Effects of Active Learning Environments and Instructional Methods in Computer Science Education

Qiang Hao
Computer Science & SMATE Program
Western Washington University
Qiang.Hao@wwu.edu

Bradley Barnes
Computer Science
University of Georgia
GA, United States
bjb211@uga.edu

Ewan Wright
Faculty of Education
University of Hong Kong
etwright@hku.hk

Eunjung Kim
College of Education
Pusan National University
ejugn@pusan.ac.kr

ABSTRACT

This research investigated the impacts of active learning environments and instructional methods adapted to such environments on the academic performance of computer science students. Two consecutive studies involving a total of 267 novice students in the same course were conducted across two different semesters. The course was taught by the same instructor and set up with two different sections. One section was taught in a conventional lecture hall, while the other was taught in an active-learning classroom with adapted instructional methods. Active learning environments and the adapted instructional methods were found to have significantly positive effects on students' learning outcomes. Fine-grained results grouped by major were discussed. The findings of this study demonstrate positive effects of active learning environments in computer science education, thereby adding to the literature on both computer science education and learning environments.

CCS CONCEPTS

• Social and professional topics ~ Computing education • Social and professional topics ~ Computer science education • Social and professional topics ~ Computational science and engineering education • Applied computing ~ Education

KEYWORDS

active learning classrooms; active learning environments; computer science education; learning outcomes

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1 INTRODUCTION

Interaction among peers is essential to many active learning strategies, such as team-based learning or problem-based learning [1]. The design of learning environments can either promote or inhibit peer interaction during class time [2-3]. Traditional lecture halls typically have fixed seats facing a central focal point, which is not conducive to peer interaction [Fig. 1].

As an alternative, active learning classrooms have been proposed and developed in the last two decades [4, 5]. An active learning classroom is characterized by round tables and movable chairs. Every table can accommodate five to nine students [Fig. 1]. Whiteboards are usually accessible through digital equipment, such as laptops and projectors, on each table. Such a design seeks to foster peer collaborations and the visibility of every student to the whole classroom [1].

Despite considerable efforts to develop and implement active learning classrooms at multiple institutions, there remains a lack of evidence on how active learning environments impact the learning outcomes of students [6]. Existing empirical studies were conducted and replicated by the same groups of scholars, and were also limited to a narrow range of academic fields [4, 5, 7]. To our best knowledge, there are no empirical studies examining the effects of active learning environments in computer science education.

To fill this gap, the current study investigated the impact of active learning environments and instructional methods adapted to such environments on the academic performance of students in computer science education.

Figure 1: Classroom comparisons at University of Georgia (Left: a traditional lecture hall; Right: an active-learning classroom).

2 RELATED WORKS

2.1 Active Learning and Computer Science Education

Computer science education, as a discipline, stresses both comprehension and knowledge retention. Active learning has been proposed and studied from different angles to encourage students to participate in knowledge construction and take control of their learning, such as peer instruction, paired programming, and cooperative learning [8-10]. However, few studies have explored active learning through investigating the effects of learning environments. Physical spaces can either encourage or discourage different styles of teaching and learning [4, 11]. Active learning environments have been found significant in improving students' learning outcomes and perceptions of learning experiences in a limited range of academic fields such as physics, chemistry or biology.

2.2 Active Learning Environments

Research on active learning environments has continuously drawn attention from academics over the last decade. A review of the literature revealed three major research projects investigating the effects of active learning environments on students' learning outcomes and experiences, including SCALE-UP project at North Carolina State University, TEAL project at Massachusetts Institute of Technology, and ALC project at University of Minnesota. The SCALE-UP project investigated the impact of active learning environments and the effects of course redesign in the context of physics education, and found that active learning environments and adapted course design could improve problem-solving capabilities and decrease course failure rates [4]. The TEAL project studied the usage of virtual simulations in an active learning environment also in the context of physics education. The researchers of TEAL projects demonstrated that students had lower failure rates and better conceptual understandings in an active learning environment [5, 8]. The ALC project, with similar focuses of the other two projects, was studied in the contexts of chemistry and biology education [6, 7, 9]. The ALC project also reported positive impacts of active learning environments.

