Applying Guided Discovery Learning to Enhance the Achievement of Information Technology Team

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Abstract. The fast development of IoT and ChatGPT is urging the change of educational method. The traditional methods are being gradually replaced with discovery learning, the method of teacher-centered learning is transferred to student-centered learning. The discovery learning method is developed to guided discovery learning model to apply in educational institutions. This experimental research applied guided discovery learning method for training the information technology team of a gifted high school to take national excellent student prize. A clustering algorithm is applied to set up the team. The research also constitutes an algorithm to evaluate the efficiency of guided discovery learning method for each lecture, where teacher is involved in the evaluation. The result of guided discovery learning method is proved with 3 prizes got by the 2022 team comparing with 1 prize of the 2021 team applying traditional learning method, which is considered as control team of this experiment. An issue which need to be discussed is the increase of teacher's time and energy for the preparation before class and teacher's self-motivation during class to apply guided discovery learning method.

Keywords: Discovery Learning · Guided Discovery Learning · National Excellent Student

1 Introduction

The rapid development of data sources on internet and ChatGPT has been urging educational institutions to change educational method, from centered-teacher learning to centered-student learning. For the methods of centered-student learning [1], several

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institutions applies discovery learning, where student is the center of all learning and teaching activities. So far, the model of discovery learning for educational institutions is still being discussed, some authors are arguing about the role of teacher in discovery learning model, discovery learning with teacher or without teacher.

In a traditional class, the teacher is not necessary to completely cognize in order to stimulate students' skills of creativity, criticalness as well as their self-motivation in learning. The lecture is still designed according to the purpose of curriculum and the expectation of teacher. It is really difficult for teacher to cognize students' skills and attitude because of their variety in thinking and self-motivation. The problem to be solved is how to apply the discovery learning model with centered-student and guiding-teacher for an educational institution.

This research is an experiment applying guided discovery learning method in a gifted high school for the team in information technology. The research determines the teacher's functions in applying discovery learning process. The research applies a clustering algorithm to choose some students of the similarly good competence into the team. The research constitutes the algorithm to evaluate the efficiency of leaning and teaching activities after each lesson, where teacher's competence is involved as a variable of the algorithm.

The article is structured as follows. The Sect. 1 introduces the trend the development of the discovery learning in the era of internet, IoT, and ChatGPT. The Sect. 2 presents guided discovery learning method with teacher's functions in discovery learning process. The Sect. 3 experiments guided discovery learning with the information technology team of a gifted high school to take national excellent student prize; this section applies a clustering algorithm to set up the team and constitutes the algorithm evaluating the efficiency of guided discovery learning process. The Sect. 4 presents the results of the experiment by comparing with the team of the last year, and some issues to discuss. Finally, the conclusion summarizes the results of the research.

2 Guided Discovery Learning Model

2.1 Discovery Learning

Since early 21st century, active learning has emerged as new trend of educational systems. Indeed, several authors are arguing that the learning method of students at educational institutions is nowadays developing from expository to discovery learning [2, 3], in which the central position of educational activities is transferred from teacher to student [4] to promote students' role in learning activities [5]. As an active learning approach, discovery learning with centered-student contrasts with the traditional learning and is superior to the traditional learning with centered-teacher and passive students [1, 2].

Discovery learning is a new educational model, where students' ability and self-reliance are promoted to self-find and construct new knowledge easy to long store in memory [6, 7]. Some authors consider that the basic characteristics of discovery learning model are active learning, meaningful learning, self-efficacy [3, 8–10], meanwhile, Piaget's theory of cognitive development considers that students cannot self-process and self-understand information which they receive [11], hence some educational institutions are developing the guided discovery learning approach [12–14].

2.2 Guided Discovery Learning

For discovery learning or guided discovery learning, each student has to self-discover the concepts or rules from collected data to acquire into long-term memory as new private knowledge [15]. For guided discovery learning in educational institutions, teacher guides the students of a class to identify learning topic and problems, discover concepts and/or rules to acquire into long-term memory as new knowledge. Teacher applies the graph theory [16–18] and visualization techniques [19, 20] to design the lectures for guiding students to carry out process of discovery learning [4, 21–23].

• *Step 1: Stimulating activity and thinking*

The visual lecture designed by teacher applies visual graphs to attract students' interest and attention in learning activities and motivate their self-reliance as well as thinking to focus on the academic field of topic.

