Peer Instruction for Undergraduate Data Science Education in India– A Collaborative Pilot Study

Geetha Jenifel M

First Author: M. Geetha Jenifel, Ph.D, Assistant Professor, Department of Data Science and Business Systems, SRM Institute of Science and Technology jenifel.it@gmail.com, Orcid: 0000-0002-0961-3722 Second Author: Bhuvana Gopal, Ph.D, Assistant Professor of Practice School of Computing University of Nebraska–Lincoln bhuvana.gopal@unl.edu, Orcid: 0000-0002-1796-2789. Third Author: Byrav Ramamurthy, Professor, School of Computing University of Nebraska–Lincoln

Dr. Bhuvana Gopal, University of Nebraska - Lincoln

Dr. Bhuvaneswari (Bhuvana) Gopal is an Assistant Professor of Practice in the School of Computing at the University of Nebraska-Lincoln where she teaches Software Engineering, Software Security in Practice, the industry internship course, and leads the Learning Assistant Program that serves several computing courses at the School of Computing. Dr. Gopal is a College of Engineering Teaching Fellow at UNL. Dr. Gopal has extensive experience in the software industry, where she spent 14 years in various roles, including Software Architect and Lead software engineer positions before switching to full time academia. She is also a Microsoft certified professional, with an MCPD certification. Her research work is focused on evidence-based, active learning pedagogies to improve software engineering education. She has published papers specifically on Peer Instruction and Process Oriented Guided Inquiry-based Learning-like pedagogical approaches in the undergraduate software engineering classroom, both in person and virtual. She holds a Bachelors degree in Physics from the University of Madras, Chennai, India. She holds two Masters degrees - one in Computer Science from the University of Nebraska-Lincoln, and one in Medical Physics from Anna University, Chennai, India. She holds a Ph.D. in Computer Science from the University of Nebraska-Lincoln.

Byrav Ramamurthy, University of Nebraska - Lincoln

Byrav Ramamurthy is currently a Professor in the Department of UNL School of Computing at the University of Nebraska-Lincoln (UNL). He is the author of the book "Design of Optical WDM Networks - LAN, MAN and WAN Architectures" and a co-author of the book "Secure Group Communications over Data Networks" published by Kluwer Academic Publishers/Springer in 2000 and 2004 respectively. He served as the Chair of the IEEE Communication Society's Optical Networking Technical Committee (ONTC) during 2009-2011. He served as the IEEE INFOCOM 2011 TPC Co-Chair. He is currently the Editor-in-Chief for the Springer Photonic Network Communications (PNET) journal.

His research areas include optical and wireless networks, peer-to-peer networks for multimedia streaming, network security and telecommunications. His research work is supported by the U.S. National Science Foundation, U.S. Department of Energy, U.S. Department of Agriculture, NASA, AT&T Corporation, Agilent Tech., Ciena, HP and OPNET Inc.

Peer Instruction for Undergraduate Data Science Education in India– A Collaborative Pilot Study

Abstract

This paper describes the adoption of Peer Instruction (PI) in an undergraduate Data Science classroom, at the School of Computing at a large University in southern India. During PI, students actively participate in their learning through small group peer discussions in real time while they answer conceptual questions posed by the instructor. This research work is one of the results of a week-long hands-on workshop conducted by American engineering educators introducing Peer Instruction (PI), an active teaching-learning pedagogy, to the academic context in India. In this international collaborative work, we studied the effectiveness of PI as a pedagogy for teaching the Fundamentals of Data Science in an in-person undergraduate Data Science and Business Systems classroom in a large University in southern India. Several studies on PI in engineering courses exist, but very few studies focus on PI in the topic of Data Science Business Systems in general and/or Fundamentals of Data Science in particular. The main research question in this pilot study focuses on comparing correctness gains for students learning Fundamentals of Data Science through Peer Instruction and lecture-based instruction. Traditional lecture-based teaching was conducted in the academic year 2023-2024(one semester). PI-based teaching was conducted in the academic year 2024-2025(one semester). Ten PI questions were developed for Fundamentals of Data Science. Pre and Post-course surveys were conducted through Google Forms. This paper analyses 48 students' responses to determine if PI has helped students learn and recognize the fundamentals of data science more effectively than lectures. The results show significant correctness gains for students with PI over lectures. Average answer correctness for students improved from 2.38 to 9.29 out of a possible maximum of 10. Statistical significance of student scores was compared using ANOVA tests. We found a statistically significant correlation between using PI and improved student scores, than through traditional lectures. PI as an approach seemed to have helped students obtain clarity in their understanding, and seemed to have leveraged the social aspect of learning, as students often seemed to find explanations from peers more relatable and easier to understand than those from instructors.

