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Quantifying the effects of active learning environments: separating physical learning classrooms from pedagogical approaches

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Abstract
Prior findings on the effects of active learning environments were limited by both research design and data-analysis techniques, such as lack of controls over confounding factors and misuse of statistical modeling. We (1) investigated the effects of active learning environments on student achievement and motivation and (2) overcame the limitations of prior studies. Using a three-group design, the effects of physical learning environments and pedagogical approaches were successfully separated. Active learning environments were found to have little influence, whereas active learning and teaching were found to have a significantly-positive influence on student achievements. The findings contribute to understandings of active learning environments in higher education, and invite more debate about whether further investments in active learning classrooms are worthwhile.

Keywords Active learning environments · Computing education · Higher education · Physical environments

Introduction

Educational research has demonstrated that effective knowledge construction requires interactions among students and instructors on problem solving (Barkley et al. 2014; Crouch and Mazur 2001). The design of conventional classrooms with bolted seats all facing the teaching stage might not be ideal for interactive and collaborative activities (Whiteside et al. 2010) (see Fig. 1 left). As pointed out by many learning environment researchers, physical learning environments can either encourage or inhibit learning activities (Brooks 2011).

As learning environment research progresses, there have been innovations in classroom designs. Active learning classrooms, as alternatives to conventional classrooms, have been

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Fig. 1 Classroom comparisons (*Left* conventional classroom; *Right* active learning classroom)

explored and constructed in multiple higher-education institutions. Active learning classrooms, characterised by open learning spaces, movable tables and seats, and learning technologies, are designed to better support effective learning (Oliver-Hoyo et al. 2004) (see Fig. 1 right). However, active learning classrooms require significantly-more resources to construct (Park and Choi 2014). Therefore, both educational researchers and school administrators are interested in understanding the efficacy of active learning classrooms.

Various active learning methods as pedagogical approaches have been widely documented as effective. Nonetheless, prior studies examining impacts of active learning classrooms on student achievements were limited by their research design and data-analysis techniques, such as lack of control over variables and misuse of statistical modeling (Baepler et al. 2014; Brooks 2011). Positive results have only been replicated by the same or a few other scholars. Furthermore, these studies were mainly conducted in the fields such as physics or biology education. Although computer science is gradually becoming one of the most-popular STEM majors across the United States, few studies have examined the effects of active learning classrooms in computer science or engineering education.

To fill this gap, the current study reviews literature on active learning environments with a focus on the limits of prior studies, and further investigate the effects of learning environments on student gains in computer science. This study intends to contribute to the literature of both learning environments and computer science education, while also making progress in terms of research design and data analysis techniques.

Literature review

Active learning and teaching

Active learning is an umbrella term for pedagogical approaches for putting students in charge of learning through engagement in meaningful activities. In contrast to passive lectures, active learning emphasises real-life application, learning by doing and collaborations, which contribute to the ultimate goal of preparing students for lasting achievements and future roles outside school. The effectiveness of active learning has been well documented in computer-science education. Decades of research has revealed that students from active learning classes perform significantly better than their counterparts in conventional classes (Baldwin 1996; Beck and Chizhik 2008; McConnell 2005).

Active learning strategies studied in computer-science education include peer instruction, Process Oriented Guided Inquiry Learning (POGIL), Peer Led Team Learning (PLTL) and studio-based instructional techniques. All of these techniques share a lot of similarities, but also bear some differences. The greatest similarity across all the strategies is group-based collaboration on problem solving. When one active learning strategy is adopted in class, students are typically required to work together in groups on carefully-designed problems or activities (Barkley et al. 2014; Crouch and Mazur 2001; Park and Choi 2014). Peer instruction, POGIL and PLTL share some features unique to themselves. PLTL involves recruiting qualified team leaders and stresses out-of-class learning activities (Horwitz et al. 2009). POGIL emphasises knowledge construction from student perspectives through inquiry activities (Hu and Shepherd 2014). Studio-based instructional techniques focus more on the process of creating and building products, which might not be the centre of many entry-level computer-science courses (Carter and Hundhausen 2011). Peer instruction, usually associated with ‘flipped classrooms’, focuses on moving information transfer out of classroom and moving information assimilation into the classroom (Porter et al. 2013). It is worth noting that more studies have focused on peer instruction in computing education than other active learning approaches.

