teachers. Assuming μ_p represents the weight coefficients of the three learning input responses, then, these three learning input responses were weighted to attain the amount of effective information transmission between nodes u_i and u_j which can measure the size of TI:

$$q_{ij} = \mu_1 a^1_{ij} + \mu_2 a^2_{ij} + \mu_3 a^3_{ij}, 0 \le \mu_p \le 1, \sum_{p=1}^{3} \mu_p = 1 \tag{1}$$

In this paper, the weight values attained by the entropy weight method can truthfully reflect the relative importance of each student's learning input responses. The specific steps are:

At first, for each node u_i, the amount of its learning input responses of online teaching activities was summed and denoted as $A_i^p = \sum_{ij=1} |\phi| a_{ij}^p$, then A_{ij}^p was normalized so that the value range of the summation result was [0,1].

Assuming: when the value of p takes 1, 2, and 3, for different nodes u_i, $\min_i\{A_i^p\}$ and $\max_i\{A_i^p\}$ represent the minimum and maximum values of the sum of the learning input responses of online teaching activities, since the three learning input responses (understand, participate, and raise questions) all describe the influence degree of TI on students' learning engagement, and the more the better, so B_i^p can be expressed as:

$$B_i^p = \frac{A_i^p - \min_i\{A_i^p\}}{\max_i\{A_i^p\} - \min_i\{A_i^p\}}, i \in \{1, 2, \ldots, m\} \tag{2}$$

The following formula calculates the proportion of learning input responses of the i-th node under the learning input responses of the p-th student:

$$w_i^p = B_i^p / \sum_{i=1}^{m} B_i^p \tag{3}$$

At this time, if $w_i^p = 0$, then $\lim_{wpi \to 0} w_i^p \, lnw_i^p = 0$. The following formula calculates the entropy of the learning input responses of the p-th student:

$$O_p = -1 / ln(m) \cdot \sum_{i=1}^{m} w_i^p \cdot lnw_i^p \tag{4}$$

Then, based on the following formula, the weights of the learning input responses of each student were determined:

$$\mu_p = (1 - O_p) / \sum_{p=1}^{3} (1 - O_p) \tag{5}$$

The model constructed in this paper realized the meaning of the interactions of teacher and student nodes during actual online teaching activities. After comprehensively considering the number of student nodes in online class and the interaction amount of student nodes when participating in online teaching activities, this paper set edge weight of the TI model, that is, an influence probability model can be constructed as follows:

$$GO(u_j, u_i) = \frac{q_{ij}}{\sum_{l \in \varphi_i} q_{il}} \tag{6}$$

Figure 2 gives a calculation example of influence probability. Taking node u_4 as an example, $u_5, u_3, u_1 \in \phi_{u4}$, $u_2, u_7, u_6 \notin \phi_{u4}$. Set $x_{41}^1 = 3, x_{41}^2 = 6, x_{41}^3 = 9$, then, between nodes u_4 and u_1, the amount of learning input responses of online teaching activities is $q_{41} = \mu_1 x_{41}^1 + \mu_2 x_{41}^2 + \mu_3 x_{41}^3 = 3\mu_1 + 6\mu_2 + 9\mu_3$ and the influence probability is:

$$GO(u_1, u_4) = \frac{q_{41}}{\sum_{l=5,3,1} q_{4l}} = \frac{3\mu_1 + 6\mu_2 + 9\mu_3}{q_{41} + q_{43} + q_{41}} \tag{7}$$

Therefore, an active teacher node u1 will activate an inactive student node u4 with a probability of $GO(u_1, u_4)$. After student node u_4 is activated, it will also affect other inactive student nodes to participate in online teaching activities, thereby mobilizing the atmosphere of online teaching classroom.