1. Introduction

Peer Instruction (PI), an active learning method, has attracted interest from the computing education community in recent years [1]. PI emphasizes active student participation through discussions, encouraging students to answer and debate multiple-choice questions. This approach typically involves collecting real-time feedback from students using response systems during class to enhance their understanding of the topic.

Teaching Data Science

The field of Data Science education has gained significant attention in recent years due to the increasing demand for data-driven decision-making across industries. Several studies and frameworks have been proposed to enhance the teaching and learning of Data Science at various levels, including undergraduate, graduate, and professional training programs. Data Science plays a crucial role in Computer Science and Engineering (CSE) by integrating statistical analysis, machine learning, and big data technologies to extract insights from large datasets. It involves various computational techniques such as data preprocessing, visualization, predictive modelling, and artificial intelligence. In CSE, Data Science is applied in areas like natural language processing, image recognition, cybersecurity, and recommendation systems. Programming languages like Python, R, and SQL, along with frameworks such as TensorFlow and PyTorch, are commonly used in data-driven applications. With the growing demand for data-driven decision-making, Data Science has become a vital field in CSE, offering opportunities in research, industry, and innovation across multiple domains.

Data Science combines concepts from statistics, computer science, and domain-specific knowledge, making it challenging to design interdisciplinary curriculum [2]. There is an ongoing debate on the appropriate mix of theoretical foundations (e.g., statistics, machine learning) and hands-on skills (e.g., programming, data wrangling) [3]. The field continuously changes with new tools like Python, R, TensorFlow, and cloud computing platforms, making it difficult for educators to maintain up-to-date courses [4]. These factors also make teaching Data Science a difficult endeavour.

This paper explores whether teaching Data Science principles to computing majors—such as Computer Science (CS), Computer Engineering (CE), and Big Data Analytics (BDA)—would be more effective using PI rather than traditional lecture-based methods. To assess student learning, pre- and post- surveys were conducted with a purely lecture based classroom in one semester, and a PI based classroom in the next semester. Our goal was to examine whether PI helped students learn Data Science better than purely lecture based instruction.

The remainder of the paper is structured as follows: Section II reviews related literature, while Section III outlines the survey design and methodology in this study. Section IV presents the results. Section V discusses these results, and explores threats to the validity of this study. Section VI explores future research directions and concludes.

2. Related Literature

This paper examines two key topics: Data Science principles related to Big Data Analytics, and Peer Instruction (PI), an active learning pedagogy centered on small group discussions. Accordingly, this section explores previous research on both subjects within the context of teaching Computer Science (CS), Computer Engineering (CE), and Big Data Analytics (BDA).

Peer Instruction in Computer Science and Engineering

In this section we present related literature pertaining to Peer Instruction in the context of teaching Computer Science (CS) and Computer Engineering (CE). Several studies advocate for real-world projects as an effective way to engage students and reinforce learning [5]. Interactive teaching techniques, such as flipped classrooms, coding labs, and group discussions, have been shown to improve student engagement and retention of concepts [6]. Gopal and Cooper [7] replicated their research in an online learning environment, examining the effectiveness of PI in teaching software testing and continuous integration remotely. The replication study confirmed that PI remains effective in online settings, maintaining high levels of student engagement and learning outcomes.

Research has examined how student discussions, prompted by in-class multiple-choice questions, contribute to learning and how this learning is reflected in final exam performance in introductory Computer Science courses [8 -10]. Several studies have explored the application of PI in CS education, with notable contributions from Porter, Cutts, and Simon [8-14]. These studies have established a statistically significant relationship between improved in-class performance due to PI and final exam results. PI has been successfully implemented in both introductory CS courses and cybersecurity education [14,15]. Porter and his team conducted studies that provided empirical evidence supporting the efficacy of peer instruction in computing education [16-19]. In Peer Instruction (2017), the original researcher who devised PI, Mazur [20] provides an in-depth discussion on the theoretical foundations, implementation strategies, and empirical evidence supporting PI's effectiveness in improving conceptual understanding and student engagement.

