

Application of Contextualized 5E Inquiry-Based Learning in Undergraduate Image Processing Courses Using a Service Robot

Tarinee Tonggoed*, Ponpawee Tungrattanachote, Ratchata Ngamsawat, Sarut Panjan & Sasithorn Chookeaw

Faculty of Technical Education, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

Received: August 2, 2026 Revised: August 25, 2026 Accepted: September 7, 2026

Abstract

Background: Image processing and computer vision are increasingly important competencies in mechatronics and robotics education, yet lecture-centered instruction may leave a gap between algorithmic knowledge and practical application. Purpose: This study examined changes in undergraduate students' image-processing achievement and their satisfaction following a service robot-contextualized 5E inquiry-based learning intervention. Methods: Thirty second-year students in an Image Processing and Artificial Intelligence course participated in a one-group pretest-posttest study conducted during a single 3-hour session. Students observed an autonomous mobile robot scenario and completed structured inquiry activities involving camera calibration and distance-based person localization. Two content-matched 20-item achievement-test forms underwent two rounds of review by three experts; after revision, all items met the predefined Index of Item-Objective Congruence criterion (IOC = 0.67-1.00). Results: For the full sample, the mean score increased from 12.87 (SD = 3.63) to 14.23 (SD = 2.91), $t(29) = 2.16$, $p = .039$, 95% CI [0.07, 2.66], $d_z = 0.39$. The class-average normalized gain was low ($g = 0.19$). Exploratory subgroup results showed a significant increase among students in the lower pretest half and no significant change among those in the higher pretest half. Overall satisfaction was at the highest level ($M = 4.68$, $SD = 0.48$). Conclusion: The findings provide preliminary evidence that the instructional approach was feasible and was associated with short-term achievement gains and high student satisfaction. Because the study used a one-group pretest-posttest design, causal effectiveness cannot be established. Further studies with comparison groups, larger samples, longer implementation periods, and delayed posttests are needed.

Keywords: 5E instructional model; inquiry-based learning; image processing; service robot; camera calibration; learning achievement

*Corresponding author.

Email address: tarinee.t@fte.kmutnb.ac.th

■ Introduction

The convergence of artificial intelligence, digital automation, and cyber-physical systems has reshaped the technical competency profile expected of engineering graduates (World Economic Forum, 2025). Image processing and computer vision are central to this profile because they support manufacturing inspection (Zhou et al., 2023), infrastructure monitoring (Munawar et al., 2022), medical image analysis (Esteva et al., 2021), autonomous navigation, and human-robot interaction (Szeliski, 2022). These applications require students not only to understand algorithms but also to calibrate cameras, diagnose measurement errors, and adapt vision pipelines to changing physical environments. Inquiry-based learning (IBL) offers a learner-centered approach in which students investigate problems, analyze evidence, construct explanations, and reflect on their findings. The 5E instructional model - Engage, Explore, Explain, Elaborate, and Evaluate - provides a structured sequence for guided inquiry and is particularly useful when novice learners must work with technically demanding content (Bybee et al., 2006). Evidence from STEM education also indicates that active-learning approaches generally improve achievement relative to lecture-only instruction (Freeman et al., 2014).

In engineering education, structured inquiry can connect conceptual knowledge with observable system behavior. Luo et al. (2023) reported that process-oriented guided inquiry supported active participation in an engineering course while also requiring careful facilitation and scaffolding. Physical robotic platforms can provide an authentic context for this type of inquiry. Guerrero-Osuna et al. (2023), for example, developed a computer-vision-based mechatronics training system in which a mobile robot and real-time position data were integrated with an instructional design. Such systems make abstract relationships visible and allow students to examine how sensing, calibration, and control decisions influence real behavior.

Teaching image processing presents instructional challenges that make guided inquiry especially relevant. The subject combines mathematical foundations, such as projective geometry and matrix operations, with context-dependent engineering judgment. A calibration procedure that performs well under controlled conditions may produce inaccurate results when lighting, viewing angle, lens distortion, or target placement changes. Hands-on activities using a live camera and checkerboard therefore allow students to connect camera parameters and reprojection error with visible measurement consequences (Chen et al., 2023; Szeliski, 2022). Extending the activity to person localization with pose estimation further demonstrates how calibrated image measurements can support service-robot perception (Kim et al., 2023).