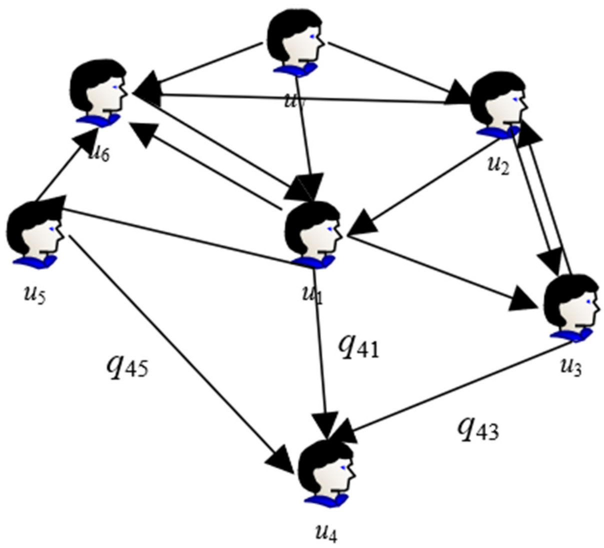

Fig. 2. A calculation example of influence probability

4 Maximization of TI

Given the complexity of the TI model, this paper fully considered the meaning of the interactions of teacher and student nodes during actual online teaching activities, in order to comprehensively quantify TI, this proposed a two-stage TI maximization algorithm based on the learning input response of nodes according to activation effects of student nodes, the framework of the method is given in Figure 3.

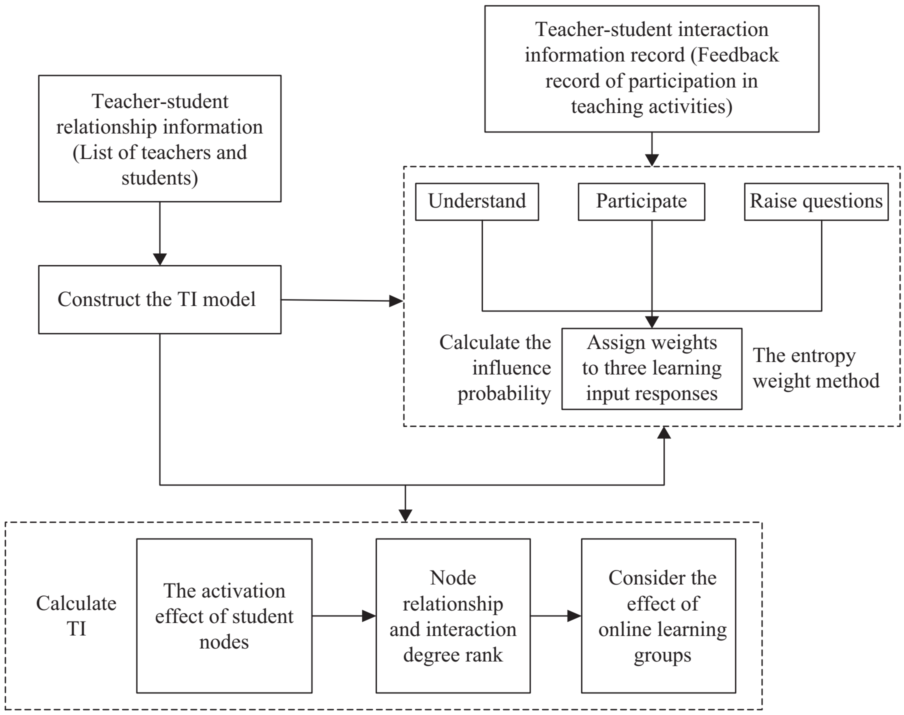

Fig. 3. Framework of the TI maximization method

In the initial stage, a rank was attained from two aspects, the teacher-student node relationship and the interaction degree. The greater the u_i, the sum of two learning input responses of students (namely the number of student nodes interacted with the teacher node c_{ui}^{out}, and the participation of student nodes in teaching activities $\Sigma_{p=1,2,3}A_i^p$) can be taken as the index for measuring the overall activeness degree of nodes in the TI model, denoted as ρ_i, then there is:

$$\rho_i = c_{u_i}^{out} + \sum_{p=1,2,3} A_i^p, i \in \{1, 2, \dots, m\} \tag{8}$$

Based on the value of ρ_i, the initial rank of TI on students could be attained and described by a function from the node set to $\{1,2, \dots, m\}$, and $s(u)$ is the rank of node u.