Gopal and Cooper studied PI in the context of software engineering, and their study contributes to the growing body of evidence supporting active learning methodologies in computer science education, particularly in the realms of software testing and DevOps [21, 22]. Their findings suggest that PI can be successfully adapted to online synchronous environments, with careful consideration of technological tools and instructional design [23-25]. Cutts, Esper, and Simon [26] observed that students reported gaining core skills applicable beyond computing, such as problem-solving and analytical thinking. These outcomes suggest that a well-structured computing course can contribute significantly to a student's overall education.

Peer Instruction - Indian Context

In this section we present related literature pertaining to Peer Instruction in the Indian context, as our study was conducted in India. Rajaputra [27] and his team examined the effectiveness of peer tutoring in enhancing learning among first-year engineering students. The 2001 study by Ramaswamy, Harris, and Tschirner [28] introduced an innovative instructional method in a senior paper science and engineering class, focusing on student peer teaching to enhance problem-solving skills and deepen material comprehension.

As we can see from the studies above, there are several studies that delineate the implementation of PI and PI like techniques. However, there is a lack of literature on active learning in Data Science particularly PI, and our study is focused on implementing PI in the Data Science classroom.

Research Questions

This paper presents a study involving undergraduate students in a Fundamentals of Data Science (FDS) class where PI was implemented. The study aims to address one primary research question:

RQ1: Does PI enhance students' understanding of the fundamentals of Data Science more effectively than a traditional lecture-based approach?

3. Survey Design and Methodology

We set up a quasi-experimental study with two groups of students at a large University in Southern India. The treatment group and control group were made up of consecutive cohorts of honors sophomore students belonging to different majors including Blockchain Technology, Gaming Technology, Computer Engineering, Humanities and Science, Business and Math. This Data Science course was a compulsory component of their cohort-based program. The control group was instructed using traditional lectures. The treatment group was instructed using PI. The control group and treatment group were both taught in successive semesters by the same instructor with the same content. There were 48 students in the treatment group and 45 students in the control group.

Reasoning instrument – pre/post course surveys

The reasoning section of the surveys included 10 questions from fundamentals of data science, administered using Google Forms. To both groups, we administered a set of identical short answer questions at the commencement of the course (Pre-course survey) and again at the culmination of the course (Post-course survey). The authors of this paper created our own set of questions. Students were not rewarded for responding to the pre- and post-course surveys. A detailed rubric guided the grading process, assigning one point for each correct answer and zero points for incorrect ones. There were three sub sections in the reasoning section – Remember, Understand, and Apply, based on Bloom's taxonomy [11]. While formulating questions for the Pre- and Post- survey, we ensured that each question is challenging enough to spark discussion and requires more than rote memorization.

Questions at the Remember level

Q1. Which method supports deleting a column in Pandas?

Q2. Groupby() command is the aggregation of the following operations.

Q3. Which function is used to create a violin plot in Seaborn?

Q4. Which function takes three arguments to describe the layout of the figure?

Q5. Which module is used for data visualization in Python?

Questions at the Understand level

Q6. Which of the following is NOT a type of plot available in Seaborn?

Q7. Which encoding is not suitable for categorical data?

Questions at the Apply level

Q8. How do you set the title of a plot in Matplotlib?

Q9. df.iloc[:, 0:2] is used to select which of the following?

Q10. How do you plot a simple line graph using Matplotlib in Python?

Workflow of PI in Data Science

Pre-class Preparation: We utilized a flipped classroom approach [14,29] and shared required readings, videos and tutorials covering the topic (e.g., regression analysis, machine learning, or data visualization) with students prior to the class session. Students were required to prepare themselves for the class session using these materials.

Class Structure: During class, we implemented PI. We used the format of PI implementation detailed by Porter [16-18], Simon [19] and Gopal [21-25]. After each mini lecture, we posed a conceptual question related to the topic (e.g., " Which encoding is not suitable for categorical data?"). We asked students to answer the question individually by raising hands.