While findings from these projects promote the concept of active learning environments to a great extent, the research suffers from two major problems. The first problem is the lack of replication. The majority of previous studies were conducted by the same groups of researchers, and limited to academic fields such as physics, chemistry and biology. As more institutions implement active-learning classrooms, more studies within different academic fields are in need. The second problem is that many previous studies had methodological or research-design issues. The noted issues include a lack of control for confounding variables, increased randomness of significant results, and misuse of inaccurate models. As examples, both the SCALE-UP project and TEAL project involved multiple iterations of similar courses. New factors such as classroom modification and changes of instruction materials and methods were brought in over the iterations, but the factors were not well controlled in either of the two projects [12]. The study by Baepler et al. [7] under the ALC project conducted multiple t-tests over same two groups of students without reducing the possibility of getting random significant results. The study by Cotner, et al. [13] also under the ALC project used a linear regression model with less than 50% accuracy rate to predict students' grades, and further used the prediction result for comparison purposes.

By studying the impacts of active learning environments and instructional methods adapted to such environments in the context of computer science education, this study aims to contribute to the literature of both computer science education and learning environments, and make progress in terms of methodology.

3 RESEARCH DESIGN

Two studies adopting control-group design were conducted in the same course at University of Georgia. The course serves the purpose of an introduction to computing and programming. Students in other majors are also allowed to take this course.

Two class sections were set up in the course and taught by the same instructor for experimental purposes. The major differences between the two class sections include learning environments and content delivery formats. First, one class section was conducted in a conventional lecture hall, while the other was conducted in an active learning (SCALE-UP) classroom designed to promote collaborative work. Second, the content delivery formats were adapted to the learning environments of particular class sections. In the traditional lecture section, students were encouraged to read the course textbook outside of class but receive the content in a traditional lecture style. In the active learning section, the students were assigned daily reading and short quizzes based on content from the course textbook and videos developed by the instructor. These short quizzes were graded assignments that had to be completed before the beginning of class. During a typical lecture, students in the active learning section worked in groups of three to solve more complex questions on material read prior to the start of class. As they worked, the professor and three undergraduate teaching assistants (TA) were available to answer questions and work through solutions on the whiteboard. In addition, both the traditional and the active learning sections had a breakout lab section with 24-30 students enrolled in each. In these lab classes, the students worked with the guidance of two TAs to solve lab and project assignments. The lab met twice per week for 50

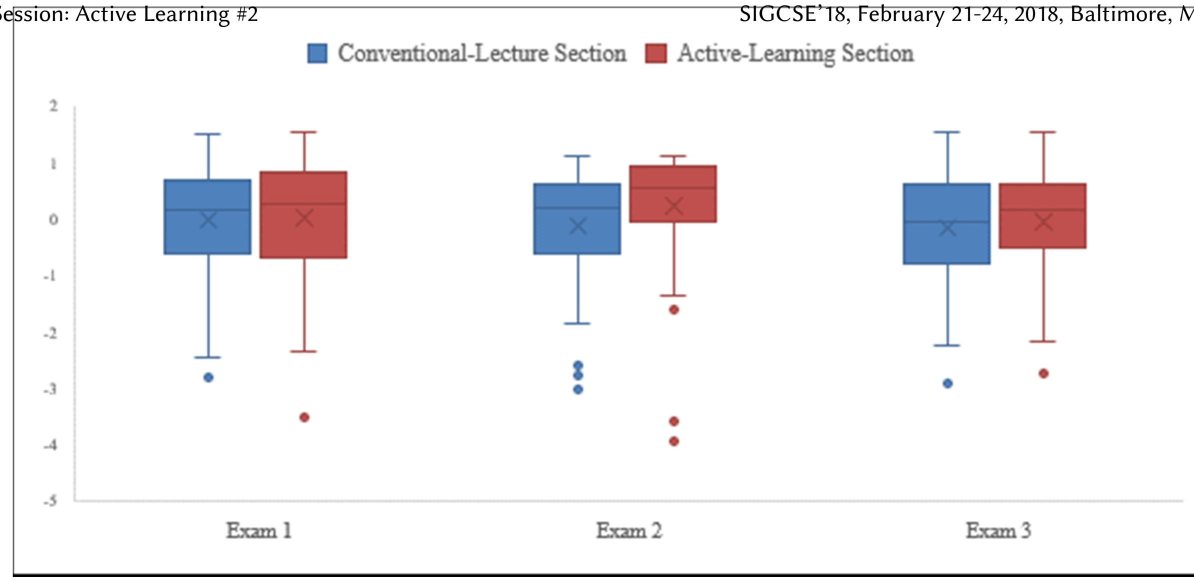

Figure 2: Standardized exam results of fall 2016 semester.

minutes. All students in both class sections completed three non-overlapping exams developed by the instructor.

A preliminary study in such a course was conducted in fall 2016. Students' major information was collected. The follow-up study in the same course was conducted in spring 2017. Students' information, including major, gender and age, was collected through a survey.