Weight value could be assigned to each student node based on the ranking function. The size of the weight values describes the intensity of TI. Assuming: f is a positive integer that satisfies $1 \leq f \leq m$, $s^{-1}(f)$ represents the node u with a rank of $s(u) = f$, then the inverse rank could be expressed by the following formula:

$$RO(s^{-1}(f)) = m + 1 - f \tag{9}$$

In the second stage, this paper calculated the value of TI. The intensity of TI is affected by the student number and the quality of student-student interaction, but the influence probability at this time is not just a certain threshold, so the maximum TI value of teacher node u_j is:

$$MAXI(u_j) = RO(u_j) + \sum_{u_i \in ON(u_j)} RO(u_i) * GO(u_j, u_i) \tag{10}$$

When calculating the maximum TI of u_j, if a student node u_i interacts with some other student nodes u_c, then the contribution of other student nodes is reduced; at this time, the probability of u_i being activated by u_j can be calculated as follows:

$$1 - \prod\nolimits_{u_c \in ON(u_i)} (1 - GO(u_c, u_i)) \tag{11}$$

So the expected TI efficiency of u_j is:

$$RO(u_i) * GO(u_j, u_i) * \prod\nolimits_{u_c \in ON(u_i)} (1 - GO(u_c, u_i)) \tag{12}$$

5 Online teaching class division

In the TI model which contains the complicated teacher-student relationships, we can identify the structural features of online teaching classes. Because in each online learning group there're some individual students with similar learning preferences, and the interactions between them will enhance TI, so it'll be more convincing and scientific to measure the TI of each node based on the online teaching classroom division relationships and the overall relationships of nodes in the TI model. This paper revealed the hierarchical structure of online teaching classes based on the *Louvain* algorithm. Assuming: n represents the sum of weights of all edges in the TI model; $l_{i,in}$ represents the sum of weights of edges between node i and the nodes in online learning group D; Σ_{tot} represents the sum of weights of all edges connecting to the online learning group D; l_i represents the weight associated with node i, then there is:

$$\begin{aligned}\Delta W &= \left[\frac{\sum_{in} + l_{i,in}}{2n} - \left(\frac{\sum_{tot} + l_i}{2n}\right)^2\right] - \left[\frac{\sum_{in}}{2n} - \left(\frac{\sum_{tot}}{2n}\right)^2 - \left(\frac{l_i}{2n}\right)^2\right] \\ &= \frac{l_{i,in}}{2n} - \frac{2\sum_{tot} * l_i}{(2n)^2}\end{aligned} \tag{13}$$

The implementation process of the algorithm had two stages: at first, nodes in the TI mode were walked through constantly and introduced into the online learning group with the largest *modularity* increment until all the nodes no longer changed; second, the learning groups were merged to build a new TI model.

6 Experimental results and analysis

Table 1. Descriptive statistics of students' learning engagement in online teaching environment

Variable Name	Sample Size	Minimum	Maximum	Mean	Standard Deviation
Online learning effect	236	1.025	5.362	3.138	0.718
Life outlook and values	214	1.629	5.829	3.516	0.764
Teacher-student relationship	295	1.527	5.341	3.548	0.639
Optimism	271	1.692	5.526	3.621	0.602

Table 1 gives the descriptive statistics of students' learning engagement in the online teaching environment. According to the data in the table, the mean values of online learning effect, life outlook and values, teacher-student relationship, and optimism were respectively 3.138, 3.516, 3.548, and 3.621. and students' engagement levels of each aspect were relatively high, wherein the students' engagement level of the optimism of online learning was the highest, but still its value was less than 4, indicating that for the learning engagement of students, there's still room for improvement in this aspect.

Table 2 shows the changes in students' learning engagement under different influence dimensions. According to the table, under the action of TI, students' learning engagement had been significantly improved. In the five influence dimensions of TI on students' learning engagement, the significance levels were all less than 0.01, indicating that there're significant differences in students' learning engagement before and after the action of TI. Figure 4 compares the scores of different influence dimensions.

Table 2. Changes in students' learning engagement under different influence dimensions

Dimension	Changes in Engagement (Mean ± Standard deviation)			*F*	*P*
	Yes	No	No Change		
	(*n* = 285)	(*n* = 277)	(*n* = 289)		
Online learning effect	3.62 ± 0.68	3.94 ± 0.55	3.41 ± 0.58	36.374	0.023
Life outlook and values	3.48 ± 0.74	3.62 ± 0.79	3.56 ± 0.75	21.528	0.015
Teacher-student relationship	3.29 ± 0.85	3.48 ± 0.72	3.15 ± 0.79	26.395	0.041
Optimism	3.27 ± 0.71	3.51 ± 0.68	3.68 ± 0.62	17.521	0.069
Learning resilience	3.95 ± 0.94	3.26 ± 0.84	3.05 ± 0.85	8.263	0.026
Learning efficiency	3.13 ± 0.72	3.57 ± 0.69	3.62 ± 0.69	22.519	0.021

