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PAPER

A Machine Learning Based Method to Evaluate Learning in Gamification Practices

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ABSTRACT

With the integration of advanced methods and technologies in higher vocational education, educational gamification has emerged as a new approach to encourage students' active participation in learning. However, it is difficult to accurately evaluate student participation in this environment and delve into the process of interactive evolution. Most existing research methods primarily focus on qualitative analysis, while attempts to conduct quantitative analysis are often constrained by traditional statistical methods. Moreover, these methods frequently fail to consider the interactive dynamics that occur between teachers and students. This study proposes a method to evaluate learning participation in educational gamification. K-means clustering was used, and a framework for educational gamification was constructed using a process interaction evolutionary game. By conducting a thorough analysis of the interactive dynamics between teachers and students, this study offers practical guidance and strategies for educators.

KEYWORDS

educational gamification, K-means clustering, interactive evolution, game framework, evaluation of learning participation

1 INTRODUCTION

With the continuous progress and increasing popularity of information technology, the methods of higher vocational education are also undergoing profound changes. As a new teaching method that combines education with game elements, educational gamification has gradually attracted the attention of educators and scholars [1–4]. This method aims to enhance students' learning motivation through gamified design, thereby encouraging them to participate more actively in the learning process [5, 6]. However, an unresolved issue is accurately evaluating the participation of students in gamified educational environments and analyzing the interactive evolution of the educational gamification process [7–10].

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The essence of educational gamification is to motivate students to actively engage, enabling them to achieve the desired learning objectives while also experiencing the enjoyment of playing games [11]. Therefore, effective evaluation of students' learning participation not only helps teachers understand their actual learning situations but also provides educators with more targeted teaching strategies [12–16]. In addition, conducting a thorough analysis of interactive evolution in the process of educational gamification helps to uncover the dynamic relationships between students, educational content, and teachers. This, in turn, provides educators with more accurate teaching feedback.

Most existing research methods on educational gamification primarily focus on qualitative analysis, neglecting quantitative research on students' participation and interactive evolution [17, 18]. Although some studies have attempted to conduct quantitative analysis, they are often constrained by traditional statistical methods, which makes it challenging for them to uncover the underlying patterns in complex educational gamification environments [19, 20]. In addition, existing methods often fail to take into account the game relationships between teachers and students, neglecting their interactive dynamics in the teaching process [21].

First, this study evaluated the level of engagement in educational gamification using the K-means clustering method and support vector machines (SVM). The aim was to establish a more scientific and systematic framework for evaluating learning outcomes. Secondly, this study developed a framework for process interaction in an evolutionary game in educational gamification and conducted a comprehensive analysis of the teaching efficiency of teachers and the learning efficiency of students. An assignment-dynamic equation was established for students actively participating in teaching activities. This equation reveals the interactive evolution law in the educational gamification process, providing valuable guiding suggestions for educators. This study not only enriches the research content in the field of educational gamification but also provides a powerful tool and strategy for practical teaching.

2 LEARNING PARTICIPATION IN EDUCATIONAL GAMIFICATION

K-means clustering is an unsupervised learning algorithm used to divide data points into K clusters. When evaluating the learning participation of students in educational gamification, the K-means algorithm helps classify the students into different participation classes, such as high, medium, and low participation, based on their behaviors and reactions in educational games.

When evaluating student participation in educational gamification using K-means clustering, it is important to select appropriate features or variables, such as student interaction frequency, task completion duration, scores obtained, etc., to represent their behaviors. These features were used to assign a point to each student in the feature space. The specific steps of the K-means clustering algorithm are described as follows:

Step 1. Initialization: K initial center points were selected randomly from the data points.

Step 2. Assigning data points: Let $F = \{z_1, z_2, \ldots, z_b\}$ be a given sample set. For each data point, its distance to all K center points was calculated. Then, the data point was assigned to the nearest centroid, which formed K clusters. The cluster or class $V = \{V_1, V_2, \ldots, V_b\}$ was obtained based on the clustering.

Step 3. Recalculating the center point: The new center point for each cluster was calculated as the mean of all data points.

Step 4. Convergence check: The new center point is compared with the center point from the previous step. If there were no or only minor changes, i.e. minimized square error $R = \sum_{k=1}^{J} \sum_{z \in V_u} \left\| z - \omega_u \right\|^2$, the algorithm converged, with $\omega_u = 1/\left|V_u\right| \sum_{z \in V_u} z$ being the mean vector of the cluster V_u. If the center point still changed, the second step was revisited and the process was repeated.