Before the intervention, classroom observations and diagnostic assessment in the participating course indicated a theory-practice gap. Although many students could reproduce calibration code from worked examples, they had difficulty diagnosing calibration failure in unfamiliar environments, explaining why localization accuracy changed with camera angle, and adapting a person-localization pipeline to the geometry of a mobile robot camera. These local observations motivated the development of an instructional sequence in which students first encountered a visible robot-perception problem and then investigated the underlying image-processing principles through structured activities.

To address this instructional need, the present study implemented a service robot-contextualized 5E IBL intervention during a single 3-hour session. An autonomous mobile robot operating in a simulated indoor corridor was used in the Engage phase to establish the application context. Students then completed hands-on activities involving camera calibration, image undistortion, distance estimation, and MediaPipe Pose using laboratory webcams. The study examined pretest-posttest achievement change and student satisfaction following the intervention. The objectives were to compare students' image-processing achievement before and after the service robot-contextualized 5E IBL session and to describe their satisfaction with the instructional approach.

■ Research Question

This study addressed two research questions:

RQ1: Were students' posttest scores significantly higher than their pretest scores following the service robot-contextualized 5E IBL session?

RQ2: What level of satisfaction did students report toward the instructional approach?

■ Research Objectives

The objectives were to compare students' image-processing achievement before and after the service robot-contextualized 5E IBL session and to describe their satisfaction with the instructional approach.

■ Literature Review and Study Rationale

Research on active and inquiry-oriented learning provides the pedagogical basis for the intervention. Freeman et al. (2014), in a meta-analysis of 225 STEM studies, found higher examination performance and lower failure rates under active learning than under traditional lecturing. In an engineering-course case study, Luo et al. (2023) found that guided inquiry promoted participation and positive perceptions while highlighting the importance of sequenced instructor support. The 5E model operationalizes this support by moving learners from an initial problem context to exploration, explanation, application, and evaluation (Bybee et al., 2006).

Robotic platforms can serve as professionally credible anchors for inquiry without requiring the robot to be the sole object of programming. Guerrero-Osuna et al. (2023) presented an educational mechatronics system that combined computer vision, a mobile robot, and an instructional framework. The present study adopted a related contextual principle but used the autonomous mobile robot specifically to motivate subsequent image-processing activities performed on students' own webcams.

The technical content of the intervention was selected for direct relevance to service-robot perception. Camera calibration estimates intrinsic parameters and lens distortion needed for geometrically meaningful measurements (Chen et al., 2023; Szeliski, 2022). MediaPipe Pose provides a computationally accessible basis for extracting body landmarks without dedicated GPU hardware and can be integrated into real-time pose-estimation applications (Kim et al., 2023). Together, calibration, undistortion, and pose-based localization form a coherent sequence from image acquisition to spatial interpretation.

The reviewed literature therefore supports three components of the study: structured inquiry as an active-learning strategy, a physical robot as an authentic application context, and camera calibration and pose estimation as technically relevant learning content. Empirical evidence on combining these components within a short undergraduate image-processing intervention remains limited. The present one-group study provides preliminary classroom-level evidence while recognizing that a stronger causal test would require a comparison group and repeated implementation.

■ Research Methodology

Participants

A pre-experimental, one-group pretest-posttest design was adopted for this study. The intact class comprised 30 second-year undergraduate students (25 males and 5 females) enrolled in the Image Processing and Artificial Intelligence course. All participants had completed prerequisite coursework in Python programming and basic electronics. While the full sample was used for the primary pretest-posttest analysis, exploratory subgroup analyses divided the students into two equal groups (higher- and lower-pretest scoring) based on their baseline score rankings.

Hardware and Software Setup

The service robot platform used during the Engage-phase demonstration was a differential-drive autonomous mobile robot equipped with a forward-facing Orbbec camera operated in RGB-only mode (1280 x 720 pixels, 30 fps) mounted 1.0 m above floor level, as shown in Figure 1. During the Explore, Explain, and Elaborate phases, students used the integrated webcams on their notebook computers to complete calibration and person-localization tasks at their own workstations. All computers ran Python 3.10 with OpenCV 4.8.0, NumPy 1.24, and MediaPipe 0.10 under Windows 11. The calibration target was a 9 x 6 inner-corner checkerboard with SQUARE_SIZE = 25 mm, printed on rigid foam board to minimize warping. Students captured at least 20 images from varied positions and orientations before running `cv2.calibrateCamera()`. Calibration was performed separately for each webcam because intrinsic parameters differ across devices. Students were instructed to distribute the checkerboard across the image plane and vary viewing angle to reduce parameter-estimation bias and improve reprojection accuracy.