Learning environments

Classroom is the foremost essential environment that supports students’ learning and it is usually where learning happens. Some scholars argue that physical learning environments have influences that either enhance or inhibit learning (Whiteside et al. 2010). Active learning classrooms are believed to have more-positive effects on student achievements than conventional classrooms (Cotner et al. 2013; Dori and Belcher 2005). However, an active learning classroom typically requires more resources in construction and can accommodate a smaller number of students because of its design (Park and Choi 2014). Therefore, both educators and school administrators are interested in whether the benefits of active learning classrooms can justify the extra expenses.

In the history of learning environments research, two projects that pioneered the study of the effects of active learning classrooms are SCALE-UP at North Carolina State University and TEAL at Massachusetts Institute of Technology (Dori 2007; Dori and Belcher 2005; Oliver-Hoyo et al. 2004). These efforts were continued through ALC project at University of Minnesota (Baepler et al. 2014; Brooks 2011; Cotner et al. 2013). Multiple studies have been conducted involving such projects in different academic fields, such as biology and chemistry (Brooks 2011; Oliver-Hoyo et al. 2004). Most of these studies concluded that active learning classrooms are more beneficial than conventional classrooms in terms of student achievements (Brooks 2011; Cotner et al. 2013; Park and Choi 2014). Undoubtedly, it is easier for instructors to practice certain pedagogical approaches, such as peer instruction and group learning, in active learning classrooms. However, the question of the extent to which active learning classrooms impact student achievements was not well answered in prior studies because of both research design and methodological limits. First, prior studies lacked sufficient controls to separate the effects of physical spaces from the pedagogical approaches (Dori and Belcher 2005; Gaffney et al. 2008; Hao et al. 2018). Second, problems of misusing statistical modeling were noticeable across multiple studies. Such previous work compared students’ actual performance with their expected performance predicted by regression models with less than 30% accuracy rate (Baepler et al. 2014; Brooks 2011; Dori and Belcher 2005). The predicted performance was too inaccurate to be applicable and should not be used as expected performance. Third, the possibility of getting false positive results were rarely controlled. It is common for studies on this topic to compare multiple dependent variables across two groups, which is likely to lead to false positive results. Yet, most prior studies failed to implement practices to prevent inflating false positive rates (Baepler et al. 2014; Brooks 2011).

Computer science education

Aiming to use computing techniques to solve real-world problems, computer science is among the disciplines that involved pioneering novel pedagogies for enhancing students' comprehension, retention and problem-solving skills. Given the subject nature of computer science, pedagogical approaches such as paired programming and team-based learning have been explored extensively and found to be effective empirically (Porter et al. 2011; Simon et al. 2010; Timmerman and Lingard 2003).

Although pedagogical approaches have been extensively explored, the impacts of physical learning environments on student gains are rarely studied in computer-science education. There have been reports on the implementation of active learning classrooms and laboratories for programming courses, but empirical studies are thin on the ground (Hakimzadeh et al. 2011; Hao et al. 2018; Greer et al. 2019). Hao et al. (2018) compared novice computer-science students' performance in conventional and active learning classrooms, but treated learning environments and pedagogical approaches as a combined factor. Therefore, how physical learning environments affect computer science student gains remains unclear.

Research questions

The main research questions guiding this study were:

1. To what extent do active learning environments and active learning and teaching influence students' (a) academic performance, (b) participation, (c) confidence, (d) motivation and (e) attitude towards taking computer-science courses?
2. How effective are physical learning environments compared with pedagogical approaches in contributing to student gains?

These two questions ultimately will help answer the question "Are active learning classrooms worth the investment?"