Step 5. Result output: Once the algorithm has converged, it outputs K clusters, with each cluster having its own center point. The student classes obtained (e.g., students with high, medium, and low participation) were explained. Finally, the result was validated or optimized by combining it with the expertise of educators or other qualitative data.

This study was conducted to evaluate the level of students' engagement in educational gamification by combining K-means clustering with SVM. They may be combined for application as follows:

First, the behavioral data of students needed to be extracted from educational games, such as interaction frequency, task completion duration, and game scores. These data were then input into the algorithm as features. According to the aforementioned steps, the K-means clustering algorithm was utilized to categorize students into different participation classes, such as high, medium, and low participation. A label was assigned to each student, representing the participation class to which they belonged.

Support vector machines was further used for predicting participation. The core principle of SVM is to find a hyperplane (in high-dimensional space) on a given training sample set $F = \{(z_1, t_1), (z_2, t_2), \ldots, (z_l, t_l)\}, t_u \in \{-1, +1\}$, thereby maximizing the boundary between two classes. This boundary is called the "interval." The hyperplane is selected based on the closest data points to it, which are called "support vectors." When faced with nonlinear data, SVM uses so-called kernel techniques to map the data from the original space to a higher-dimensional space, making it linearly separable in the new space.

The algorithm was performed in the following steps:

Step 1. Data preparation: The behavior data of students were collected from educational games and then pre-processed, including missing value processing, standardization or normalization, etc.

Step 2. Defining tags: A tag was defined for each student based on their game behaviors or existing participation evaluation methods, such as high, medium, and low participation.

Step 3. Choosing a suitable kernel function: A suitable kernel function is selected based on the features of the data. The evaluation of student learning participation in educational gamification is a complex issue because their behaviors and participation can be influenced by multiple factors, and the relationships between these factors may be nonlinear. In this situation, using the radial basis function (RBF) as the kernel function of SVM has obvious advantages. First, the RBF kernel is a nonlinear kernel function that maps the original data to a high-dimensional space. This transformation makes the data linearly separable in the new space. The RBF kernel is particularly suitable for analyzing student participation data because the relationships between their game behaviors and true participation may be nonlinear. Secondly, the RBF kernel has only one parameter that can be adjusted to control the complexity of mapping to the high-dimensional space. This provides more flexibility for model optimization, enabling it to better adapt to different datasets and problem scenarios. Let $\delta > 0$ be the bandwidth of the function, then the expression of RBF was:

$$J(z_u, z_k) = \exp\left(-\frac{\left\| Z_u^Y Z_k \right\|^2}{2\delta^2}\right) \tag{1}$$

Step 4. Training the SVM model: The SVM model was trained using the collected feature data and corresponding tags. This process involved optimizing an objective function to ensure that most data points were correctly classified while maximizing the interval.

Step 5. Model validation: In the educational gamification environment, students' participation may be influenced by various factors, such as game design, content, and interactive modes. Consistency checks ensure that the evaluation tool consistently and reliably assesses their participation among these changing factors. Meanwhile, if the results obtained by an evaluation method are consistent on different test conditions or at different time points, it can be more confidently believed that this method indeed accurately measures the participation of students, rather than being influenced by certain accidental factors. Moreover, a consistency check indicates defects or deficiencies in the evaluation method. If the consistency scores of a certain method are low, then researchers or educators know that the method needs to be further improved or revised. Therefore, this study validated the model using the consistency verification method, ensuring that it also performs well on unknown data.

This study utilized the following equation for the intra-class correlation coefficient (ICC):

$$ICC = \frac{(LA_{block} - LA_{error})/l}{\frac{LA_{block} - LA_{error}}{l} + LA_{error}} \tag{2}$$

Let "l" be the number of measurements. It is assumed that L experts evaluated B participants. Let A represent the sum of ranks in each column, and E_k the total ranks assigned to the k-th participant. Kendall's coefficient of concordance can be calculated using the following equation:

$$Q = \frac{A\sum_{k=1}^{B} E_k^2 - 3L^2 B(B+1)}{L^2 B(B^2 - 1)} \tag{3}$$

Step 6. Prediction of students' participation: The trained SVM model was used to predict student participation using new student data.