4 RESULTS OF TWO STUDIES

4.1 Preliminary Study

4.1.1 Descriptive Summary. 162 students participated in the preliminary study. The descriptive summary established similarity in terms of major between the two class sections [Table 1].

Table 1: Descriptive summary of fall 2016 participants.

	Conventional-Lecture Section	Active-Learning Section
Numbers of Students	103	59
Major		
Computer Science Major	53.4%	52.5%
Non-Computer Science Major	46.6%	47.5%

4.1.2 Comparisons between Class Sections. As the three exams covered different learning content and therefore potentially had different difficulty levels, the exam results were standardized to enable comparison among the exams. It is noteworthy that students in the active-learning section tended to outperform their counterparts in the conventional lecture section [Fig. 2].

Repeated Measures MANOVA was conducted to further investigate the effects of class type and major on students' academic performance in the three exams. All two-way and three-way interaction among major, class type and exam were also examined. Using Pillai's trace, the exam*class type interaction ($p < .05$) was significant. However, separate univariate t-test on the class type revealed non-significant difference between class sections across the three exams.

4.2 Follow-Up Study

4.2.1 Descriptive Summary. To further minimize the possibility that some unobservable variables overinfluence the observed effects in our experiments, a follow-up study was conducted. 105 students participated in the follow-up study. Students' information – major, gender and age – was collected through a survey. A descriptive summary of the participants is presented in Table 2.

The group differences on gender is less than 5%. Although students in the active-learning section ($M = 19.41$) tended to be younger than students in the conventional lecture section ($M = 19.86$), t-test did not show any significant difference between the two groups [$t(103) = 1.26$; $p = 0.21$]. The difference on whether majoring in computer science between the two groups was 24.8%. This difference is likely due to randomness given that students did not have prior knowledge of class sections before enrolling in the course.

Table 2: Descriptive summary of spring 2017 participants.

	Conventional-Lecture Section	Active-Learning Section
Numbers of Students	64	41
Gender (Binary)		
Male	57.8%	56.1%
Female	42.2%	43.9%
Major (Binary)		
Computer Science Major	31.3%	56.1%
Non-Computer Science Major	68.8%	43.9%
Age (Continuous)		
< 20	48.4%	63.4%
≥ 20 and < 22	42.2%	26.8%
≥ 22	9.4%	9.7%

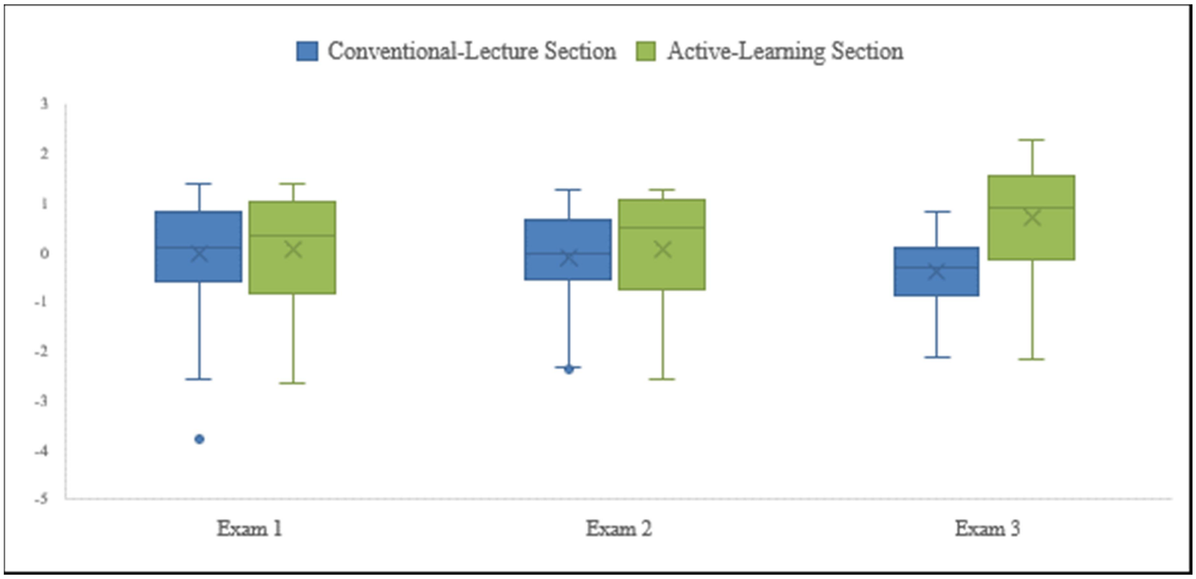

Figure 3: Standardized exam results of spring 2017 semester.