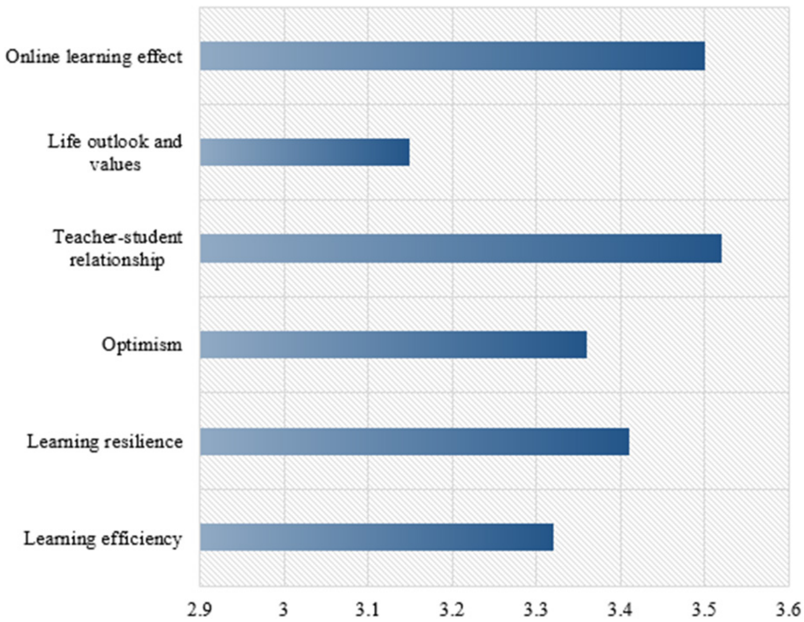

Fig. 4. Scores of different influence dimensions

The experimental results showed that, scores of the five dimensions of TI were all greater than the observed values of middle intensity, and there's only a small difference. The score of teacher-student relationship was the highest, followed by online learning effect, learning resilience, and optimism, indicating that under the action of TI, the online learning effect of college students had been significantly improved, students showed higher learning resilience and optimism levels, the frequencies of student-student and teacher-student interactions were higher, and the interaction atmosphere was better. Although the score of life outlook and values was relatively lower, which means that within a short period of time, the TI only slightly acted on college students' online learning engagement via affecting their life outlook and values, but in the long run, the longer the action time of TI, the better the improvement effect of the learning engagement of students.