3 PROCESS INTERACTION EVOLUTION ANALYSIS OF EDUCATIONAL GAMIFICATION

According to Professor Friedman, this study developed a framework for educational gamification based on a process evolutionary game framework for educational gamification, as depicted in Figure 1. The framework provides a method for understanding how multiple decision-makers choose strategies based on their interactions over a long period of time.

Under this framework, it is necessary to clearly define that the game participant is the foundation for establishing any game model. Teachers and students are the core interaction participants in an educational environment, and their strategy choices directly affect educational results. At the same time, to understand which strategy combinations best optimize the educational effect, it is necessary to calculate the expected energy efficiency for each strategy combination in advance, which provides clear references for teachers and students, helping them choose the best strategy. This study constructed a payment matrix for an evolutionary game, which is a tool used to describe the returns (or "payments") obtained by both parties when adopting various combinations of strategies. In an educational gamification environment, both parties to the game are teachers and students.

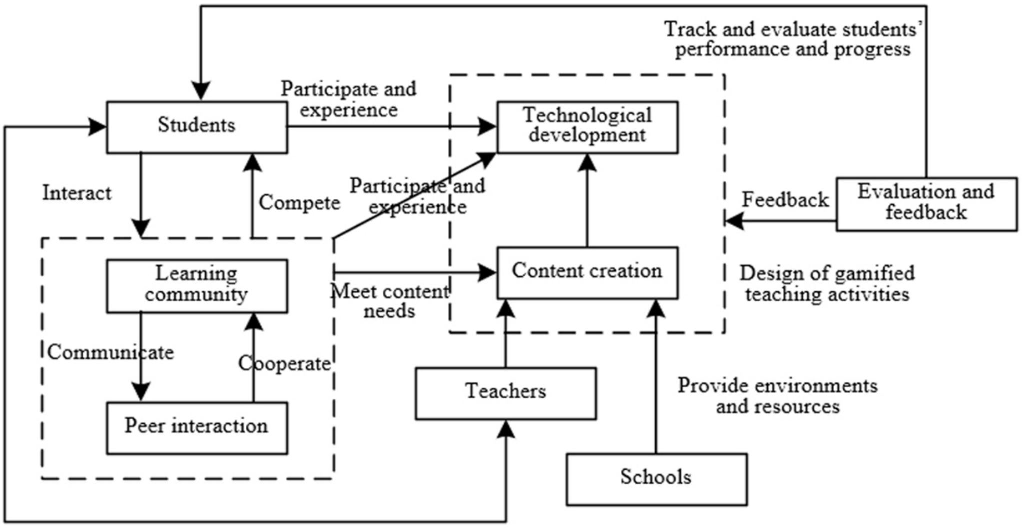

Fig. 1. Process evolutionary game framework for gamified teaching activities

3.1 Analyzing the teaching energy efficiency of teachers

According to the payment matrix of the evolutionary game, when teachers chose the strategy of encouraging students to participate, the expected energy efficiency R_{11} was the energy efficiency sum of the two strategy combinations: active participation of teachers + active participation of students, and active participation of teachers + passive participation of students.

$$R_{11} = t\left(\beta\Delta E - \frac{s^2}{8} + \frac{w_1^2}{2} - Q + V_1\right) + E_1 - \frac{w_1^2}{2} + Q - V_1 + e_2B_2 \tag{4}$$

Similarly, when teachers choose the strategy of not encouraging students to participate, the expected energy efficiency R_{12} is:

$$R_{12} = t(E_1 - Q) + E_1 - \frac{w_1^2}{2} \tag{5}$$

The above two equations were combined, which obtained the average expected energy efficiency $\bar{R}_1$ of teachers:

$$\bar{R}_1 = zR_{11} + (1-z)R_{12} \tag{6}$$

3.2 Analyzing the energy efficiency of student learning

Let R_{22} represent the expected energy efficiency when students choose the strategy of active participation. This value is obtained by calculating the following equation:

$$R_{12} = z\left[(1-\beta)\Delta E - \frac{s^2}{8} + \frac{w_2^2}{2} - Q + V_2\right] + \left(E_2 - \frac{w_2^2}{2} + Q - V_2 + e_1 B_1\right) \tag{7}$$