• *Step 2: Identifying topic and expressing problems*

Identifying topic and expressing problems is an important step, the visual lecture shows students some literatures to evoke some similar topics, e.g. the topic of hand, foot, mouth disease [9, 10], the topic of dengue fever [24], etc. Each student can state his thinking to be feedbacked by the teacher about the topic which he expresses. After accepting a topic for the whole class, the teacher utilizes visual graphs to continuously evokes students many problems, e.g. the development of epidemic in the year of 2021? [24], the dangers happening disease? [9, 10], etc. After that, the teacher guides students to express problems along with the purpose accordant with the topic.

• *Step 3: Collecting data*

The visual lecture evokes students the models of data tables and shows them data sources related to each variable. The teacher guides students how to collect data from the various sources and fill appropriate data in the chosen tables. Data can be collected by accessing internet, by reading literature, or by interviewing related persons, etc… The visual lecture can evoke students the way to cluster and arrange data according to variables and their relations.

• *Step 4: Analyzing data*

Analyzing data refers to answer questions based on data [10]. The teacher guides students to represent the data tables as visual graphs and creatively make analytical questions composed of local questions, global questions, relative questions [10]. Analytical questions can be answered by visualization or algorithm approach [25]. The answers of analytical questions can result in the rules which students have not known, e.g. the high correlation among rainfall, humidity, and time can happen the danger of hand, foot, mouth disease, meanwhile average temperature does not relate to [10].

• *Step 5: Verifying*

The teacher guides students how to compare the step-4 answers with the purposes of the problems asked at the step 2 and utilize several various data sources to examine the results of data analysis. The teacher guides students to examine the conclusions with several data sources, e.g. it is necessary to have to collect more data in several years to verify the discovery in the example (e.g.) at the step 4 [10]. With the confident data sources, if only an analytical result is not verified, all results are considered as not be verified.

• *Step 6: Extracting conclusions*

If all results of the examination are verified and can be understood as knowledge, they may be generalized as rules to apply for similar problems [25]. The teacher guides students to express the results as conclusions of the topic or the rules for other similar problems. Consequently, the teacher guided students to discover rules as their new knowledge.

3 Research Method

This research is experimented at a gifted high school for training the information technology team taking national excellent student prize. The research applies a clustering approach to group the information technology students of the similarly good competence into the team. The coach is responsible for coordinating training activities which is carried out by several teachers, each guides a topic. After each topic, the leaning and training activity is evaluated by the algorithm assessing efficiency, constituted by the research.

3.1 Grouping Students into Team by Competence

Student's competence is represented as a vector of features which are composed of learning features and non-learning features [26]. Learning features are prior learning outcomes. Non-learning features are composed of skills and attitude as self-motivation, self-confidence, self-reliance, self-finding, self-investigation, self-analysis, critical thinking, creative thinking; and socio-economic factors as demographic, family, behavior backgrounds, interaction, where family background including finance factor and interest is important. The non-learning features are evaluated by pre-tests and interviews of candidates together with their parents.

Input

$\mathbf{X} = \{\mathbf{x}_n | n = 1, 2, .., N\}$ is the vector set representing the students who are candidates for the team, where $\mathbf{x}_n = [s_{1.n}, .., s_{i.n}, .., s_{I.n}]^T = [s_{1.n}; ..; s_{i.n}; ..; s_{I.n}]$ is the feature vector of the student $\mathbf{x}_n$, and $s_{i.n}$ is a feature of learning or non-learning of the student $\mathbf{x}_n$.
$W^{dis} = [w_1^{dis}, .., w_i^{dis}, .., w_I^{dis}]$ is the weight-tuple of competence features defined by each discipline, e.g. information technology.

Output

$\mathbf{Y} = \{\mathbf{y}_1, .., \mathbf{y}_m, .., \mathbf{y}_M\}$ is the team composed of $M\,|M < N$ teamers (team members).