PI Group Discussion: Then we organized students into small groups (2–4 members) to discuss their answers and encouraged students to explain their reasoning and persuade their peers if their answers differ. After the discussion, we had students answer the same question again, counting answers by show of hands again. Improved accuracy indicates successful peer learning. Then the instructor summarized the correct answer and clarified common misconceptions, using visual aids or coding demos to deepen understanding (e.g., showing scatterplots to explain overfitting).

Apply Concepts to Data Science Problems: For apply level questions, we assigned a task, such as building a predictive model, cleaning data, and visualizing a dataset to every student. Student's groups have shared their solutions with the class and comparing approaches.

Post-Class Follow-Up: We provided a recap of the session and assigned homework to reinforce the concepts (e.g., analysing a dataset independently or writing code to implement a specific algorithm).

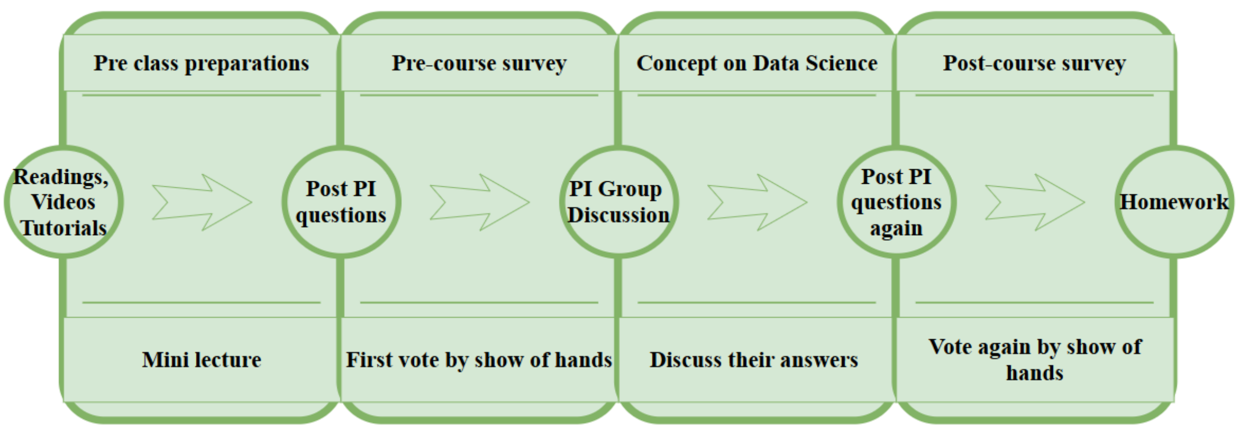

Fig. 1. Workflow of Peer Instruction on Fundamentals of Data Science

Equations

This structured PI approach integrates active participation, collaborative learning, and follow-up tasks to enhance understanding of data science concepts. The students were taught using PI in five sessions. In each session, multiple PI (Peer Instruction) questions were posed to students.

These questions were integrated throughout the lecture to encourage continuous engagement, discussion, and deeper understanding of the concepts being taught. PI (Peer Instruction) was not used for half of the semester, and traditional lectures were used for the other half to allow a clear and fair comparison of the two teaching methods within the same cohort. This approach helps isolate the impact of PI by minimizing variability between different groups of students. these materials.

In this approach, in-class questions used during Peer Instruction did not directly contribute to assessments. They were designed to promote engagement, understanding, and discussion rather than for grading purposes. A pre/post survey was chosen to measure the impact of the Peer Instruction (PI) intervention because it allows for a focused evaluation of changes in students' conceptual understanding, attitudes, and perceptions specifically related to the teaching method. Unlike course assessments or exams—which may test a broad range of skills and content not directly tied to the intervention—the survey was designed to isolate and measure the specific effects of PI on learning and engagement. We show a pictorial representation of the PI workflow we adopted in our class is shown in figure 1. The workflow of traditional lecture on control group is shown in figure 2.