Let R_{22} represent the expected energy efficiency when students choose the strategy of passive participation. This value is obtained by calculating the following equation:

$$R_{22} = z(E_2 - Q) + E_2 - \frac{w_2^2}{2} \tag{8}$$

The above two equations were combined, which obtained the average expected energy efficiency $\bar{R}_2$ of students:

$$\bar{R}_2 = tR_{21} + (1-t)R_{22} \tag{9}$$

The replicator dynamics equation describes the evolution of strategies over time. In an educational environment, teachers and students may adjust their strategies based on previous experience and feedback. A replicator dynamics equation was used to simulate this process in order to predict future changes in strategies, thereby providing guidance for formulating educational strategies. In the case of teachers choosing the strategy of encouraging student participation, the following replicator dynamics equation was derived from evolutionary game theory:

$$D(z) = \frac{dz}{dy} = z(R_{11} - \bar{R}_1) = z(1-z)(R_{11} - R_{12}) \tag{10}$$

The above equation was combined with equations 4 and 5, resulting in:

$$D(z) = z(1-z)\left[t\left(\beta\Delta E - \frac{s^2}{8} + \frac{w_1^2}{2} - E_1 + V_1\right) + Q - V_1 + e_2 B_2\right] \tag{11}$$

Similarly, the equation above was combined with equations 7 and 8 to obtain a replicator dynamics equation for the scenario where students actively choose to participate in teaching activities.

$$\begin{aligned} D(z) &= \frac{dz}{dy} = t(R_{21} - \bar{R}_2) = t(1-t)(R_{21} - R_{22}) \\ &= t(1-t)\left[z\left((1-\beta)\Delta E - \frac{s^2}{8} + \frac{w_2^2}{2} - E_2 + V_2\right) + Q - V_2 + e_1 B_1\right] \end{aligned} \tag{12}$$

The equilibrium point is a stable state of the game where neither teachers nor students have the motivation to change their strategies. Finding such an equilibrium point in the educational environment helps us understand which strategies are optimal under specific conditions. At the same time, understanding how to reach these equilibrium points also offers clear strategy recommendations for educators. These equilibrium points can be determined and reached through mathematical analysis. After combining equation 11 with equation 12, game equilibrium analysis and equilibrium point stability analysis were conducted.

$$\begin{cases} D(z) = z(1-z)\left[t\left(\beta\Delta E - \dfrac{s^2}{8} + \dfrac{w_1^2}{2} - E_1 + V_1\right) + Q - V_1 + e_2 B_2\right] \\ D(t) = t(1-t)\left[z\left((1-\beta)\Delta E - \dfrac{s^2}{8} + \dfrac{w_2^2}{2} - E_2 + V_2\right) + Q - V_2 + e_1 B_1\right] \end{cases} \tag{13}$$

The equilibrium point of a game corresponds to a situation, where all participants have no motivation to change their strategies because they have already obtained the maximum returns. Under the assumption that $D(z) = D(t) = 0$, five possible local equilibrium points were obtained, namely, (0,0), (1,0), (0,1), (1,1), and (o,w). The expressions for "o" and "w" were given as follows:

$$o = \frac{V_2 - e_1 B_1 - Q}{(1-\beta)\Delta E - \dfrac{s^2}{8} + \dfrac{w_2^2}{2} - E_2 + V_2} \tag{14}$$

$$w = \frac{V_1 - e_2 B_2 - Q}{\beta\Delta E - \dfrac{s^2}{8} + \dfrac{w_1^2}{2} - E_1 + V_1} \tag{15}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Based on the data in Table 1, the score consistency of participants in gamified teaching activities given by different experts can be analyzed. The ICC value of experts in the professional field is 0.958, which means that the scores of these experts have very high consistency, almost achieving perfect consistency. The ICC value of experts in the non-professional field is 0.926, which is slightly lower than that of experts in the professional field, but it is still a high value, indicating that the scores of this group of experts also have high consistency. The confidence interval (CI) of experts in the professional field ranges from 0.921 to 0.985, which means that the true consistency value is within this range with 95% certainty. The CI for experts in the non-professional field ranges from 0.861 to 0.963. Although the range is slightly wider, it also indicates that the consistency of this group of experts is quite high. The p-value for both groups of experts is 0.000, significantly lower than the typical significance level of 0.05. This suggests that the null hypothesis, which states that there is no consistency in the scores of both groups of experts, is rejected in favor of the alternative hypothesis, which suggests that there is consistency in the scores of both groups of experts. The F-value can be seen as the relative size of scoring consistency. In this case, the F-value (18.264) of experts in the professional field is higher than that (14.268) of experts in the non-professional field, further proving that the scoring consistency of experts in the professional field is slightly higher.