Algorithm

Step 1: Defining the competence features of each candidate $\mathbf{x}_n | n = 1, 2, .., N$ according to the discipline:

$$\mathbf{x}_n^{dis} = W^{dis}\mathbf{x}_n = [w_1^{dis}, .., w_i^{dis}, .., w_I^{dis}][s_{1.n}; ..; s_{i.n}; ..; s_{I.n}]$$
$$\mathbf{x}_n^{dis} = [w_1^{dis}s_{1.n}; ..; w_i^{dis}s_{i.n}; ..; w_I^{dis}s_{I.n}]$$

Step 2: Calculating candidate competence for the discipline

$$\left\|\mathbf{x}_n^{dis}\right\| = \sqrt{\left(w_1^{dis}s_{1.n}\right)^2 + .. + \left(w_i^{dis}s_{i.n}\right)^2 + .. + \left(w_I^{dis}s_{I.n}\right)^2}$$

Step 3: Arranging $\left\|\mathbf{x}_n^{dis}\right\|$ as a descending sequence of N elements, then map them onto $\{\mathbf{y}_1, .., \mathbf{y}_n, .., \mathbf{y}_N\}$, where $\|\mathbf{y}_{n-1}\| \geq \|\mathbf{y}_n\| | n = 2, 3, .., N$, with $\mathbf{y}_n = [s_{1.n}^{dis}; ..; s_{i.n}^{dis}; ..; s_{I.n}^{dis}]$
Step 4: Choosing the segment $\mathbf{Y} = \{\mathbf{y}_1, .., \mathbf{y}_M\}$ as the team.

3.2 Evaluating the Efficiency

The output O refers to the new information and concepts discovered by teamers and the new knowledge learned by teamers. The inputs refer to the brain power which teamers must load and the time which teamers have to take to generate outcomes (Fig. 1). The relation between output and input is mathematically represented by the expression 1.

The input factors which affect teamers' brain load to generate outcomes are composed of the characteristics of lecture as the match H, visualization V, and complexity C; the characteristics of teamers as prior-knowledge K, skill S, and attitude A; and the pedagogic competence of teacher P (Fig. 1), mathematically represented by the expressions 2 and 3.

$$B \times T \rightarrow O \tag{1}$$

$$K \times S \times A \times H \times V \times C \times P \rightarrow B \tag{2}$$

O: Outcome. The outcome refers to the things that the teamers discover. The outcome of each teamer evaluated by the post-test is $o_m | o_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The outcome of team is defined as the median or the arithmetic mean of $\{o_m | m = 1, 2, .., M\}$, mathematically $O = median\{o_m | m = 1, 2, .., M\}$ or $O = \left(1/M\right) \sum_{m=1}^{M} o_m$.

B: Brain Load. The brain load is the resources of working memory mobilized by teamers to obtain the outcomes. The lighter the brain is loaded, the higher the efficiency of activity is.

T: Time. The time is the time interval which teamers take to obtain the outcomes. The shorter the time is taken; the higher the efficiency of activity is. The time is considered as a cognitive cost of all activities. Hence, the relation between the variable of time and others is not necessary to study. T is the time of teamers taken by the teacher to guide them by visual lecture according to discovery learning process. The real times are normalized by the range [1, 2,.., 10] for all teamers and all topics.

K: Prior-knowledge. The prior-knowledge refers to available knowledge of teamers before approaching the topic. The more compatible with available knowledge of teamers the lecture is, the lighter the brain is loaded. The prior knowledge of each teamer evaluated by the pre-test (the test before approaching the topic) is $k_m|k_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The prior knowledge of team is defined as the median or the arithmetic mean of $\{k_m|m = 1, 2, .., M\}$, mathematically $K = median\{k_m|m = 1, 2, .., M\}$ or $K = \left({}^{1}/{}_{M}\right) \sum_{m=1}^{M} k_m$.

S: Skill. The skill refers to teamer' ability of logical, creative and critical thinking utilized during discovery learning. The easier the skills of thinking are mobilized, the lighter the brain is loaded. The skill of each teamer evaluated by the pre-test is $s_m|s_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The skill of team is defined as the median or the arithmetic mean of $\{s_m|m = 1, 2, .., M\}$, mathematically $S = median\{s_m|m = 1, 2, .., M\}$ or $S = \left({}^{1}/{}_{M}\right) \sum_{m=1}^{M} s_m$.

A: Attitude. The attitude refers to teamers' behaviors in learning such as self-motivation, self-confidence, self-reliance, self-finding, self-investigation, self-analysis, and interaction. The more active the attitude is, the lighter the brain is loaded. The attitude of each teamer evaluated by the pre-test is $a_m|a_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The attitude of team is defined as the median or the arithmetic mean of $\{a_m|m = 1, 2, .., M\}$, mathematically $A = median\{a_m|m = 1, 2, .., M\}$ or $A = \left({}^{1}/{}_{M}\right) \sum_{m=1}^{M} a_m$.