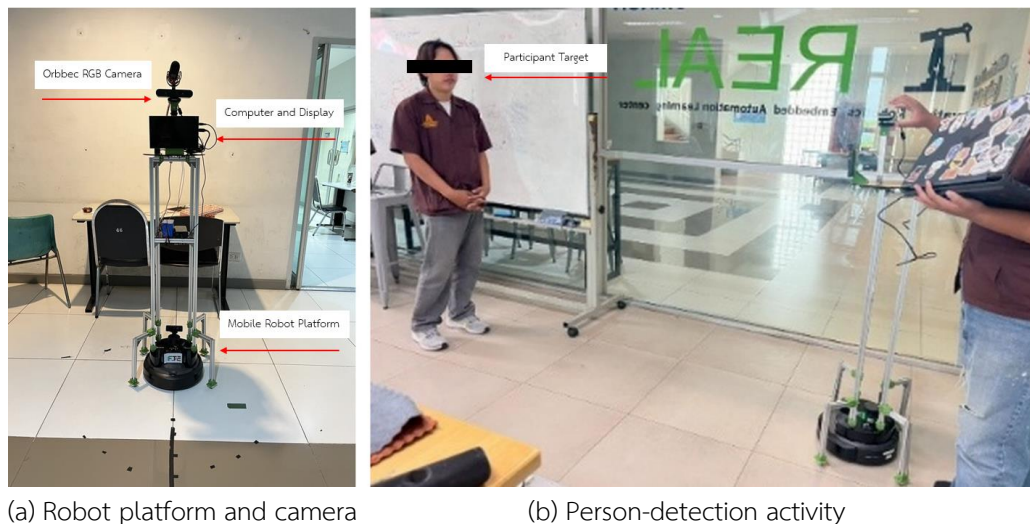


Figure 1. Service robot platform and Engage-phase demonstration: (a) differential-drive autonomous mobile robot equipped with a forward-facing Orbec camera operated in RGB-only mode and mounted 1.0 m above the floor; and (b) person-detection demonstration in the simulated indoor corridor used to introduce the learning problem.

Instructional Design Using the 5E Model

The session began with the Engage phase, in which the robot navigated an indoor corridor while attempting to detect and track a person. The students observed how inaccurate or unstable estimates could affect robot behavior and identified possible causes. During Explore, students captured checkerboard images and implemented `cv2.findChessboardCorners` and `cv2.cornerSubPix` before inspecting calibration outputs and reprojection error. During Explain, groups presented their camera matrix and distortion coefficients, followed by instructor formalization of the relevant projective geometry. During Elaborate, students applied `cv2.undistort`, implemented focal-length-based distance estimation, and integrated MediaPipe Pose for person localization. During Evaluate, students completed a 20-item posttest covering the 12 behavioral objectives and then responded to the 11-item satisfaction questionnaire. The sequence followed the guided-inquiry logic of the 5E model (Bybee et al., 2006).

Figure 2 illustrates the instructional and technical activities performed during the 5E session. The instructor first demonstrated the visible difference between uncalibrated and calibrated camera outputs. Students then worked in groups to acquire checkerboard images from multiple positions and orientations, detect corner points, estimate camera parameters, and apply image undistortion. This sequence provided direct visual evidence of how calibration changes image geometry before students extended the workflow to distance estimation and person localization.