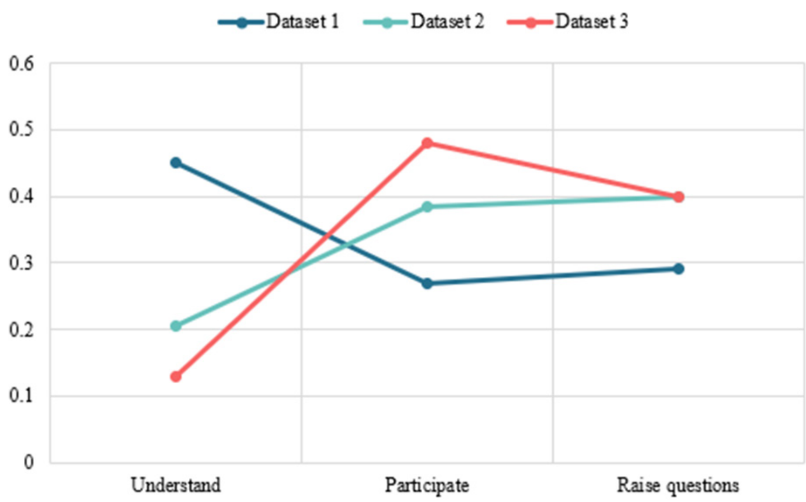

Fig. 5. Weights of three learning input responses

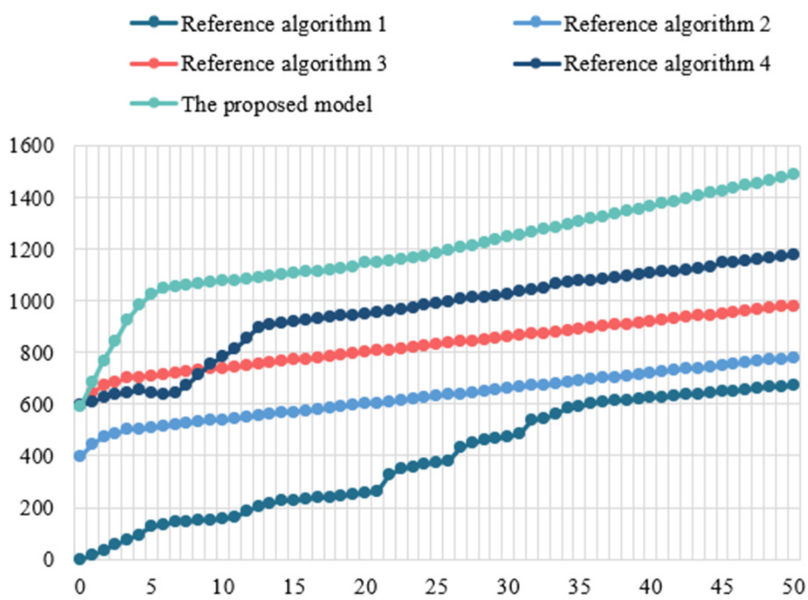

Fig. 6. The influence range of TI of different algorithms

Figure 5 shows the weights of three learning input responses calculated by the entropy weight method. According to the figure, the three learning input responses (understand, participate, and raise questions) didn't exhibit any extreme situation. When the size of the dataset was relatively small, the weights were relatively high. Then, with the increase of the number of student nodes, the response value of "understand" declined, and its advantage was not much different from that of the response of "participate", and the response of "raise questions" was established based on the response of "participate". The TI models constructed based on the three dataset conditions didn't show large differences in the three learning input responses, indicating that the experimental results were consistent with the normal student-student and teacher-student interactions on the online teaching platforms.

Figures 6 and 7 respectively compare the influence range and efficiency of TI of different algorithms. The horizontal axis in Figure 6 is the number of student nodes, and the horizontal axis in Figure 7 is the time step. There are four reference algorithms: IC (Reference algorithm 1), LT (Reference algorithm 2), KK (Reference algorithm 3), and CELF (Reference algorithm 4). According to Figure 6, with the increase of the number of student nodes, the number of activated student nodes increased as well. The influence range of TI on student nodes showed obvious changes, although the number of teacher-student relationships and the diversity of interaction information feedback can affect the influence probability of TI, the proposed algorithm rose first and kept at a stable state during the increasing process of the number of student nodes, and it still outperformed the other four reference algorithms in terms of overall performance and running efficiency.

According to Figure 7, the efficiency of TI of the proposed algorithm was satisfactory, on the whole, it was better than the other reference algorithms. As the time step increased, the efficiency of the proposed algorithm increased to a relatively high level first and then remained stable afterwards, on the whole, its overall performance was obviously better than that of the other four reference algorithms, and there's not much difference for different time steps.