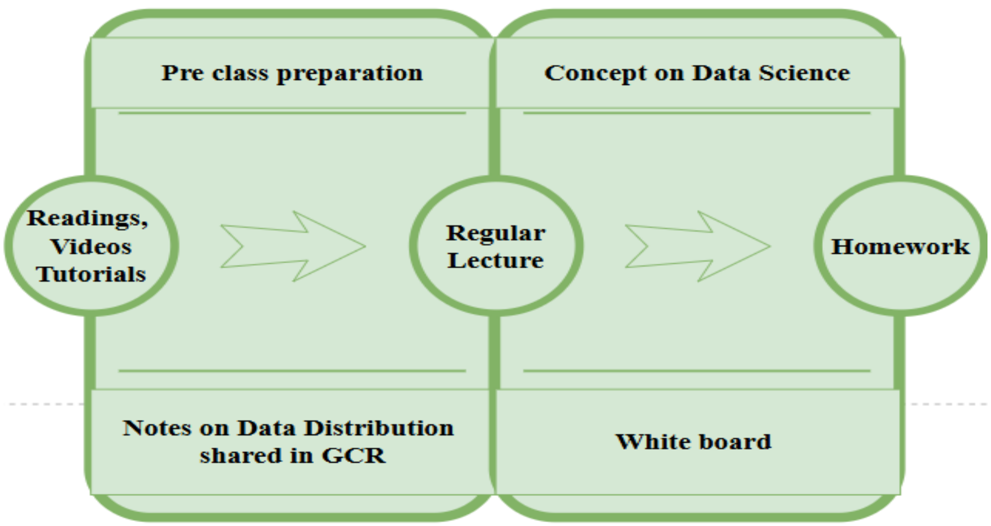

Fig. 2. Workflow of traditional lecture on control group.

4. Results

Statistical analysis

Pre-survey and Post-survey scores for PI were analyzed using a one-way ANOVA, with a significance level of 0.05. The response score data for each question were analyzed for normality, revealing that the skewness of each distribution was close to zero. However, the kurtosis values fell outside the acceptable range for a normal distribution, and the shape of the curves also deviated from normality. Consequently, we conducted nonparametric one-way analysis of variance tests on four distributions: pre-control vs. pre-treatment, pre-control vs. post-control, pre-treatment vs. post-treatment, and post-control vs. post-treatment.

Using group information as a categorical variable indicating different groups (e.g., control vs. experimental), we conducted within-groups analysis which involved a comparison of Pre-survey and Post-survey scores for the same group. Again, we conducted between-groups analysis, comparing Post-survey scores for the control group and treatment group. To this end, we employed a F-test one way ANOVA for our data analysis.

We observed that both groups showed improvements across all three categories, as shown in Table 1. The overall average scores for the treatment group increased substantially from 23.75% to 92.91%, whereas the control group demonstrated a much smaller increase, rising from 19.375% to 33.75%. Additionally, the cognitive gains in the treatment group were significantly greater than those in the control group for each of the three topics individually. The treatment group consisted of 48 students, while the control group had 45 students. Table 1 provides the percentage of students who answered each question correctly on the Pre- and Post-surveys. For instance, if 10 students in the treatment group answered Question 2 correctly on the Pre-survey, the percentage would be calculated as 10/25, or 0.4.

TABLE 1. PERCENTAGE OF STUDENTS WHO ATTENDED PRE SURVEY AND POST SURVEY

	Treatment Group (n=48)		**Control Group(n=45)**	
	Pre-survey responses	**Post-survey responses**	**Pre-survey responses**	**Post-survey responses**
Q1	17	47	8	19
Q2	13	46	11	16
Q3	6	31	6	13
Q4	10	46	9	12
Q5	11	46	12	18
Q6	14	45	12	20
Q7	11	46	11	19
Q8	9	47	7	13
Q9	9	45	7	15
Q10	14	47	10	17

Pre vs Post-survey results in control group

We found that there were few statistically significant differences in the overall pre and post survey scores for the control group. The detailed ANOVA results for the control group is as follows Sum of Squares (SS): total: 355.75, subjects: 97.25, time (Pre vs Post Effect): 238.05 and error: 20.45. Degrees of Freedom (df): total: 19, subjects: 9, time: 1and error: 9. Mean Squares (MS): time: 238.05 and error: 2.27 F-Ratio: 104.77 and P-Value: 2.95×10^{-6} (statistically significant). This suggests a strong significant difference between pre and post responses in the control group.

Pre vs Post-survey results in treatment group

We found that there were statistically significant differences in the overall pre and post survey scores for the treatment group. The detailed ANOVA results for the treatment group is as follows Sum of Squares (SS): total: 5812.00, subjects: 237.00, time (Pre vs Post Effect): 5511.20 and error: 63.80. Degrees of Freedom (df): total: 19, subjects: 9, time: 1and error: 9. Mean Squares (MS): time: 5511.20 and error: 7.09. F-Ratio: 777.44 and P-Value: 4.77×10^{-10} (highly statistically significant). This indicates a statistically significant difference between pre and post responses in the treatment group.