H: Match. The match refers to the compatibility of visual graphs in lecture with teamers' prior-knowledge schemata. The match of visual lecture assists teamers in carrying out discovery learning process. The higher the match of visual graphs with teamers' prior-knowledge schemata is, the lighter the brain is loaded. The match of visual lecture is evaluated by the teamers' answers to questionnaires, where the arithmetic mean of scores assigned to questions by the teamer m is rounded up or down to $h_m|h_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The match of visual lecture evaluated by team is defined as the median or the arithmetic mean of $\{h_m|m = 1, 2, .., M\}$, mathematically $H = median\{h_m|m = 1, 2, .., M\}$ or $H = \left({}^{1}/{}_{M}\right) \sum_{m=1}^{M} h_m$.

V: Visualization. The visualization refers to the visual features of lecture such as beauty, orientation, and stimulation. The higher the visual features are, the lighter the brain is loaded. The complexity generated by visualization is considered as part of the complexity of lecture. The visualization of visual lecture is evaluated by the teamers' answers to questionnaires, where the arithmetic mean of scores assigned to questions by the teamer m is rounded up or down to $v_m|v_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The visualization of visual lecture evaluated by team is defined as the median or the arithmetic mean of $\{v_m|m = 1, 2, .., M\}$, mathematically $V = median\{v_m|m = 1, 2, .., M\}$ or $V = \left({}^{1}/{}_{M}\right) \sum_{m=1}^{M} v_m$.

C: Complexity. The complexity refers to the structure of visual lecture, domain, issue, data, visual model, and reference time. The more the complexity is, the heavier the brain is loaded. The complexity of visual lecture is evaluated by the teamers' answers to questionnaires, where the arithmetic mean of scores assigned to questions by the teamer *m* is rounded up or down to $c_m | c_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The complexity of visual lecture evaluated by team is defined as the median or the arithmetic mean of $\{c_m | m = 1, 2, .., M\}$, mathematically $C = median\{c_m | m = 1, 2, .., M\}$ or $C = \left({}^{1}/_{M}\right) \sum_{m=1}^{M} c_m$.

P: Pedagogic Competence. The pedagogic competence refers to teacher's skill applying guided discovery learning method. The higher the teacher's pedagogic competence is, the lighter teamers' brain is loaded. The teacher's pedagogic competence is evaluated by the teamers' answers to questionnaires, where the arithmetic mean of scores assigned to questions by the teamer *m* is rounded up or down to $p_m | p_m \in \{1, 2, .., 10\}$ for $m = 1,.., M$. The teacher's pedagogic competence evaluated by team is defined as the median or the arithmetic mean of $\{p_m | m = 1, 2, .., M\}$, mathematically $P = median\{p_m | m = 1, 2, .., M\}$ or $P = \left({}^{1}/_{M}\right) \sum_{m=1}^{M} p_m$.

The Efficiency. The efficiency of a lecture for guided discovery learning method is defined as the correlation between outcomes and the power of brain which teamers must load, and the time they must take (Fig. 1). The efficiency of the lecture is evaluated by the expressions 4 and 5.

$$B \equiv C \times K^{-1} \times S^{-1} \times A^{-1} \times H^{-1} \times V^{-1} \times P^{-1} = C \times (K \times S \times A \times H \times V \times P)^{-1} \quad (3)$$

$$E \equiv \frac{O}{B \times T} \quad (4)$$

$$E \equiv \frac{O \times K \times S \times A \times H \times V \times P}{C \times T} \quad (5)$$

where the symbol ".. ≡ .." is defined as ".. is directly proportional to…"

In reality, the variables are evaluated for a team of *M* teamers with each lecture. The outcome *O* is evaluated by the post-test. The variables of *K*, *S*, *A* are evaluated by the pre-test. The variables *H*, *V*, *C*, and *P* are evaluated by surveying the teamers. The time *T* is recorded for each lecture.