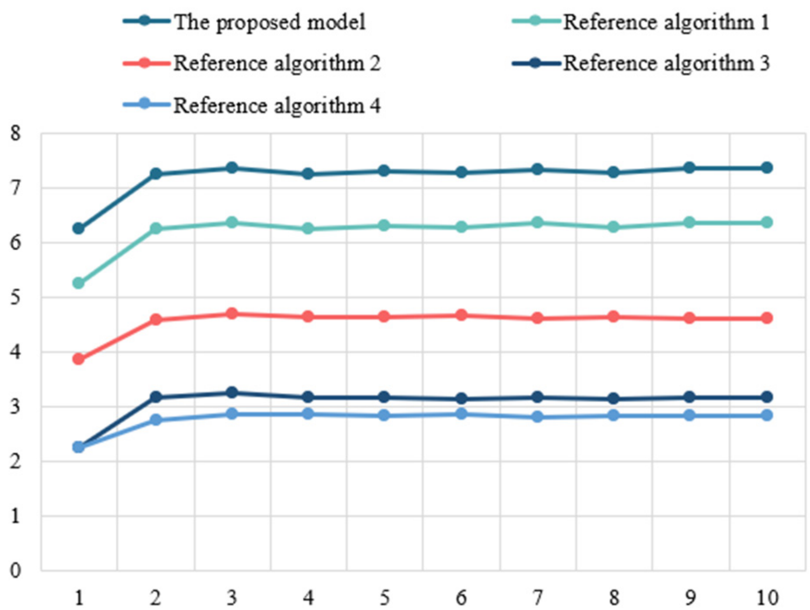

Fig. 7. The efficiency of TI of different algorithms

7 Conclusion

This paper studied the influence mechanism of TI on the learning engagement of students. At first, this paper introduced the theories about this influence mechanism and proposed a TI model for online teaching environment. Then, after investigating students' three kinds of responses (understand, participate, and raise questions) to the online teaching activities created by teachers, the said TI model was built. In view of the complexity of the constructed TI model, this paper fully considered the meaning of the interactions of teacher and student nodes during actual online teaching activities, and proposed a two-stage TI maximization algorithm based on the learning input responses of the nodes which realized comprehensive quantification of TI. After that, experimental results gave the descriptive statistics of students' learning engagement in an online teaching environment, showed the changes of students' learning engagement under different influence dimensions, and verified that under the action of TI, students' online learning effect had been significantly improved. Moreover, the weights of the three learning input responses were calculated by the entropy weight method, and the experimental results were in line with the normal situations of student-student and teacher-student interactions on the online teaching platforms. At last, this paper compared the influence range and efficiency of TI of different algorithms and verified that the proposed algorithm outperformed the other four reference algorithms in terms of overall performance and running efficiency.

8 References

[1] Qu, Z., Zhang, H., Liu, D., Li, F., Liu, G. (2019). An investigation on the factors influencing preservice information technology teacher's TPACK level in China. In 2019 International Joint Conference on Information, Media and Engineering (IJCIME), 47–50. https://doi.org/10.1109/IJCIME49369.2019.00019
[2] Nugraha, I. (2019). Factors influencing pre-service science teacher's GPA on bilingual science teacher education program. In Journal of Physics: Conference Series, 1280(3): 032056. https://doi.org/10.1088/1742-6596/1280/3/032056
[3] Hidayati, A. (2019). The analysis of influencing factors of learning styles, teacher's perceptions and the availability of learning resources in elementary schools in Padang, West Sumatra. In Journal of Physics: Conference Series, 1185(1): 012149. https://doi.org/10.1088/1742-6596/1185/1/012149
[4] Furtak, E.M., Heredia, S.C. (2014). Exploring the influence of learning progressions in two teacher communities. Journal of Research in Science Teaching, 51(8): 982–1020. https://doi.org/10.1002/tea.21156
[5] Goodale, T.A. (2013). The influence of a ROV themed engineering design workshop on in-service teacher self-efficacy. In 2013 IEEE Integrated STEM Education Conference (ISEC), 1–5. https://doi.org/10.1109/ISECon.2013.6525202
[6] Qin, L., Li, N., Zha, S., He, W. (2017). Research on factors influencing perceived usefulness of a virtual teacher community. Telematics and Informatics, 34(5): 463–471. https://doi.org/10.1016/j.tele.2016.09.008
[7] Shin, M.H., Kim, K.H. (2011). Teacher, student, content connections that influence student subject interest. In Green and Smart Technology with Sensor Applications, 209–217. https://doi.org/10.1007/978-3-642-35251-5_29

[8] Beck, D. (2012). Influence of avatar choice on teacher expectations and perceptions of student success. International Journal of Gaming and Computer-Mediated Simulations (IJGCMS), 4(1): 1–24. https://doi.org/10.4018/jgcms.2012010101

[9] Smith, J.A., Sivo, S.A. (2012). Predicting continued use of online teacher professional development and the influence of social presence and sociability. British Journal of Educational Technology, 43(6): 871–882. https://doi.org/10.1111/j.1467-8535.2011.01223.x

[10] Wang, L. (2022). Influence of teacher behaviors on student activities in information-based classroom teaching. International Journal of Emerging Technologies in Learning (iJET), 17(2): 19–31. https://doi.org/10.3991/ijet.v17i02.28271

[11] Zhang, Y. (2022). Influence of teacher-student interaction on course learning effect in distance education. International Journal of Emerging Technologies in Learning, 17(10): 215–226. https://doi.org/10.3991/ijet.v17i10.30913

[12] Nardi, R., dos Reis Belíssimo, J., Parma, F.W. (2021). The influence of high school teachers on the representations of the role of an "exemplary teacher" according to future physics teachers. In Journal of Physics: Conference Series, 1929(1): 012083. https://doi.org/10.1088/1742-6596/1929/1/012083

[13] Zhang, Y. (2021). Influence of teacher-student matching on knowledge innovation of college students. International Journal of Emerging Technologies in Learning (iJET), 16(1): 262–274. https://doi.org/10.3991/ijet.v16i01.19721