Table 1. Score consistency check results of each participant given by different experts

Groups	ICC Value	95% CI	F-Value	P-Value
Experts in the professional field	0.958	0.921, 0.985	18.264	0.000
Experts in the non-professional field	0.926	0.861, 0.963	14.268	0.000

It can be seen from the table that experts in both professional and non-professional fields demonstrate a high level of scoring consistency among participants in gamified teaching activities. However, the scoring consistency among experts in the professional field is slightly higher. This indicates that experts with professional knowledge have more standardized evaluation criteria for scoring gamified teaching activities.

Table 2 shows the consistency check results of different teaching game levels given by different experts. For professionals in the field, Kendall's coefficient of concordance ranges from 0.45 to 0.71, indicating moderate to high consistency. For non-professionals, the range is between 0.43 and 0.71, which is similar to that of professionals. At certain game levels, such as Level 1, the proficiency of experts is slightly higher than that of professional experts. The P-value of both groups of experts at all game levels is 0.0001, which is far below the standard significance level of 0.05, indicating that these checks are statistically significant. Levels 1–3, 4–6, and 7–10 are level subsets. The consistency of each subset and total scores is relatively high, indicating that overall evaluations of these levels made by different experts tend to be consistent. In terms of subsets and total scores of levels, the consistency of both groups of experts is similar and relatively high.

Table 2. Consistency check results of teaching game levels provided by various experts

Teaching Game Level No.	Experts in the Professional Field			Experts in the Non-Professional Field		
	Kendall's Coefficient of Concordance	Chi-Square Value	P-Value	Kendall's Coefficient of Concordance	Chi-Square Value	P-Value
1	0.61	152.268	0.0001	0.71	175.254	0.0001
2	0.53	134.261	0.0001	0.66	175.325	0.0001
3	0.52	131.264	0.0001	0.52	132.052	0.0001
4	0.46	109.325	0.0001	0.43	98.324	0.0001
5	0.58	145.236	0.0001	0.48	124.368	0.0001
6	0.53	123.584	0.0001	0.64	164.328	0.0001
7	0.46	108.324	0.0001	0.55	143.256	0.0001
8	0.48	121.368	0.0001	0.58	154.238	0.0001
9	0.45	125.321	0.0001	0.48	123.564	0.0001
10	0.58	145.368	0.0001	0.52	135.681	0.0001
1–3*	0.63	162.358	0.0001	0.67	156.238	0.0001
4–6**	0.58	152.321	0.0001	0.55	145.239	0.0001
7–10***	0.62	154.369	0.0001	0.67	175.238	0.0001
Total Scores	0.71	176.234	0.0001	0.68	174.236	0.0001

It can be seen from the analysis that the scores of experts in both professional and non-professional fields at different teaching game levels show medium to high consistency. The consistency of experts in the non-professional field is slightly higher than that of those in the professional field at some game levels, but this difference is not fixed and can be reversed at other game levels. Considering the subsets and total scores of game levels, both groups of experts show high consistency in their scores. This indicates they have similar evaluations of the overall game structure and progress.

In summary, different experts show high consistency in their evaluations of teaching game levels on the whole, though there are some differences.

Table 3 shows the judgment results of students' participation (high or low participation) given by two groups of experts (in both non-professional and professional fields). There are nine cases that are judged to have high participation by experts in both non-professional and professional fields. There is no case that is judged as having high participation by experts in the non-professional field but low participation by those in the professional field. There is one case that is judged to have low participation by experts in the non-professional field but high participation by those in the professional field. There are 15 cases where experts in both non-professional and professional fields.

Table 3. Kappa test results from various experts

Experts in the Non-Professional Field	Experts in the Professional Field		Kappa Value	P-value in McNemar's Test
	High Participation	Low Participation		
High Participation	9	0	0.9235	0.3215
Low Participation	1	15		

The Kappa value is 0.9235, which is very close to 1, indicating that both groups of experts have a high level of consistency when evaluating student participation. The P-value is 0.3215. Assuming that this value correctly represents the insignificant difference, it indicates that there is no significant difference between the two groups of experts when evaluating students' participation. It can be seen from the table that both groups of experts have 23 consistent evaluations out of all 24 evaluations, with only one inconsistent evaluation. This inconsistency is also reflected in the high Kappa value.