4.2.2 Comparisons between Class Sections. In alignment with the preliminary study, each exam result was standardized to allow comparisons across exams. The comparison result confirmed the findings in the preliminary study that students in the active-learning section tended to outperform students in the conventional lecture section [Fig. 3].

Repeated Measures MANCOVA was conducted to further examine the effects of four attributes, including class type, gender, age and major on students' academic performance in the three exams. All two-way and three-way interaction among the attributes and exam were examined. Using Pillai's trace, the exam*class type interaction ($p < .01$) and exam*class type*major interaction ($p < .05$) were both significant. This finding indicated that the relationship among exam results, class type and major needed further examinations. Separate univariate ANOVA testing effects of the attributes and their interactions on exam results further confirmed the significant difference between class sections on academic performance ($p < .01$) [Table 3].

Table 3: Between-group effects of all attributes and their interactions on exam results.

Attribute	Mean Square	F	Significance Level
age	11.54	5.72	0.02*
class type	13.84	6.86	0.01*
major	7.33	3.63	0.06
gender	0.70	0.35	0.56
class type * major	2.02	1.00	0.32
class type * gender	5.93	2.94	0.09
gender * major	0.12	0.06	0.81
class type * gender * major	0.38	0.19	0.67

** p < 0.05; **p < 0.01; ***p < 0.001.*

Given that the exam*class type interaction ($p < .01$) and exam*class type*major interaction ($p < .05$) were both significant in the Pillai's trace, there is a need to further study the interaction between class type and major. To gain a deeper understanding their interaction, we further conducted individual t-test on each of the three tests a) *by major* and b) *by both major and class type*. Bonferroni Correction was applied to the significance levels to avoid possibly false positive results. The adjusted significance levels were:

$* p < 0.016; ** p < 0.003; *** p < 0.0003$

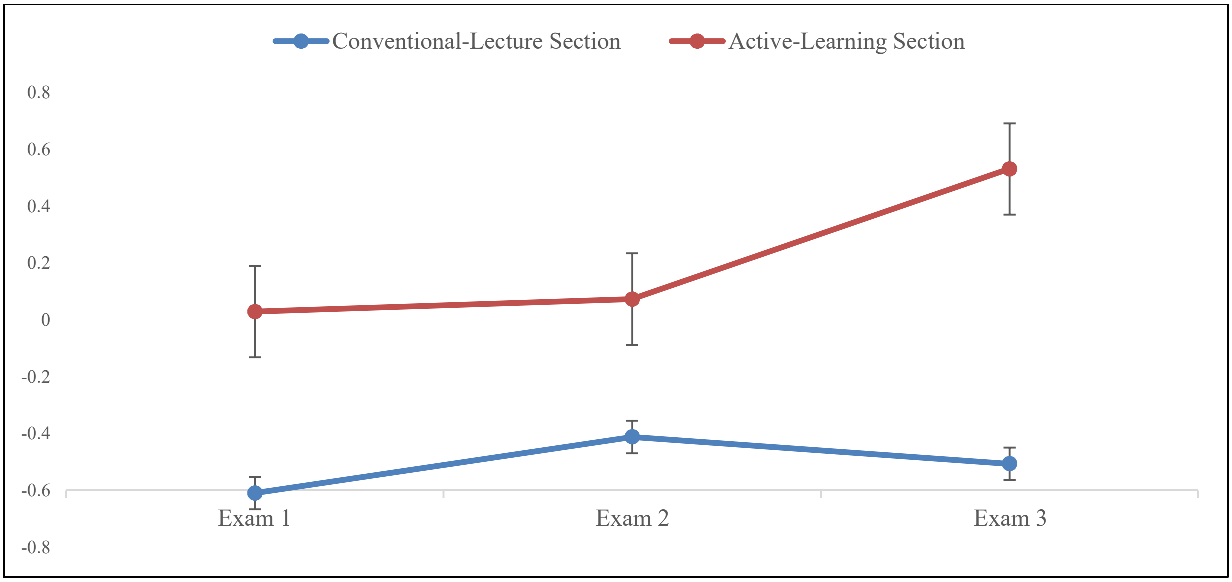

Figure 4: Standardized exam results of computer science majors.