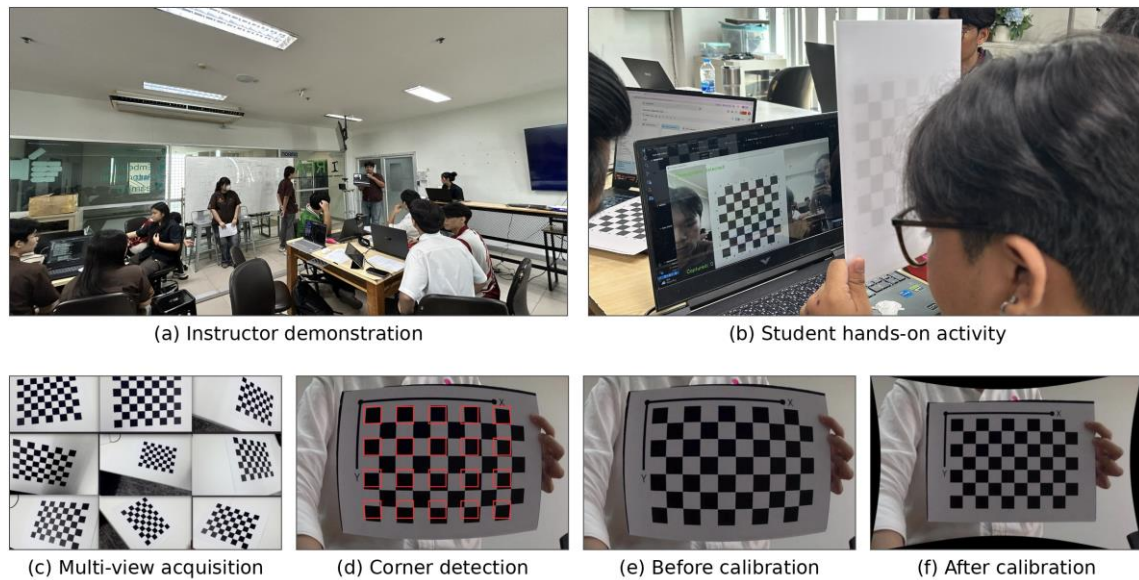


Figure 2. Instructional and technical activities during the 5E session: (a) instructor demonstration comparing uncalibrated and calibrated camera outputs; (b) students performing checkerboard-based camera calibration; (c) checkerboard images acquired from multiple positions and orientations; (d) checkerboard-corner detection during calibration; (e) image before calibration; and (f) image after undistortion using the estimated calibration parameters.

Figure 3 presents an illustrative comparison of distance-to-person estimation based on body landmarks detected using MediaPipe Pose from Orbbec RGB images under the same reference setup. After applying the camera calibration parameters, the estimated distance was closer to the known reference distance than the uncalibrated output. This example illustrates the practical role of camera calibration in the learning activity.

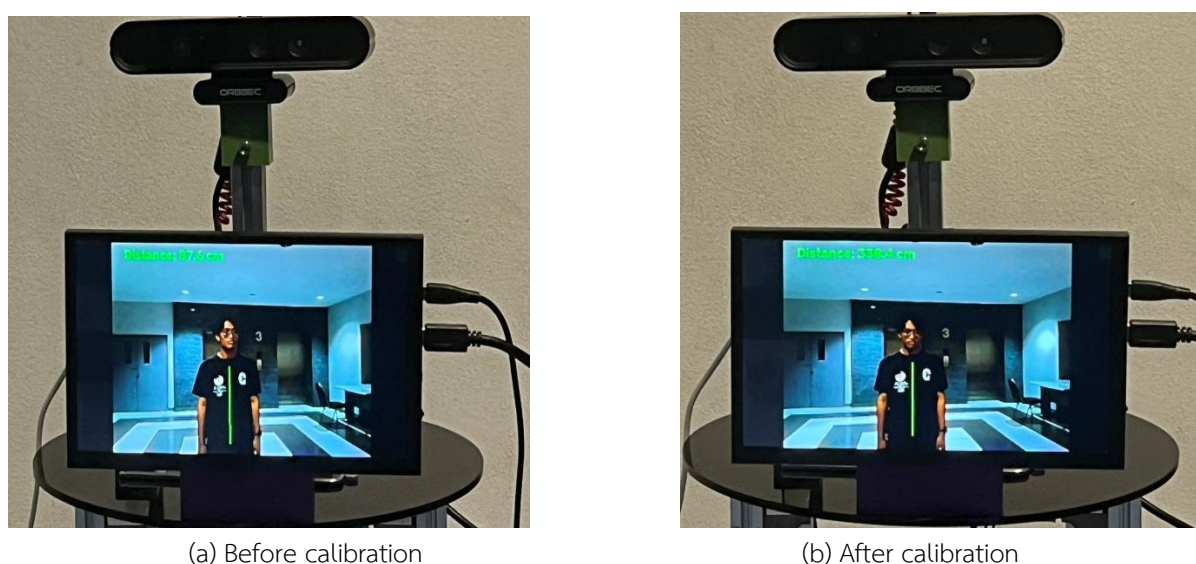


Figure 3. Illustrative distance-to-person estimation based on body landmarks detected using MediaPipe Pose before and after camera calibration under the same RGB-based reference setup. (a) output obtained before camera calibration; and (b) output obtained after applying the estimated camera parameters.