Pre-survey scores between the control and treatment groups

We found that there were no statistically significant differences in the overall Pre-survey scores between the control and treatment groups. The detailed ANOVA results for this case is as follows Sum of Squares (SS): total: 156.55, between groups: 22.05 and within groups: 134.50. Degrees of Freedom (df): total: 19, between groups: 1 and within groups: 18. Mean Squares (MS): between groups: 22.05 and within groups: 7.47. F-Ratio: 2.95 and P-Value: 0.103. Since the p-value is greater than 0.05, there is no statistically significant difference in pre-test scores between the control and treatment groups. This suggests that both groups started at a similar baseline before the intervention.

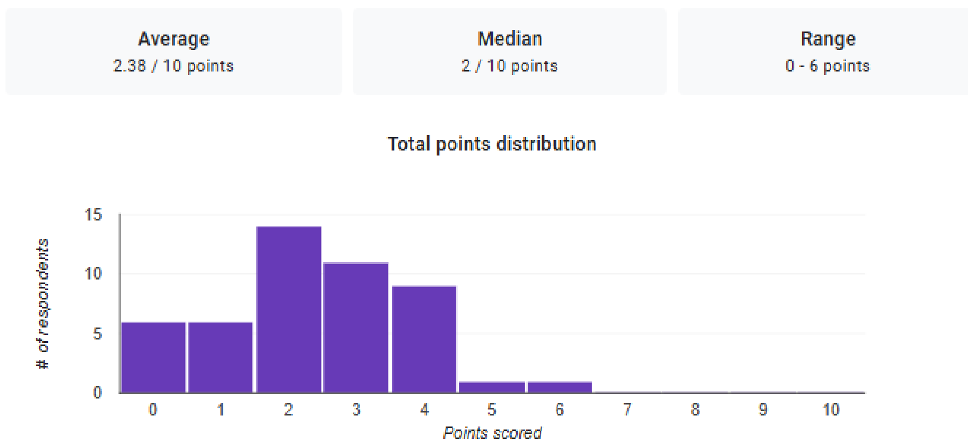

Fig. 3. Pre-survey results for treatment group

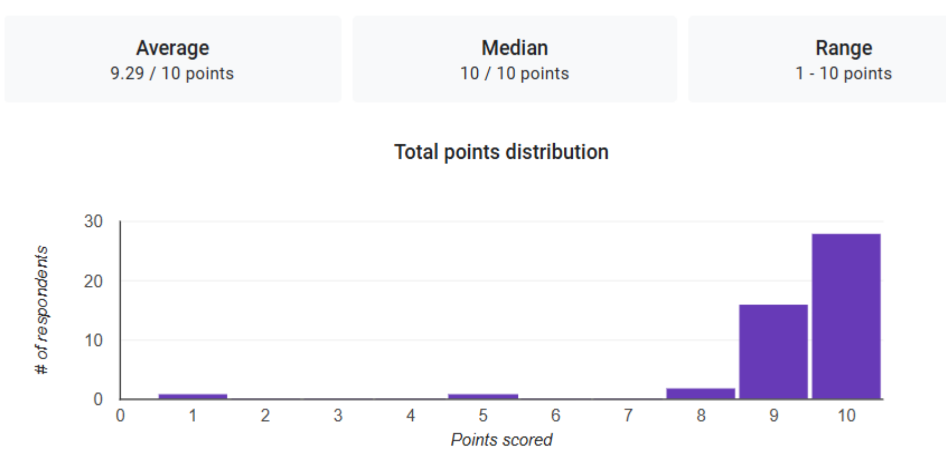

Fig. 4. Post-survey results for treatment group

Post-survey scores between the control and treatment groups

We found that there was a statistically significant difference in the overall Post-survey scores between the control and treatment groups. The detailed ANOVA results for this case is as follows Sum of Squares (SS): total: 4316.80, between groups: 4032.80 and within groups: 284.00. Degrees of Freedom (df): total: 19, between groups: 1 and within groups: 18. Mean Squares (MS): between groups: 4032.80, within groups: 15.78. F-Ratio: 255.60 and P-Value: 4.42×10^{-12} (highly statistically significant). This suggests that the intervention had a strong effect on the treatment group.