Research design

Data were collected from three sections of an introductory computer-science course in a large research university in the southeastern United States in spring of 2017. The three sections, taught by the same instructor, shared the same content and examinations. The major differences among the three sections included physical learning environments and adopted pedagogical approaches:

- Course One: Conventional classroom + Conventional lecture

- Course Two: Conventional classroom + Active Learning and Teaching
- Course Three: Active learning classroom + Active Learning and Teaching

First, Courses One and Two were conducted in conventional lecture halls, while Course Three was conducted in an active learning classroom. Second, peer instruction was adopted in Courses Two and Three. In course One, students were encouraged to read the textbook outside class, but received the content in a series of passive lectures. In the other two courses, students were assigned daily reading and short quizzes based on content from the 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 class of Courses Two and Three, students worked in groups of three to solve questions on material read prior to the start of class. As they worked, the instructor and teaching assistants (TAs) were available to answer questions. In addition, two midterm examinations and one final examination were given in each course.

Moreover, when active learning and teaching is practised in lecture halls, group-based activities and interactions were expected to be limited. For instance, when the instructor and TAs circled around to answer students' questions during in-class practice time, it would be difficult for them to reach students sitting in middle areas of each row. By contrast, the physical environment of active learning classrooms is much easier for communication among peers and instructors. This study intentionally did not do anything to overcome the physical barriers of lecture halls, in order that the physical advantages of active learning classrooms over lecture halls could be accurately tested.

Results

Participants

A descriptive summary of the 148 participants is presented in Table 1. One-way MANOVA was used to examine group differences in terms of gender, age and whether a student was majoring in computer science. The Bonferroni correction was applied to significance levels

Table 1 Descriptive summary for participants

Attributes	Course One	Course Two	Course Three
Number of students	65	42	41
Gender (binary)			
Male (%)	58.5	81	56.1
Female (%)	41.5	19	43.9
Major (binary)			
CS major (%)	30.8	35.7	43.9
Non-CS major (%)	69.2	64.3	56.1
Age (continuous)			
Mean value	19.88	20.86	19.41

Course One Conventional classroom + Traditional lecture; *Course Two* Conventional classroom + Active Learning and Teaching; *Course Three* Active learning classroom + Active Learning and Teaching to avoid possibly false positive results given that there were more than two comparisons over the same groups. The adjusted significance levels were:

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

Between-subject effects did not show any significant group difference in terms of gender [$F(2, 145)=3.72$, $p=0.026$] or major [$F(2, 145)=3.63$, $p=0.029$]. However, a significant difference in terms of age [$F(2, 145)=4.46$, $p=0.013*$] was found. Participants enrolled in Course Two were older than their counterparts in the other two courses. Given that students did not have prior knowledge of different set-ups for the three sections before course registration, this difference probably was random.

Academic performance

Examination results (two mid-term and one final) were collected as measures of student academic performance. Three 100-point examinations (two mid-terms and a final) developed by the instructor were given in all sections of the course to evaluate students' mastery of the learning content.

Repeated-measure MANCOVA was conducted to examine the effects of learning environments and pedagogical approaches on participants' performance in three examinations. Control variables included age, gender and whether students were majoring in computer science. To counter for the varied difficulty levels of examinations and enable cross-examination grade comparison, participants' grades were standardised for each examination prior to conducting MANCOVA. All two-way and three-way interactions among independent and control variables were examined.

Mauchly's test indicated that the assumption of sphericity had been met (χ^2 $(5)=0.95$, $p=0.62$). Using Pillai's trace, a significant three-way time-by-gender-by-pedagogy interaction ($p<0.01$) was found, indicating that further examination was needed for the three individual variables. Between-group effects of all attributes on examination results (see Table 2) further confirmed the significance of pedagogical approaches ($p<0.01$).

Table 2 Between-group effects of all attributes and their interactions on examination results

Attributes	Mean square	*F*	Significance level
Age	8.00	3.87	0.05
Major	6.19	2.99	0.09
Gender	2.52	1.22	0.27
Env	4.58	2.21	0.14
Ped	11.15	5.39	0.02*
Major × Gender	0.14	0.07	0.80
Major × Env	0.09	0.04	0.83
Major × Ped	4.65	2.25	0.14
Gender × Env	0.86	0.42	0.52
Gender × Ped	10.40	5.03	0.03*
Major × Gender × Env	1.52	0.74	0.39
Major × Gender × Ped	0.64	0.31	0.58

Major Whether majoring in computer science; *Ped* Pedagogical approaches; *Env* Active learning environments

The MANCOVA was followed up with discriminant analysis, which revealed two discriminant functions. The first explained 94.6% of the variance (canonical $R^2=0.06$), whereas the second explained only 5.4% (canonical $R^2=0.004$). In combination, these discriminant functions significantly differentiated Course Two from Course One and Course Three ($\Lambda=0.92$, $\chi^2=12.86$, $p=0.045$; see Fig. 2). But removal of the first function indicated that the second function did not significantly differentiate Course One and Course Three ($\Lambda=0.995$, $\chi^2=0.72$, $p=0.698$; see Fig. 2). In other words, a significant difference existed when active learning and teaching is adopted as the learning and teaching method, but no significant difference was observed despite the learning environment differences.