[14] Chinnathambi, K., Anandan, L., Ayari, C.M.Y. (2022). Online teaching and online assessment: a critical study. ECS Transactions, 107(1): 4099–4106. https://doi.org/10.1149/10701.4099ecst

[15] Zhou, N., Zhang, Z.F., Li, J. (2020). Analysis on course scores of learners of online teaching platforms based on data mining. Ingénierie des Systèmes d'Information, 25(5): 609–617. https://doi.org/10.18280/isi.250508

[16] Voštinár, P., Dobrota, R. (2022). Minecraft as a tool for teaching online programming. In 2022 45th Jubilee International Convention on Information, Communication and Electronic Technology (MIPRO), 648–653. https://doi.org/10.23919/MIPRO55190.2022.9803384

[17] Wang, S.Y. (2021). Online learning behavior analysis based on image emotion recognition. Traitement du Signal, 38(3): 865–873. https://doi.org/10.1134/S105466182103024X

[18] Wu, X. (2022). Cloud-based collaborative English online and offline hybrid teaching. Wireless Communications and Mobile Computing, 2022: 8048646. https://doi.org/10.1155/2022/8048646

[19] Utomo, M.N.Y., Sudaryanto, M., Saddhono, K. (2020). Tools and strategy for distance learning to respond COVID-19 pandemic in Indonesia. Ingénierie des Systèmes d'Information, 25(3): 383–390. https://doi.org/10.18280/isi.250314

[20] Wang, C.Y. (2022). Emotion recognition of college students' online learning engagement based on deep learning. International Journal of Emerging Technologies in Learning, 17(6): 110–110. https://doi.org/10.3991/ijet.v17i06.30019

[21] Karaoglan Yilmaz, F.G., Yilmaz, R. (2022). Learning analytics intervention improves students' engagement in online learning. Technology, Knowledge and Learning, 27(2): 449–460. https://doi.org/10.1007/s10758-021-09547-w

[22] You, W. (2022). Research on the relationship between learning engagement and learning completion of online learning students. International Journal of Emerging Technologies in Learning (iJET), 17(1): 102–117. https://doi.org/10.3991/ijet.v17i01.28545

[23] Seifan, M., Lal, N., Berenjian, A. (2022). Effect of undergraduate research on students' learning and engagement. International Journal of Mechanical Engineering Education, 50(2): 326–348. https://doi.org/10.1177/0306419021988962

[24] Sercenia, J.C., Prudente, M.S. (2022). Assessing students' perception, engagement and metacognitive skills on mobile learning. In 2022 13th International Conference on E-Education, E-Business, E-Management, and E-Learning (IC4E), 209–215. https://doi.org/10.1145/3514262.3514270
[25] Copur, O., Nakıp, M., Scardapane, S., Slowack, J. (2022). Engagement detection with multi-task training in e-learning environments. In International Conference on Image Analysis and Processing, 13233: 411–422. https://doi.org/10.1007/978-3-031-06433-3_35
[26] Liu, X., Li, X., Chen, W., Qiu, Y. (2021). The influence of university teacher leadership on student learning satisfaction: The mediating role of teacher-student interaction. In 2021 The 6th International Conference on Information and Education Innovations, 35–40. https://doi.org/10.1145/3470716.3470723
[27] Liu, L., Ma, W., Han, G. (2021). A research on the influence of teacher-student interaction on college student engagement in online learning. In 2021 13th International Conference on Education Technology and Computers, 214–222. https://doi.org/10.1145/3498765.3498799
[28] Hegarty, B., Thompson, M. (2019). A teacher's influence on student engagement: Using smartphones for creating vocational assessment ePortfolios. Journal of Information Technology Education. Research, 18: 113–159. https://doi.org/10.28945/4244
[29] Harisman, Y., Kusumah, Y.S., Kusnandi, K. (2019). How teacher professionalism influences student behaviour in mathematical problem-solving process. In Journal of Physics: Conference Series, 1188(1): 012080. https://doi.org/10.1088/1742-6596/1188/1/012080
[30] Zhang, Y., Yang, Y. (2022). The evaluation method for distance learning engagement of college English under the mixed teaching mode. International Journal of Continuing Engineering Education and Life Long Learning, 32(2): 159–175. https://doi.org/10.1504/IJCEELL.2022.121947

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Article submitted 2022-09-02. Resubmitted 2022-10-14. Final acceptance 2022-10-14. Final version published as submitted by the authors.