S. L. Wong et al. (Eds.) (2010). Proceedings of the 18th International Conference on Computers in Education. Putrajaya, Malaysia: Asia-Pacific Society for Computers in Education.

The Effectiveness of Inductive Discovery Learning in 1: 1 Mathematics Classroom

Euphony F. Y. YANG[a*], Calvin C. Y. LIAO[b], Emily CHING[c], Tina CHANG[d], & Tak-Wai CHAN[e]

Graduate Institute of Network Learning Technology, National Central University, Taiwan

*euphony@cl.ncu.edu.tw

Abstract: This study proposes inductive discovery learning supported with computers to facilitate mathematics learning in Taiwan's elementary education. It is hypothesized that students can learn mathematics concepts better when they are engaged in the induction process, including observing some instances of a concept, searching and testing the pattern behind those instances, and generalizing their findings with proper written words. With supports of the one-to-one technology, students can devote their thinking efforts in such an individual learning task and discover on their own. To investigate the effectiveness of inductive discovery learning, three third-grade classes were involved in the experiment. The result suggests that students have better concept retention, especially for the high and medium performance students through the learning material of inductive discovery.

Keywords: discovery learning, inductive learning, inductive discovery learning, elementary mathematics, 1: 1 classroom

1. Introduction

It is important that students active engage in math learning activity to develop better understanding of the knowledge. Unfortunately, today many mathematics teachers still adopt teach-than-solve method which disadvantages the learning opportunities of students [14]. However, passive attitude and mechanical memory lead to quickly forget [13]. One-on-one digital classroom environment were developed to solve this important issues [7], involving every student in an active learning process [5]. But besides the learning environment, effective pedagogic strategies also play a crucial role.

Discovery learning is one of the pedagogic strategies which reduce teachers' direct instruction and have students construct knowledge on their own. Advocates of discovery learning hypothesize the human learn better and deeper when they are required to discover and construct essential information for themselves [3] to look for patterns and underlying principles [13]. Worthen [15] found that comparing with expository method, discovery learning leads students perform superior on retention and transfer of heuristics in the mathematics tasks. Olander and Robertson [11] implied that students learning under the discovery approach could benefit more in concept understanding.

However, pure discovery environment lack of structure, guidance, and minimal feedback would get into trial and error, lost and frustrated situations [16]. Guided discovery are superior to pure discovery in helping students learning and transferring [9]. Moreno [10] noted that students learn more deeply from strongly guided learning than from discovery. Kirschner [8] also argued that learning via direct instruction have great amount of examples guidance were relatively greater quality of learning compare to discovery. All of them emphasized the importance of guidance and examples, otherwise false starts cause inefficient result [1] and misconceptions [4]. Nevertheless, if discovery guide too much would similar to direct instruction, and lose the advantage of it.

In current study, we implemented a computer supported inductive discovery learning approach in a third-grade elementary mathematics classroom to solve those problems above. Inductive discovery [6] means students learn the key concept by observing a series carefully designed instances reflecting the target concept, discerning the pattern behind those instances while interacting with computers, and then making conclusion of what is discovered. Specifically, the key feature of inductive discovery is providing instances which reflect the same concept to have students discover the underlying principle during interacting with computers—no direct instruction is involved.

2. Inductive Discovery Learning: Design and Consideration

2.1 Define critical attributes of a concept, and focus on one attribute at a time

Every concept has four elements: a name, examples, attributes, and value of attribute [2]. To have students see what is expected to be seen, the critical attributes have to be identified and singled out [8]. Take the meaning of denominator as an example, critical attributes include the number of parts and whole, and each part is equal. Separating critical attribute of a concept and only presenting one at a time make students learning material easier.

2.2 Make the critical attribute obvious

Once the target critical attribute is decided, it has to be obvious to be noticed. Lo, Pong, and Chik [8] pointed out that people tend to aware something when (1) the thing keeps change while other things remain the same; and (2) the thing remains the same while other things keep change. For the first situation, if the target attribute of denominator is the number of parts into which one whole is divided, similar examples can be given. For example, the pie graph share the same representation, which only the numbers of parts are different so that the meaning of denominator can be discerned. Or, for the second situation, examples of different representations can be given while the fraction number keeps the same.