Participation rate

The results of attendance checking each day across the three courses were taken as the student participation rate. The average participation rate is summarised in Table 3. It is worth noting that Course Three had the highest participation rate.

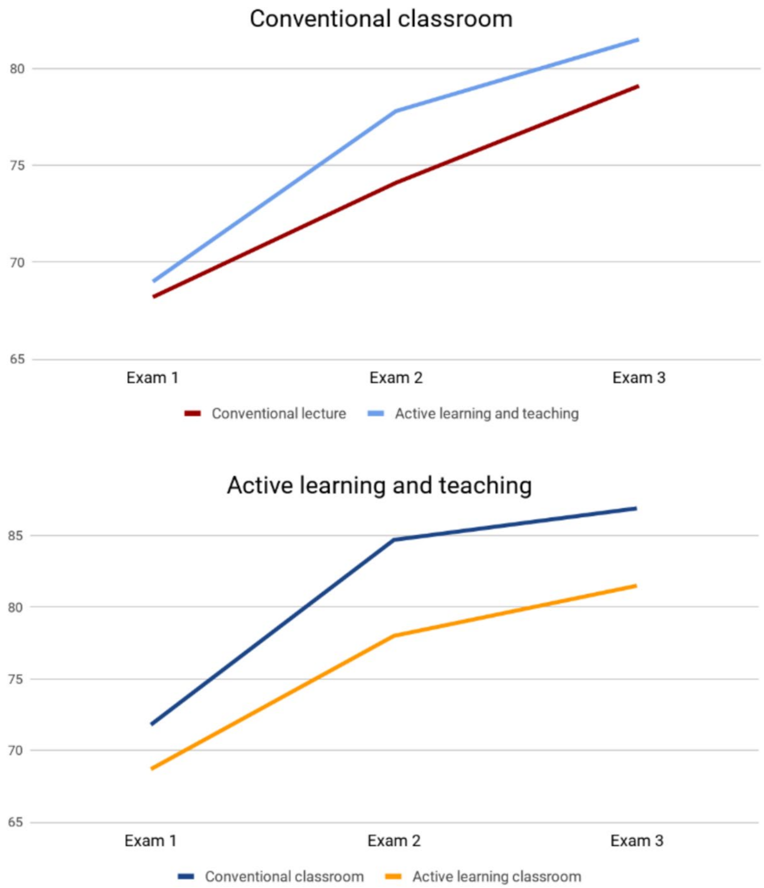

Fig. 2 Effects of active learning and teaching and active learning environment on students' academic performance

Table 3 Participation rate comparison across three courses

Statistic	Course One	Course Two	Course Three
Average participation rate (%)	76.92	88.10	92.68
Standard deviation	2.56	4.91	4.21

Course One Conventional classroom + Traditional lecture; *Course Two* Conventional classroom + Active Learning and Teaching; *Course Three* Active learning classroom + Active Learning and Teaching

When one-way ANOVA was conducted to compare participations rate across the three courses, a significant difference was found [$F(2, 145) = 4.5$, $p = 0.03$*]. Follow-up *t*-tests indicated that the participation rate of Course Three was significantly higher than Course One [$t(102) = 2.76$, $p = 0.03$], but not significantly higher than Course Two [$t(69) = 1.89$, $p = 0.06$].