It can be seen from the analysis that both groups of experts demonstrate a high level of consistency in evaluating student participation. Their evaluations are almost always consistent, with few exceptions, which indicates that there is a relatively stable and consistent set of standards for evaluating students' participation from both professional and non-professional perspectives.

Let A represent the probability of teachers choosing the strategy of encouraging students to actively participate, and let B represent the probability of students choosing the strategy of actively participating in gamified teaching activities. According to the data in Figure 2, the evolutionary trends of A and B can be analyzed under different energy efficiency matching. When the energy efficiency matching is 0, i.e., neither teachers nor students receive any additional benefits from the other party, the values of A and B are completely equal and increase from 0.5 to 1, which means that the probability of teachers encouraging students to actively participate completely matches the probability of students choosing to actively participate in the absence of external rewards or incentives, with both showing an upward trend. When the energy efficiency matching is 0.2, the growth rate of A is slightly higher than that of B. That is, the probability of teachers encouraging students to participate is slightly higher than the probability of students actually choosing to participate. Under this energy efficiency measure, teachers are more willing to encourage students, while the reactions of students are slightly conservative. When the energy efficiency matching is 0.5, the values of A and B are very close but not exactly the same, which means that the reaction trends of teachers and students are relatively consistent, but they have small deviations at certain points. When the energy efficiency matching is 0.8, the values of *A* and *B* are perfectly matched, similar to the situation where the energy efficiency matching is 0. However, there are many data points, and the increase from 0.53 to 1 means that both teachers and students have more diverse choices under this energy efficiency matching, but their choices still remain consistent. The energy efficiency matching of 1 is an extreme case, with only two data points, i.e., 0.5 and 1.

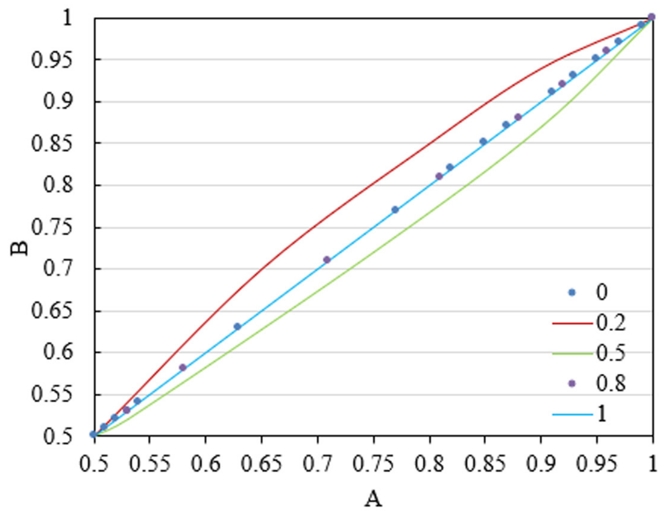

Fig. 2. Evolution trends of *A* and *B* under different energy efficiency matching

It can be seen from the analysis that the choices of teachers and students are perfectly matched when external rewards or incentives do not exist (with the energy efficiency matching of 0) or are very high (with the energy efficiency matching of 0.8 and 1). When there are moderate external incentives (with the energy efficiency matching of 0.2 and 0.5), the choice trends of teachers and students are similar, but there are some deviations. In all cases, both teachers and students tend to choose active participation over time or as the number of iterations increases. This indicates that active participation is considered a more beneficial choice, regardless of external incentives.