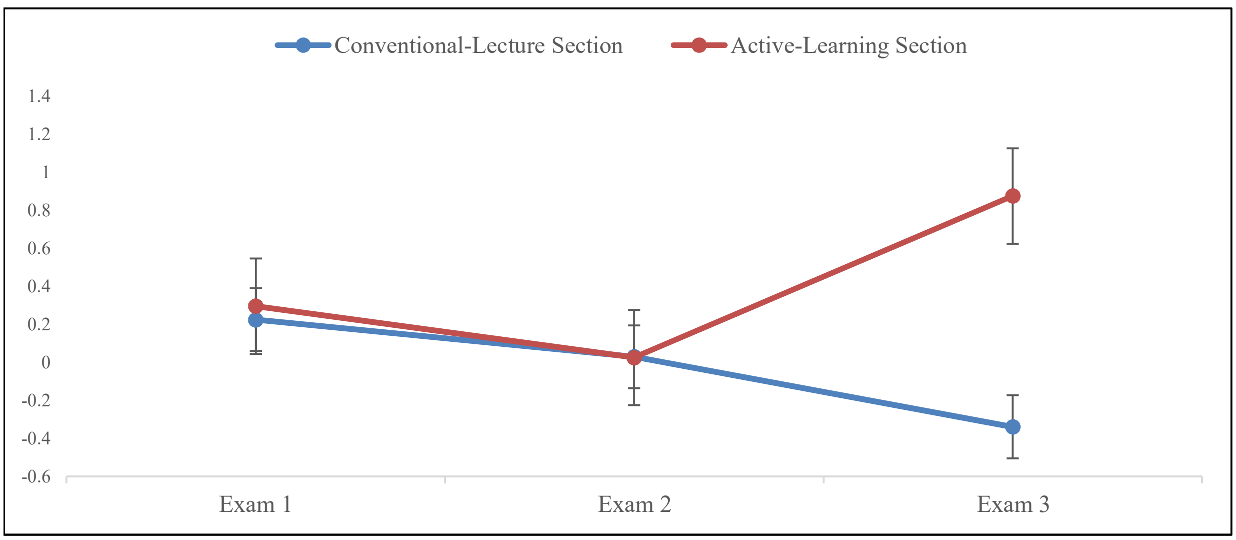

Figure 5: Standardized exam results of non-computer science majors.

First, no significant difference was found between computer science majors and non-computer science majors on any of the exam results. Second, computer science majors performed significantly better in the active-learning section than in the conventional-lecture section on 1st exam ($p < .016$) and 3rd exam ($p < .003$). The visualization shows a very clear pattern for computer science majors in two different class sections [Fig. 4]. Nonetheless, non-computer science majors performed significantly better in the active-learning section than in the conventional-lecture section only on 3rd exam ($p < .016$), and no clear patterns could be found among non-computer science majors [Fig. 5].

5 DISCUSSION

This research contributes to the literature of both computer science education and learning environments. First, although there have been reports that active learning classrooms are implemented for computer science courses [14], no empirical evidence existed on whether active learning environments make a difference to learning outcomes in computer science education. The empirical evidence of this research fills this gap, and confirms the positive effects of active learning environments in computer science education.

Second, the contrast between the preliminary study and the follow-up study demonstrates that unobservable factors, such as age or gender could overinfluence the observed effects. By controlling such factors, active learning environments and the instructional methods adapted to such environments show significant importance in learning outcomes.

Third, this research makes significant advances in terms of research design and methodology in comparison with previously published studies. The results of the preliminary study provided valuable information about whether further control of unobservable variables was in need, which helped us improve the design of the follow-up study. The application of Bonferroni Correction helped controlling the chances of getting random significant results. The combination of Repeated Measures MANCOVA and the follow-up univariate ANOVA confirmed the actual effects of the factors.

This research is not without limitations. Although the effects of active learning environments and instructional methods adapted to such environments were found significant, the two attributes were treated as a single factor in this study. The question to what extent active learning environments are effective in computer science education remained unanswered. Future studies may consider further controlling the instructional method to single out the effects of learning environment, and answer two questions raised by this study:

1. To what extent can the findings of this study be replicated?
2. What are the reasons behind different patterns in learning outcomes between computer science majors and non-computer science majors?

6 CONCLUSIONS

Active learning environments, as a research topic, has gained substantial attention from both academics and institutions over the last decade. This research, using two control-group design studies, confirmed the significant positive effects of active learning environments and instructional methods adapted to such environments on academic performance in computer science education, and contributed to the literatures of both computer science education and learning environments. To build upon the findings of this research, we call for more studies, especially replication studies, in college-level computer science education and other academic fields.

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