Confidence, motivation and attitude towards taking computer science courses

A pre- and post-survey design was used to measure the changes in participants' confidence, achievement goals and attitude towards taking computer-science courses. 142 participants completed both the pre- and post-surveys. The survey (see "Appendix") was composed of two sections: Section I developed by the author measured participants' confidence in solving technical problems and attitude towards taking computer science courses; Section II was the Achievement Goal Questionnaire-Revised, which was developed and validated by Elliot and Murayama (2008) and measures four aspects of motivation, including mastery-approach, mastery-avoidance, performance-approach and performance-avoidance motivation (Hao et al. 2017). The survey was distributed in the first and last weeks for all three courses.

Survey validation

Confirmatory factor analysis was conducted to validate Section I of the survey, using maximum likelihood estimations on the covariance matrix. Four indices, including Chi-square over degrees of freedom ratio (χ^2/df), comparative fit index (CFI), incremental fit index (IFI), and root-mean-square error of approximation (RMSEA), were used to evaluate the model fit. The results (χ^2/df = 3.09, CFI = 0.967, IFI = 0.967, RMSEA = 0.1) indicated that model fit was acceptable.

Principal component analysis was conducted to collapse the survey results into five factors, including (1) attitude towards taking computer science courses, (2) confidence in solving technical problems, (3) mastery-approach goals, (4) mastery-avoidance goals and (5) performance-avoidance goals. The reliability of each factor and average factor scores of each participant group are presented in Table 4. A Cronbach alpha coefficient above 0.55 can be acceptable for social science research (Ziegel 1995). Therefore, five factors from this survey, including confidence, attitude, mastery-approach goal, mastery-avoidance goal and performance-avoidance goal, are sufficiently reliable. The Cronbach alpha of performance-approach goals was lower than 0.55 for both pre- and post-surveys and so can be considered unreliable. Therefore, performance-approach goals were excluded from further data analysis.

Table 4 Between-group effects of all attributes and interactions on examination results

Attributes	Cronbach's α	Course One	Course Two	Course Three
Pre-survey				
Attitude	0.843	0.043	0.003	– 0.089
Confid	0.721	0.133	– 0.095	– 0.166
MApp	0.588	0.016	0.031	– 0.064
MAvd	0.578	0.128	– 0.243	0.002
PApp	0.383	0.096	– 0.110	– 0.076
PAvd	0.734	0.027	– 0.100	0.053
Post-survey				
Attitude	0.850	– 0.058	– 0.153	0.277
Confid	0.813	0.058	– 0.214	0.110
MApp	0.743	– 0.048	0.050	0.042
MAvd	0.657	0.104	– 0.090	– 0.113
PApp	0.509	0.063	– 0.093	– 0.028
PAvd	0.773	0.057	– 0.015	– 0.098

Course One Conventional classroom + Traditional lecture; *Course Two* Conventional classroom + Active Learning and Teaching; *Course Three* Active learning classroom + Active Learning and Teaching

Attitude Attitude towards taking computer science courses; *Confid* confidence in solving technical problems; *MApp* mastery-approach goals; *MAvd* mastery-avoidance goals; *PApp* performance-approach goals; *PAvd* performance-avoidance goals

Repeated-measures MANCOVA

Repeated-measure MANCOVA was conducted to examine the effects of active learning environment and active learning and teaching on the five factors of (1) attitude towards taking computer science courses, (2) confidence in solving technical problems, (3) mastery-approach goals, (4) mastery-avoidance goals and (5) performance-avoidance goals. When the Bonferroni correction was applied to the significance levels to avoid possibly false positive results, the adjusted significance levels were:

$*p < 0.01$; $**p < 0.002$; $***p < 0.0002$

The control variables were age, gender and whether students were majoring in computer science. All two-way and three-way interaction among independent and control variables were examined.

Using Pillai's trace, whether students were majoring in computer science ($p < 0.01$) was the only variable that was found significant. Both active learning environment ($p = 0.92$) and active learning and teaching ($p = 0.61$) were nonsignificant on the five factors. Separate univariate ANOVAs showed that whether students were majoring in computer science had a significant influence on students' attitudes towards taking computer science courses [$F(1, 129) = 17.97$, $p = 0.000$] and confidence of solving technical problems [$F(1, 129) = 12.15$, $p = 0.00$]. Students majoring in computer science showed significantly higher confidence and were more willing to take further computer science courses in the future (see Fig. 3).