3. Design structure and ideas of learning material

Before design learning material, we had to analyze and identify the structure of each conception in detail. The content design must focus upon each unit of the phenomenon [8], so one page only taught one critical feature to avoid students misunderstanding what we expected. Students must follow learning steps to discover the critical feature relevance. Each step based on simplifies scientific reasoning steps—modeling: stating the hypothesis; discovery: testing the hypothesis, collecting and analyzing data; and induction: making conclusions and possible revisions about the robustness of the original hypotheses [12].

3.1 Modeling

Computer performs two examples constituted by the same critical feature of new concepts. Students observed and exploited from examples without additional instruction. They compared examples and questions to infer the essential procedures and internalize them [16]. This step in scientific discovery process is stating an initial hypothesis, and then applied the hypothesis to the following new questions.

3.2 Discovery

Students discover the hidden critical feature and rule by doing questions with only critical part(s) missing. Instead of presenting the whole questions to students from the onset, we provide a simplified question to identify and examine important information. To force students carefully observe the given examples and think what the missing parts are, they have to try their answers until correct. Next question appear as this question be answered correct. If students answer incorrect, they have to observe two examples again. This is the discovery process. Students keep on testing their hypothesis by completing the critical feature in questions, collecting and analyzing the possible result.

3.3 Induction

Induction part enables students to reflect the concept structure of different questions to summarize their finding. Students check their hypothesis repeatedly. If students can't induct and externalize the critical feature by themselves, the text description or algebra as the symbolic representation would help scaffolding induction. Students should choose appropriate items fit the statement of critical feature to make their conclusion, see Figure 1.

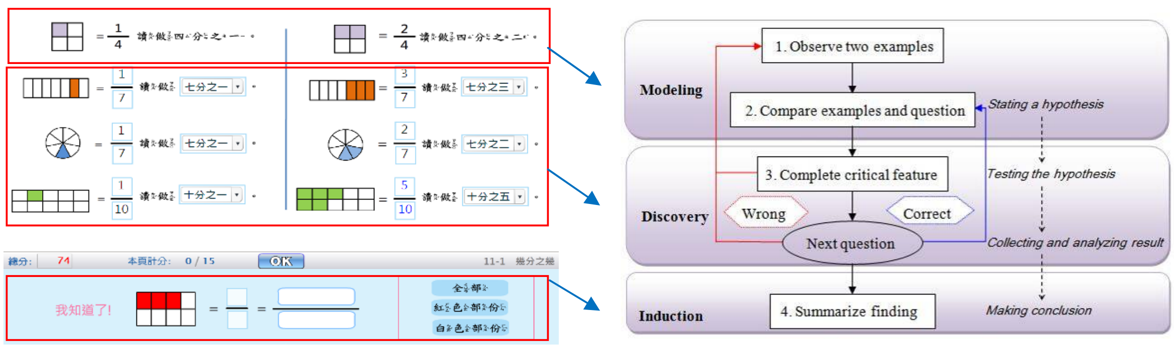

Figure 1 Mathematics content interface and corresponding steps in inductive discovery learning

4. Method

To investigate the effectiveness of inductive discovery learning in 1: 1 mathematics class, this study involved three 3-grade elementary classes in Taiwan. We would like to see if there is any different learning effect between three classes, and also examine the learning effeteness of different instructions to high, medium, and low levels according to their learning performance in their own classes.

4.1 Subjects

This study included three groups. One was experiment group (EG; n = 27), which used inductive discovery learning approach supported with one to one device to learn mathematics. The other two control groups were CG1 (n = 29) and CG2 (n = 29). Both of them used traditional direct instruction approach to explain the concepts and procedures.