5. Discussion

Comparison with previous PI studies

The results showed significant score improvements in the PI class across all data dispersion concepts, with the greatest gains observed in understanding and apply level. We build upon the findings of Porter, Simon, and Lee [16-22], reaffirming that Peer Instruction (PI) has a positive impact on student learning and affect. While previous studies assessed learning gains during individual PI sessions (i.e., within a single class session), our study measured learning gains through Pre- and Post-surveys conducted at the beginning and end of the entire course. Unlike earlier research that focused on individual PI questions, we assessed learning using a custom test instrument. Prior studies employed isomorphic questions [17-19], whereas we utilized an identical pre- and post-course format, similar to the software engineering PI studies [15-17]. Additionally, the metrics used to calculate learning gains varied across studies [17, 19, 30], making direct comparisons between our results and earlier findings challenging. For example, normalized learning gain [17] in earlier studies was calculated as the difference between the group vote and the preceding individual vote during PI sessions. In contrast, our study measured score gains as the percentage of students who answered questions correctly.

Threats to validity

A potential threat to the validity of this study is that the data were collected from a single course over two iterations, each with a relatively small sample size (treatment group: n=48, control group: n = 45). We plan to replicate this pilot study in other Fundamentals of Data Science courses and with larger student populations in the future.

Also, students in both groups might have encountered some of the studied topics during their previous industry internships. However, data on internships were not collected in this iteration of the study. Further research is needed to explore the potential impact of these factors.

6. Conclusion and future work

This paper presents the findings of a quasi-experimental pilot study in Fundamentals of Data Science (FDS) that explored the use of Peer Instruction (PI) to teach remembrance, understanding and apply level. In contrast, the lecture-based class did not demonstrate statistically significant learning gains. Based on these findings, we conclude that PI positively influences student learning in these areas.

In response to our research question RQ1, our findings indicate that Peer Instruction (PI) helps undergraduate students in a Fundamentals of Data Science (FDS) class learn concepts better than the students in a traditional lecture-based class.

Future work will focus on addressing questions such as: What role, if any, do industry internships play in learning data science concepts? How does peer discussion contribute to achieving these cognitive gains? We aim to explore these questions in our future studies and emphasize the importance of repeatability to validate the findings of this research.

References

[1] E. Mazur, (1997). Peer instruction: Getting students to think in class. AIP conference proceedings, American Institute of Physics, Vol. 399, No. 1. 981-988.

[2] Wing, Jeannette M. (2002). Ten research challenge areas in data science. arXiv preprint arXiv,05658.

[3] Hardin, Johanna. (2015). Data science in statistics curricula: Preparing students to think with data. The American Statistician 69.4, 343-353.

[4] Donoho, David. (2017). 50 years of data science. Journal of Computational and Graphical Statistics 26.4, 745-766.

[5] Kim, Yong Min. (2017). The effects of pbl-based data science education program using app inventor on elementary students. Computational thinking and creativity improvement. Ilkogretim Online.

[6] Freeman, Scott, (2014). Active learning increases student performance in science, engineering, and mathematics. Proceedings of the national academy of sciences 111.23, 8410-8415.

[7] Gopal, Bhuvana, and Stephen Cooper. (2021). Peer instruction in software testing and continuous integration. Proceedings of the 52nd ACM Technical Symposium on Computer Science Education.

[8] J. Offutt, (2013). Putting the engineering into software engineering education. IEEE software, 30(1), 96-96.

[9] C.B. Lee, S. Garcia, and L. Porter, (2013). Can peer instruction be effective in upper-division computer science courses? ACM Transactions on Computing Education (TOCE), 13(3), 1-22.

[10] L. Porter, D. Bouvier, Q. Cutts, S. Grissom, C. Lee, R. McCartney, D. Zingaro and B. Simon. (2016). A multi-institutional study of peer instruction in introductory computing. Proceedings of the 47th ACM Technical Symposium on Computing Science Education, 358-363.

[11] L. Porter, C.B. Lee, B. Simon, Q. Cutts, and D. Zingaro, D. (2011). Experience report: a multi classroom report on the value of peer instruction. 16th annual joint conference on Innovation and technology in computer science education, 138-142.