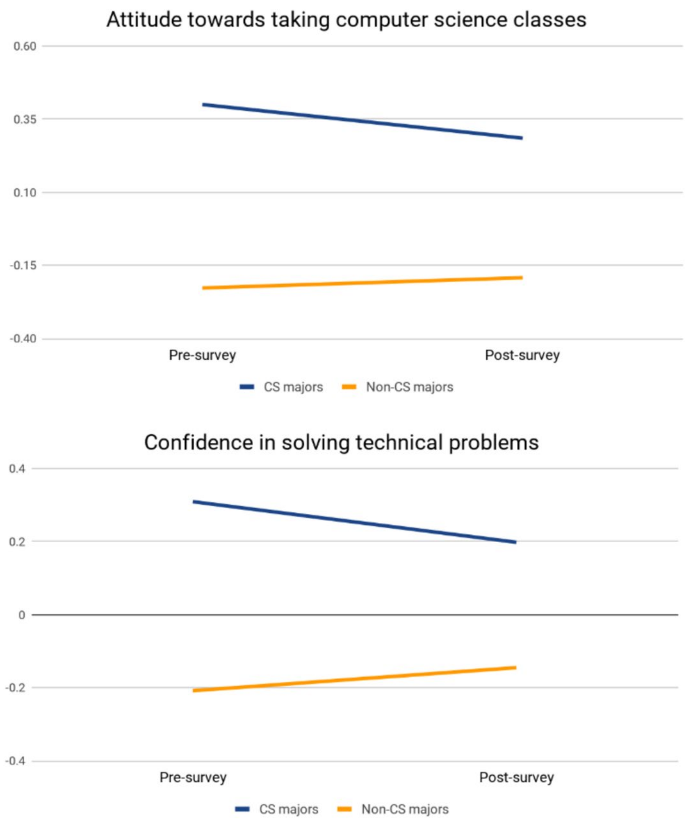

Fig. 3 Effects of majoring in computer science on students' attitude towards taking computer science courses and confidence in solving technical problems

Discussion

Do active learning environments positively affect student learning computer science?

The hypothesis that learning environments can either encourage or hinder knowledge construction (Whiteside et al. 2010) is well accepted by many educators. Undoubtedly, active learning and teaching can be conducted more easily in an active learning classroom than in a lecture hall with chairs bolted in place. However, questions about how significant the influence of learning environments are has not been well answered by prior studies because of methodological or experimental limitations. Two notable limitations in previous work on learning environments include lack of controls and misusing statistical modeling (e.g. Baepler et al. 2014; Brooks 2011; Cotner et al. 2013; Dori and Belcher 2005; Gaffney et al. 2008; Hao et al. 2018).

With a three-group design and proper statistical modelling, this study successfully separated the effects of learning environments from pedagogical approach. As anticipated, active learning and teaching was significantly beneficial to computer science students' academic performance. However, when controlling other variables, especially the pedagogical approach, learning environments did not show a significant influence on student gains. Although students studying in active learning classrooms tended to attend the course more frequently and perform better than their counterparts in lecture halls, the difference was not found to be significant. It is worth noting that, by only looking at Courses One and Three, it is tempting to conclude that active learning classrooms significantly improved computer science students' academic performance and participation rate. However, such a conclusion is misleading because pedagogical approaches should not be confused with physical learning environments.

In contrast to conclusions of prior studies, the findings of this study invite more reflections on the effects of learning environments on students. Physical learning environments indeed might encourage or hinder knowledge construction, but to a much more limited extent than expected. Therefore, it is important for educators to understand that simply putting students in active learning classrooms might not bring intended effects. Pedagogical approach, on the other hand, should be further stressed, even in a conventional classroom that is less ideal for active learning.

Additionally, neither active learning environment nor active learning and teaching showed significant effects on students' confidence, motivation and attitude towards taking more computer science courses. Perhaps one semester was not long enough for the two factors to manifest effects on confidence or motivation. Confirming the findings of prior studies (Shell and Soh 2013), a significant difference was found between computer science majors and non-majors. A longitudinal study could be needed to further investigate the relation among learning environments, pedagogical approaches, and the confidence and motivation of computer science students.

Is investment in active learning classrooms worthwhile?