4.2 Procedure

This study held on the formal mathematics classes during one semester. Each week had third times, and each time used 40 minutes. The EG had this mathematics fraction experiment was one part of all units. The fraction experiment was close to the final exams, so we adopted the final exams as our comparing reference. We used ANOVA to test their average grades of final examination. There were no significant differences. After one month winter vocation and two weeks in second semester, all the groups did the delay test to reflect their learning retention. The difficulty of the delay test was about 0.5.

5. Findings

We would illustrate the overall situation of the delay test, and then focus on comparing the performance of three levels in each group. The EG means (standard deviations) of delay test was 57.63 (22.24), CG1 was 46.41 (19.65), and CG2 was 47.79 (20.31). As you can see in Figure 2, the standard deviation of three groups was large. The students of EG around 60~80 points were more than control groups. But the highest scores in EG was 90 points which lower than 92 points of CG1 and 94 points of CG2. The EG had almost equal people in 20~39 with CG1 and CG2. But no one behind 20 points in EG, which the lowest scores were 22 points, differed from the 16 points of CG1 and 14 points of CG2. The students of EG concentrated on 30~80 points, however, CG1 and CG2 concentrated on 20~60 points. EG and CG2, CG2 all have very different distribution. The degree of dispersion in EG seemed more obvious. In sum, the mean of EG in the delay test higher than CG1 and CG2 about ten points, so the learning retention in EG longer than CG1 and CG2.

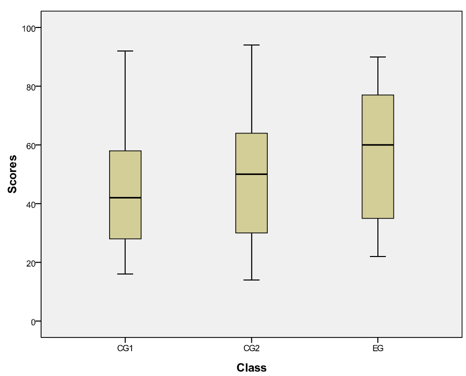

Fig 2 Box plot of three groups scores

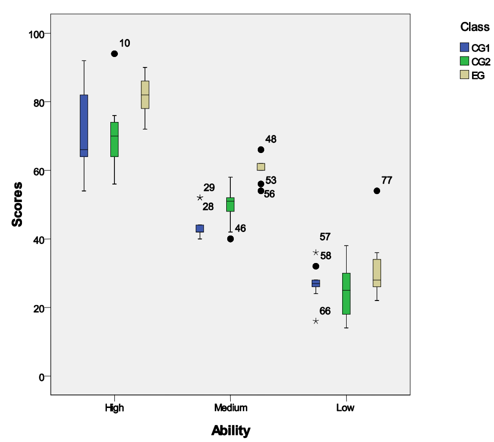

Fig 3 Box plot of three performance levels in three groups

Regarding the achievement of different level students in three groups, we used ANOVA to test the group difference, but no significant was found in low performance level, $F(2, 28) = 1.19$, $MSE = 62.90$, $p > .05$. However, significant group differences were found in medium and high performance levels. In medium performance level, the group means (standard deviations) of EG was 60.22 (3.53), CG1 was 44.00 (4.42), and CG2 was 49.60 (5.40), $F(2, 28) = 30.81$, $MSE = 62.90$, $p < .01$. The scores of EG was obviously higher than control groups about ten points. In high performance level, the group means (standard deviations) of EG was 81.78 (5.61), CG1 was 70.67 (12.61), and CG2 was 70.67 (10.58), $F(2, 26) = 3.67$, $MSE = 100.82$, $p < .05$. Unlike the CG2 have the highest scores 94 points as an outlier, yet the second high scores down to 76 points. Even though the highest scores 90 points in EG was lower than control groups, but scores in EG were more concentrate on 80~90. Similar to the medium performance level, the means of high performance level in EG was higher than the other two control groups about ten points. Therefore, our inductive discovery learning content seems more benefit to the students in medium and high performance level, but for the low performance was less use.