[12] L. Porter, C.B. Lee, B. Simon, and D. Zingaro, D. (2011). Peer instruction: Do students really learn from peer discussion in computing? Seventh international workshop on Computing education research, 45-52.

[13] B. Simon, S. Esper, L. Porter, and Q. Cutts. (2013). Student experience in a student-centered peer instruction classroom. Annual international ACM conference on International computing education research, 129-136.

[14] P. Deshpande, C.B. Lee, and I. Ahmed. (2019) Evaluation of peer instruction for cybersecurity education. Proceedings of the 50th ACM Technical Symposium on Computer Science Education, 720-725.

[15] W.E. Johnson, A. Luzader, I. Ahmed, V. Roussev, G.G. Richard III, and C.B. Lee. (2016). Development of peer instruction questions for cybersecurity education. USENIX Workshop on Advances in Security Education (ASE 16).

[16] Leo Porter, Cynthia Bailey Lee, and Beth Simon. (2013). Halving fail rates using peer instruction: A study of four computer science courses. Proceeding of the 44th ACM Technical Symposium on Computer Science Education, ACM, 177–182.

[17] Porter, L., Lee, C.B., Simon, B., Cutts, Q. and Zingaro, D. (2011). Experience report: A multi-classroom report on the value of peer instruction. Proceedings of the 16th Annual Joint Conference on Innovation and Technology in Computer Science Education, ACM, 138–142.

[18] Porter, L., Lee, C.B., Simon, B., and Zingaro, D. (2011). Peer instruction: Do students really learn from peer discussion in computing. Proceedings of the Seventh International Workshop on Computing Education Research, ACM, 45–52.

[19] Simon, B., Parris, J., and Spacco, J. (2013). How we teach impacts student learning: Peer instruction vs. lecture in cs0. Proceeding of the 44th ACM Technical Symposium on Computer Science Education, ACM, 41–46.

[20] Mazur, E. Peer Instruction. In: Kurz, G., Harten, U. (eds) Peer Instruction. Springer Spektrum, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-54377-1_2.

[21] Gopal, Bhuvana, and Stephen Cooper. (2023) A comparison of Peer Instruction and Process Oriented Guided Inquiry Learning-like pedagogies in teaching Software Testing and DevOps. IEEE Frontiers in Education Conference (FIE).

[22] Gopal, Bhuvaneswari. (2024). Teaching SOLID Software Design Principles Using Peer Instruction—A Pilot Study.ASEE Annual Conference & Exposition.

[23] B. Gopal, S. Cooper. (2021). Peer Instruction in Online Synchronous Software Engineering-Findings from fine-grained clicker data, IEEE Frontiers in Education Conference (FIE), 1-8.

[24] B. Gopal, S. Cooper. (2021). Peer instruction in software engineering-findings from fine-grained clicker data. Proceedings of the 52nd ACM Technical Symposium on Computer Science Education. 115-121.

[25] B. Gopal, S. Cooper. (2022) Peer instruction in online software testing and continuous integration: A replication study. Proceedings of the ACM/IEEE 44th International Conference on Software Engineering: Software Engineering Education and Training. 199-204.

[26] Cutts, Q., Esper, S.,and Simon, B. (2011). Computing as the 4th R: A general education approach to computing education. Proceedings of the Seventh International Workshop on Computing Education Research.

[27] Singh, Rajaputra Umamaheswara. (2023). A case study on the impact of peer tutoring in the education of freshmen engineering. Journal of Engineering Education Transformations 36.Special Issue 2.

[28] Ramaswamy, S., Harris, I. & Tschirner, U. (2001). Student Peer Teaching: An Innovative Approach to Instruction in Science and Engineering Education. Journal of Science Education and Technology 10, 165–171. https://doi.org/10.1023/A:1009421231056

[29] Van Alten, D. C., Phielix, C., Janssen, J., & Kester, L. (2019). Effects of flipping the classroom on learning outcomes and satisfaction: A meta-analysis. Educational Research Review, 28(100281), 18. https://doi.org/10.1016/j.edurev.2019.05.003

[30] Schneider, M., & Preckel, F. (2017). Variables Associated with Achievement in Higher Education: A Systematic Review of Meta-analyses. Psychological Bulletin, 143(6), 36. https://doi.org/10.1037/bul0000098.