The question of whether active learning classrooms are worth investment is of interest to both educators and school administrators. Most classrooms across large public colleges in the United States are conventional; either building new active learning classrooms or upgrading current classrooms to active learning ones requires considerable resources. For instance, Park and Choi (2014) reported that upgrading a conventional classroom at their institution to an active one with 30 seats cost $100,000. Active learning classrooms undoubtedly make it easier for teachers to practice active teaching and learning, but a decision to invest in such classrooms needs to be based on careful cost-and-benefit analysis. The findings of this study contribute important information to such analysis.

This study suggests that pedagogical approaches are more critical than learning environments for student gains. Simply putting students in active learning classrooms does not make them different from their counterparts in conventional classrooms. What truly makes a difference is the adopted pedagogical approaches of a course. Even in a conventional classroom, active learning and teaching is significantly beneficial to students. Therefore, investment in promoting active learning and teaching and building active learning and teaching communities among teaching faculty might be a better investment than active learning classrooms, especially for institutions with limited budget and resources.

Limitations

The present study is not without limitations. Because all participants came from the same institution, the generalisability of the findings needs further examination. Replication studies in other fields, such as biology and mathematics, with at least two control groups are in need to further confirm the findings of this study. In addition, prior knowledge of students was not controlled in this study. Our research was conducted in the first introductory computer-science course. Because most students in this course had never taken any computer-science course before, their prior knowledge was not controlled. Future replication studies in other fields could consider controlling students' prior knowledge level, especially for courses that have a list of prerequisites.

Conclusions

Active learning environments have gained substantial attention from different academic fields and institutions. In contrast to prior studies, this research revealed that active learning and teaching has a significantly beneficial influence on computer science students' academic achievements, but active learning environments do not. The findings of this study contribute to the literatures of both computer science education and learning environments, and invite more debate on the important question of whether investment in active learning classrooms is worthwhile. To build upon this research, we call for more replication studies in other academic fields at the college level.

Appendix: Survey

Section I Attitude towards taking computer science courses

1. I like programming
13. I like computer science
12. I am looking forward to taking more Computer Science courses

Confidence

17. I am confident in my technical knowledge
11. I am confident in my programming skills
10. I am confident in my capability of learning new technical skills

Section II Achievement goal questionnaire-revised

Mastery-approach goal

16. My aim is to completely master the material presented in this class
18. I am striving to do well compared with other students
9. My goal is to learn as much as possible

Master-avoidance goal

2. My aim is to perform well relative to other students
7. My aim is to avoid learning less than I possibly could
8. My goal is to avoid performing poorly compared with others

Performance-approach goal

3. I am striving to understand the content as thoroughly as possible
14. My goal is to perform better than the other students
4. My goal is to avoid learning less than it is possible to learn

Performance-avoidance goal

5. I am striving to avoid performing worse than others
15. My aim is to avoid doing worse than other students
6. I am striving to avoid an incomplete understanding of the course material

Likert responses: SA, A, N, D, SD

References

Baepler, P., Walker, J. D., & Driessen, M. (2014). It's not about seat time: Blending, flipping, and efficiency in active learning classrooms. *Computers and Education, 78,* 227–236.

Baldwin, D. (1996). Discovery learning in computer science. *ACM SIGCSE Bulletin, 28*(1), 222–226.

Barkley, E. F., Cross, K. P., & Major, C. H. (2014). *Collaborative learning techniques: A handbook for college faculty*. New York: Wiley.

Beck, L. L., & Chizhik, A. W. (2008). An experimental study of cooperative learning in CS1. *ACM SIGCSE Bulletin, 40*(1), 205–209.

Brooks, D. C. (2011). Space matters: The impact of formal learning environments on student learning. *British Journal of Educational Technology, 42*(5), 719–726.

Carter, A. S., & Hundhausen, C. D. (2011). A review of studio-based learning in computer science. *Journal of Computing Sciences in Colleges, 27*(1), 105–111.

Cotner, S., Loper, J., Walker, J. D., & Brooks, D. C. (2013). "It's not you, it's the room"—Are the high-tech, active learning classrooms worth it? *Journal of College Science Teaching, 42*(6), 82–88.