6. Conclusion

This study provided a basic mathematics learning framework based on inductive discovery learning in 1:1 mathematics classroom. Computer presents content, provide immediate feedback and summary of word explanations as scaffolding to facilitate students' mathematics learning. Our experiment showed that comparison with direct instruction, inductive discovery approach is feasible in the 3-grade mathematics classroom, not only learn better but also retention longer, particular for medium and high performance students. Our finding showed similar initial learning effects but better engagement effects, and students have capabilities to induct from observation, doing questions, discover critical feature of concepts, and further deepen their mathematics concepts. In the future, we will try to deepen the understanding of learning with suitable scaffolding in this learning method.

Acknowledgements

The authors would like to thank the National Science Council of the Republic of China, Taiwan for financial support (NSC-99-2631-S-008-001).

References

[1] Brown, A. & Campione, J. (1994). Guided discovery in a community of learners. In K. McGilly (Ed), Classroom Lessons: Integrating Cognitive Theory and Classroom Practice, (pp. 229-270). Cambridge, MA: MIT Press.

[2] Bruner, J. S., Goodnow, J. J., & Austin, G. A. (1956). *A study of thinking.* New York: Wiley.

[3] Bruner, J.S. (1961). The act of discovery. *Harvard Education Review, 31*(1), 21-32.

[4] Carlson, R.A., Lundy, D.H. & Schneider, W. (1992) Strategy guidance and memory aiding in learning a problem-solving skill. *Human Factors, 34*,129–145.

[5] Chan, T.W., Roschelle J., His, S., Kinshuk, Sharples, M., Brown, T., Patton, C., Cherniavsky, J., Pea, R., Norris, C., Soloway, E., Balacheff, N., Scardamalia, M., Dillenbourg, P., Looi, C.K., Milrad, M. & Hoope, U. (2006). One-to-one technology enhanced learning: an opportunity for global research collaboration. *Research and Practice in Technology Enhanced Learning, 1*(1), 3–29.

[6] Ching, E., Chang, T., & Chan. T. W. (2009, October). *Learning Elementary Mathematical Concepts with Computer-Supported Inductive Discovery*. Paper presented at The Technology Enhanced Learning Conference 2009 (TELearn 2009), Tainan, Taiwan.

[7] Liang, J., Liu, T., Wang, H., Chang, B., Deng, Y., Yang, J., Chou, C., Ko, W., Yang, S., & Chan, T. (2005). A few design perspectives on one-on-one digital classroom environment. *Journal of Computer Assisted Learning, 21*(3), 181–189.

[8] Lo, M. L., Pong, W. Y. & Chik, P. M. P. (2005). *For each and everyone: catering for individual differences through Learning Studies*. Hong Kong University Press.

[9] Mayer, R. E. (2004). Should There Be a Three-Strikes Rule Against Pure Discovery Learning? *American Psychologist, 59*(1), 14-19.

[10] Moreno, R. (2004). Decreasing cognitive load for novice students: Effects of explanatory versus corrective feedback in discovery-based multimedia. *Instructional Science, 32*, 99-113.

[11] Olander, H. T. & Robertson, H.T. (1973). The effectiveness of discovery and expository methods in the teaching of fourth grade mathematics. *Journal for Research in Mathematics Education, 4*(1), 33-44.

[12] Rieber, L. P. (2002). Supporting Discovery-Based Learning within Simulations. Available online: [http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.83.1369&rep=rep1&type=pdf[retrieved on 5/20/2010].

[13] Sawyer, R. K. (Ed.). (2006). *Cambridge handbook of the learning sciences*. New York: Cambridge University Press.

[14] Van de Walle, J. (2004). Elementary and middle school mathematics: Teaching developmentally. New York: Addison Wesley Longman.

[15] Worthen, B. R. (1968). Discovery and expository task presentation in elementary mathematics. *Journal of educational psychology monograph supplement, 59* (1), 1-13.

[16] Zhu, X., & Simon, H. (1987). Learning mathematics from examples and by doing. *Cognition and Instruction, 4*,137-166.