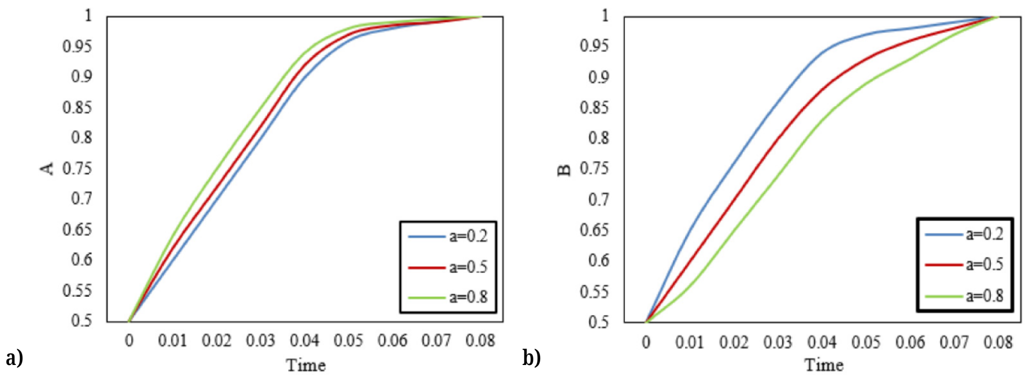

Fig. 3. Evolution trends of *A* and *B* along with time *t* under different energy efficiency matching

Figure 3a shows the variation of *A* (the probability of teachers choosing the strategy of encouraging students to actively participate) over time under different energy efficiency matching. For all energy efficiency matching, the value of *A* shows an upward trend over time, which means that teachers tend to choose to encourage students to actively participate over time regardless of the energy efficiency matching. When the energy efficiency matching is 0.2, the growth trend of *A* is relatively stable. When time increases from 0 to 0.05, *A* increases from 0.5 to 0.96. Although the growth is gradual at the beginning, it becomes particularly significant at 0.05. When the energy efficiency matching is 0.5, the initial growth rate of *A* is similar to the case when the energy efficiency matching is 0.2. But the growth rate gradually accelerates over time. When time increases from 0 to 0.05, *A* increases from 0.5 to 0.97, indicating that teachers more quickly tend to encourage students to participate under this energy efficiency matching. When the energy efficiency matching is 0.8, *A* increases with the slowest growth rate at the beginning but then increases gradually more quickly, especially after time 0.03. When time increases from 0 to 0.05, *A* increases from 0.5 to 0.98. Although this growth initially starts off slow, it accelerates in the later stages.

Under the energy efficiency matching model, the probability of teachers choosing the strategy of encouraging students to actively participate (*A*) increases over time. This indicates that teachers gradually recognize the importance of promoting student engagement. The size of the energy efficiency match indeed affects the growth rate of *A*. When the energy efficiency matching is 0.2, the growth is relatively stable. When the matching is 0.5, the growth gradually accelerates. When the matching is 0.8, the growth is slow at the beginning but significantly accelerates in the later stage. At time 0.08, the value of *A* reaches 1 for all energy efficiency matches. This indicates that teachers are highly likely to choose to encourage students to actively participate at this specific time point, regardless of the energy efficiency match.

Figure 3b shows that *B*, which represents the probability of students choosing the strategy of actively participating in gamified teaching activities, varies over time under different energy efficiency matching. For all energy efficiency matching, the value of *B* shows an upward trend over time, which means that students tend to choose to actively participate in gamified teaching activities over time regardless of the energy efficiency matching. When the energy efficiency matching is 0.2, the growth trend of *B* is relatively fast. When time increases from 0 to 0.05, *B* increases from 0.5 to 0.97. This growth remains relatively stable throughout the entire time period and tends to stabilize in the later stages. When the energy efficiency matching is 0.5, the growth of *B* is relatively slow at the beginning but gradually accelerates in the later stages. When time increases from 0 to 0.05, *B* increases from 0.5 to 0.93. This indicates that students initially choose to actively participate at a slightly slower rate under this energy efficiency match. However, the subsequent growth becomes more significant. When the energy efficiency matching is 0.8, the growth of *B* is initially the slowest but then gradually accelerates. When time increases from 0 to 0.05, *B* increases from 0.5 to 0.89. Although growth is slow at the beginning, it accelerates in the later stages.

Under all energy efficiency matching, *B* (the probability of students choosing the strategy of actively participating in gamified teaching activities) shows an upward trend over time, which indicates that students gradually realize the benefits of actively participating in gamified teaching activities over time. The size of the energy efficiency match indeed affects the growth rate of *B*. When the energy efficiency matching is 0.2, its growth is the fastest. When the matching is 0.5, the growth is slow at the beginning but then accelerates. When the matching coefficient is 0.8, the growth is slowest at the beginning but is more significant in the later stages. At time 0.08, the value of *B* reaches 1 for all energy efficiency-matching scenarios. This indicates that students are highly likely to choose to actively participate in gamified teaching activities at this specific time point, regardless of the energy efficiency matching.