Crouch, C. H., & Mazur, E. (2001). Peer instruction: Ten years of experience and results. *American Journal of Physics, 69*(9), 970–977.

Dori, Y. J. (2007). Educational reform at MIT: Advancing and evaluating technology-based projects on- and off-campus. *Journal of Science Education and Technology, 16*(4), 279–281.

Dori, Y. J., & Belcher, J. (2005). How does technology-enabled active learning affect undergraduate students' understanding of electromagnetism concepts? *The Journal of the Learning Sciences, 14*(2), 243–279.

Elliot, A. J., & Murayama, K. (2008). On the measurement of achievement goals: Critique, illustration, and application. *Journal of Educational Psychology, 100*(3), 613.

Gaffney, J. D., Richards, E., Kustusch, M. B., Ding, L., & Beichner, R. J. (2008). Scaling up education reform. *Journal of College Science Teaching, 37*(5), 48–53.

Greer, T., Hao, Q., Jing, M., & Barnes, B. (2019). On the effects of active learning environments in computing education. In *Proceedings of the 50th ACM Technical Symposium on Computer Science Education* (pp. 267–272).

Hakimzadeh, H., Adaikkalavan, R., & Batzinger, R. (2011). Successful implementation of an active learning laboratory in computer science. In *Proceedings of the 39th Annual ACM SIGUCCS Conference on User Services* (pp. 83–86).

Hao, Q., Barnes, B., Wright, E., & Branch, R. M. (2017). The influence of achievement goals on online help seeking of computer science students. *British Journal of Educational Technology, 48*(6), 1273–1283.

Hao, Q., Barnes, B., Wright, E., & Kim, E. (2018). Effects of active learning environments and instructional methods in computer science education. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education* (pp. 934–939).

Horwitz, S., Rodger, S. H., Biggers, M., Binkley, D., Frantz, C. K., Gundermann, D., et al. (2009). Using peer-led team learning to increase participation and success of under-represented groups in introductory computer science. *ACM SIGCSE Bulletin, 41*(1), 163–167.

Hu, H. H., & Shepherd, T. D. (2014). Teaching CS 1 with POGIL activities and roles. In *Proceedings of the 45th ACM Technical Symposium on Computer Science Education* (pp. 127–132).

McConnell, J. J. (2005). Active and cooperative learning: Tips and tricks (part I). *ACM SIGCSE Bulletin, 37*(2), 27–30.

Oliver-Hoyo, M. T., Allen, D., Hunt, W. F., Hutson, J., & Pitts, A. (2004). Effects of an active learning environment: Teaching innovations at a research I institution. *Journal of Chemical Education, 81*(3), 441.

Park, E. L., & Choi, B. K. (2014). Transformation of classroom spaces: Traditional versus active learning classroom in colleges. *Higher Education, 68*(5), 749–771.

Porter, L., Bailey Lee, C., & Simon, B. (2013, March). Halving fail rates using peer instruction: A study of four computer science courses. In *Proceeding of the 44th ACM Technical Symposium on Computer Science Education* (pp. 177–182).

Porter, L., Bailey Lee, C., Simon, B., & Zingaro, D. (2011). Peer instruction: Do students really learn from peer discussion in computing? In *Proceedings of the Seventh International Workshop on Computing Education Research* (pp. 45–52).

Shell, D. F., & Soh, L. K. (2013). Profiles of motivated self-regulation in college computer science courses: Differences in major versus required non-major courses. *Journal of Science Education and Technology, 22*(6), 899–913.

Simon, B., Kohanfars, M., Lee, J., Tamayo, K., & Cutts, Q. (2010). Experience report: Peer instruction in introductory computing. In *Proceedings of the 41st ACM Technical Symposium on Computer Science Education* (pp. 341–345).

Timmerman, B., & Lingard, R. (2003). Assessment of active learning with upper division computer science students. In *Proceedings of 2003 Frontiers in Education (FIE 2003).*

Whiteside, A., Brooks, D. C., & Walker, J. D. (2010). Making the case for space: Three years of empirical research on learning environments. *Educause Quarterly, 33*(3), 11–20.

Ziegel, E. R. (1995). Tie series analysis, forecasting, and control. *Technometrics*, *37*(2), 238–242.