Figure 4 presents the conceptual framework of this study. The 3-hour session was structured around the five 5E phases across two learning units. The robot demonstration established the application context during Engage, whereas subsequent phases used webcams for hands-on image processing. The contextual factors shown in the framework were treated as conceptual influences and were not entered into the statistical model. Table 1 summarizes the student activities and intended objectives.

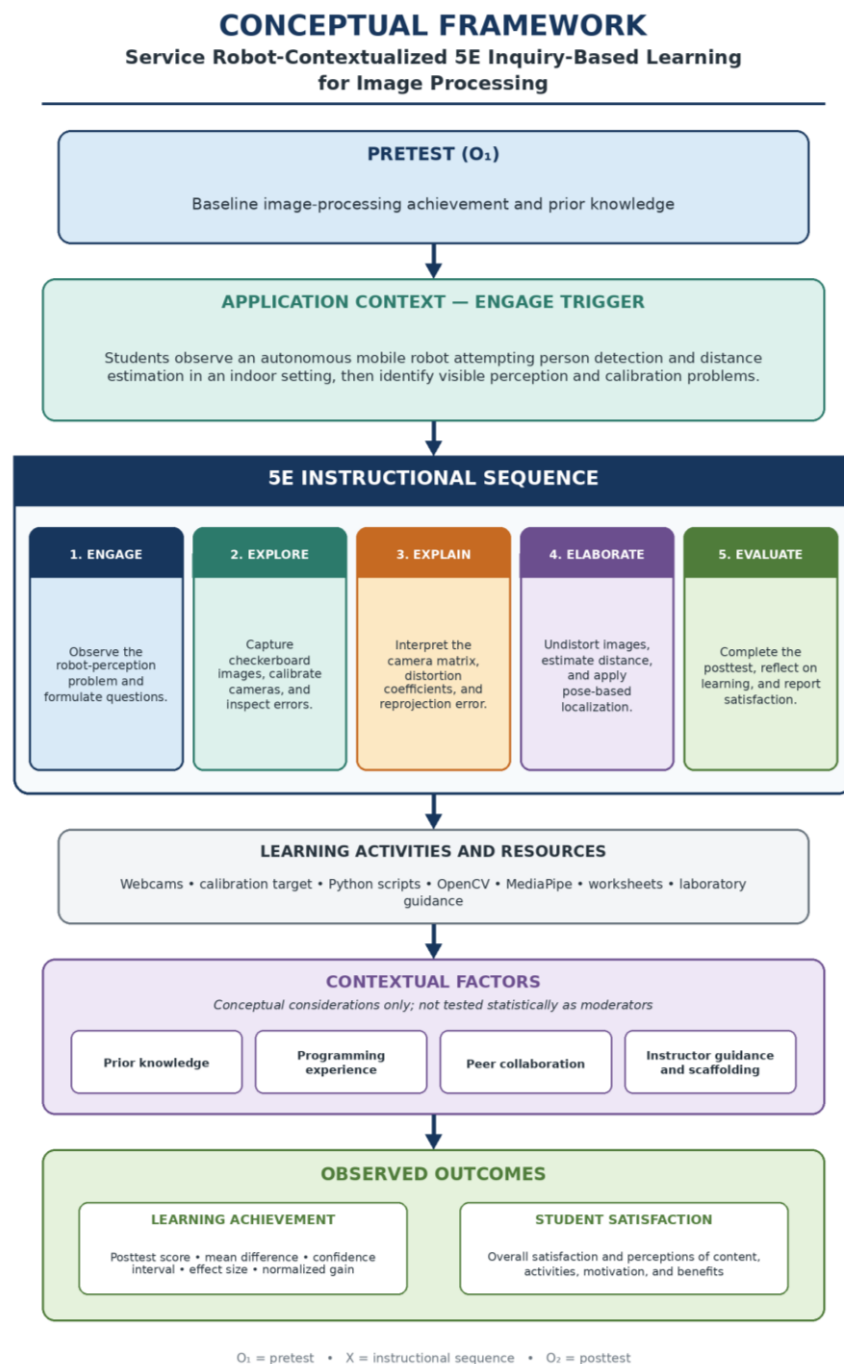


Figure 4. Conceptual framework for the service robot-contextualized 5E image-processing session.