Mathematically, the efficiency of a lecture for guided discovery learning method may be quantified from the expression Eq. (5) as follows:

$$E = \frac{O + K + S + A + H + V + P}{C + T} \quad (6)$$

The possible values of E in Eq. (6) from the minimum $\frac{7}{20}$ to the maximum $\frac{70}{2}$ may be normalized from 1% to 100% by multiplying $\frac{O+K+S+A+H+V+P}{C+T}$ and $\frac{20}{7}\%$ to obtain the efficiency of a lecture for guided discovery learning method:

$$E = \frac{O + K + S + A + H + V + P}{C + T} \times \frac{20}{7}\% \quad (7)$$

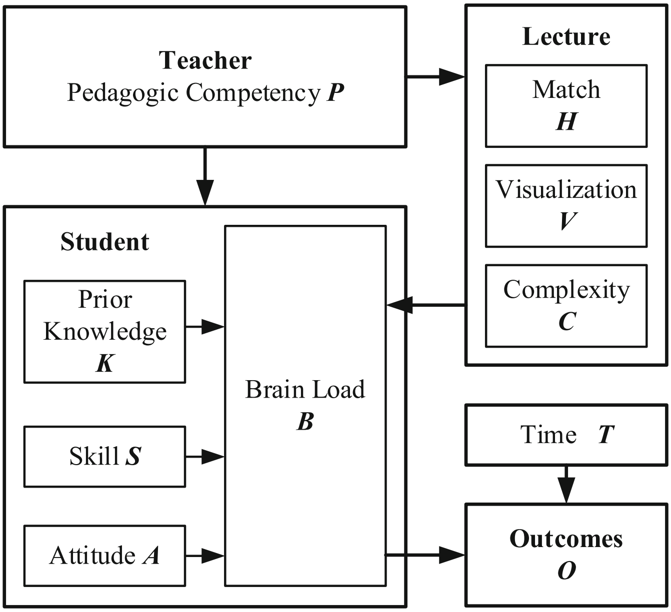

Fig. 1. The model for evaluating the efficiency of a topic in guided discovery learning method.

4 Result and Discussion

4.1 Result

The guided discovery learning method applied for training information technology teamers is estimated by comparing the results of experiment team in 2022 with control team in 2021.

In 2022, the gifted high school welcomes 3 winners from the national excellent student contest in information technology and the remainders got high scores. Meanwhile the 2021 team only got 1 prize in information technology of the contest.

Most teamers of the year 2022 are self-confident and had not lost their self-control while facing exam questions. The losing of self-control of 2021 teamers is one of causes of less result than 2022 team though their knowledge is likely to cover the problems of exam question.

4.2 Discussion

The method of guided discovery learning not only enhances academic knowledge of teamers but also practices their self-reliance and forms their skills to face new problems. This method increases of teamer's self-confidence and avoids to lose one's self-control as facing new topic or new problem.

The method of choosing teamers based on both learning and non-learning competence enhances the effectiveness of cooperative learning in warm discussions to determine topic, expressing problems, collecting and analyzing data, drawing conclusion.

The cooperative learning of teamers of the similar learning and non-learning competence increases teamer's ability facing the stress in contest.

The method assessing the efficiency of each topic encourages teacher in preparing lecture as well as guiding teamers at class because this evaluation involves teacher's working. In addition, this evaluative method assists teamers in awaking to the value of time during taking contest.

The method assessing the efficiency of each topic stimulates teacher's activities in guiding team. Though teacher is not the center in learning and teaching activities of guided discovery learning model, the method of efficiency assessment proves the necessity of teacher's role in the model.

Teachers must invest much time and energy for guided discovery learning method than traditional learning method. Before class time teachers have to set up topics and prepare problems as well as visual lecture to evoke teamers. During class time, teacher must self-motivate to grasp the development of idea of each teamer and guide him.

The experiences from the application of guided discovery learning for this team is being deployed to the information technology classes of the gifted high school. It is necessary to train teachers before extending the guided discovery learning model to the other disciplines of the school.

5 Conclusions

This research aims at experimenting to complete guided discovery leaning model for educational institutions. The experiment was applied to train a team preparing to take national excellent student contest in information technology. Teachers' functions are determined in each step of discovery learning process. The research proposes to apply a clustering approach to select good students for the team and assess guided discovery learning model based on the efficiency of learning and teaching activities of each lecture. Comparing with control team applied traditional learning method of the last year with 1 prize, the experiment team of the year 2022 applied guided discovery learning method wins 3 prizes.

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