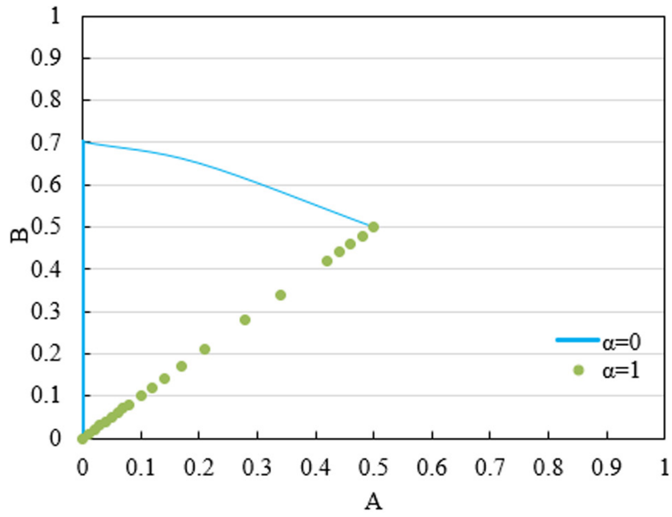

Fig. 4. Evolution trends of *A* and *B* when there are differences in energy efficiency investment between both parties

Figure 4 shows that both *A* (the probability of teachers choosing the strategy of encouraging students to actively participate) and *B* (the probability of students choosing the strategy of actively participating in gamified teaching activities) vary when the energy efficiency matching is 0 and 1. It can be seen from the figure that when the energy efficiency matching is 0, the value of *A* is always 0. This indicates that teachers do not choose to encourage students to actively participate. The value of *B* is 0 at the beginning, but suddenly increases to 0.7 in the next moment. This indicates that students choose to actively participate without any encouragement from teachers, with a probability of 70%. When the energy efficiency match is 1, both *A* and *B* start with a value of 0. However, they then steadily increase with a consistent growth rate, maintaining an equal relationship. This indicates that the willingness of teachers and students to participate increases simultaneously and remains consistent when their investment is completely equal.

When the energy efficiency matching is 0, even if teachers do not encourage students to participate the students still spontaneously choose to actively participate because of their internal drive and interests, as well as other external factors. When the energy efficiency matching is 1, the willingness of teachers and students to participate increases simultaneously, and their behaviors are consistent. This indicates that there is a strong synergistic effect between teachers and students when there is a completely balanced energy efficiency investment. Their behaviors and choices mutually influence each other. In light of the overall trends, energy efficiency matching is an important factor that affects the willingness of teachers and students to participate. Different levels of energy efficiency matching result in varying participation dynamics, offering educators and researchers valuable insights into optimizing teaching strategies to enhance student participation.

5 CONCLUSION

This study evaluated learning participation in educational gamification using the K-means clustering method and SVM, aiming to provide a more scientific and systematic evaluation framework. A framework for educational gamification called "Process Interaction Evolutionary Game" was constructed, and a comprehensive analysis was conducted to evaluate the teaching efficiency of teachers and the learning efficiency of students. The experimental study involved two main factors: the likelihood of teachers choosing the strategy of encouraging students to actively participate (A), and the likelihood of students choosing the strategy of actively participating in gamified teaching activities (B). The experimental results showed that the values of A and B exhibited different variation trends depending on the energy efficiency matching. When the energy efficiency matching was 0, even if teachers did not encourage students to participate, the students still chose to actively participate spontaneously. When the energy efficiency matching was 1, the willingness of teachers and students to participate increased simultaneously, demonstrating synergistic characteristics. The Kappa test results showed that experts in both professional and non-professional fields were highly consistent in evaluating student participation.

It can be seen from the experimental results that energy efficiency matching is a key factor that affects the willingness of teachers and students to participate. Different matching results in different participation dynamics. Based on these findings, educators and researchers can optimize teaching strategies to enhance student participation. Although teachers' encouragement strategies have an impact on students' participation, the intrinsic motivation and interest of the students cannot be ignored. For student participation evaluations, experts in both professional and non-professional fields are similar. This suggests that the evaluation criteria are universal and not influenced by the experts' backgrounds.

This study examined the interactive strategies employed by teachers and students and how they were influenced by energy efficiency matching. The study utilized experimental data and analysis to offer valuable insights and recommendations for the field of education.

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