Table 1.

5E Phase Activities and Intended Objectives

5E Phase	Student Activities	Intended Objectives
Engage	Watch AMR detect and track a person in the corridor; identify why detection fails at certain angles	Recall: camera model limitations
Explore	Capture at least 20 checkerboard images from varied angles; implement cv2.findChessboardCorners and cv2.cornerSubPix; inspect reprojection error	Identify calibration commands; describe calibration process
Explain	Groups present camera matrix K and distortion vector D; instructor formalizes projective geometry derivation	Explain role & importance of calibration
Elaborate	Apply cv2.undistort to webcam stream; implement distance estimation using calibrated focal length; integrate MediaPipe Pose for person localization in a service robot context	Apply calibration to distance measurement; analyze impact on robot task
Evaluate	Complete the 20-item posttest and 11-item satisfaction questionnaire	Assess all 12 behavioral objectives and student perceptions

Research Instruments

The 20-item learning achievement test was validated by three experts using the Index of Item-Objective Congruence (IOC) proposed by Rovinelli and Hambleton (1977). All items across both test forms met the acceptance criterion, with IOC values ranging from 0.67 to 1.00 and an average IOC of 0.83 per form. Student satisfaction was assessed using an 11-item, 5-point Likert scale questionnaire. Mean scores were interpreted using the following criteria: 4.51–5.00 = Highest, 3.51–4.50 = High, 2.51–3.50 = Moderate, 1.51–2.50 = Low, and 1.00–1.50 = Lowest. Internal consistency of the 11-item questionnaire was assessed using Cronbach's alpha and was excellent in the present sample ($\alpha = .958$).

Results and Discussion**Results**

Regarding student learning achievement, the mean posttest score ($M = 14.23$, $SD = 2.91$) significantly exceeded the mean pretest score ($M = 12.87$, $SD = 3.63$), representing a mean increase of 1.37 points, $t(29) = 2.16$, $p = .039$, 95% CI [0.07, 2.66], with a small-to-moderate paired effect size ($d_z = 0.39$). The overall

average normalized gain for the class was $g = 0.19$, which is classified as low. Exploratory subgroup analyses revealed that the higher-pretest group showed a non-significant decrease from $M = 16.00$ ($SD = 1.00$) to $M = 14.80$ ($SD = 2.51$), $t(14) = -2.02$, $p = .063$, $g = -0.30$. Conversely, the lower-pretest group demonstrated a significant increase from $M = 9.73$ ($SD = 2.28$) to $M = 13.67$ ($SD = 3.24$), $t(14) = 6.50$, $p < .001$, $g = 0.38$, as shown in Table 2.

Table 2.

Pretest-Posttest Results and Exploratory Subgroup Analyses (Total score = 20)

Analysis group	Pretest M (SD)	Posttest M (SD)	ΔM [95% CI]	Statistical results
All students (n = 30)	12.87 (3.63)	14.23 (2.91)	1.37 [0.07, 2.66]	$t(29) = 2.16$, $p = .039$ $d_z = 0.39$, $g = 0.19$
Higher pretest half (n = 15)	16.00 (1.00)	14.80 (2.51)	-1.20 [-2.48, 0.08]	$t(14) = -2.02$, $p = .063$ $d_z = -0.52$, $g = -0.30$
Lower pretest half (n = 15)	9.73 (2.28)	13.67 (3.24)	3.93 [2.64, 5.23]	$t(14) = 6.50$, $p < .001$ $d_z = 1.68$, $g = 0.38$

Note. ΔM = mean posttest-pretest difference; CI = confidence interval; d_z = Cohen's effect size for paired samples (Cohen, 1988); g = class-average normalized gain (Hake, 1998).

Student satisfaction was high across all four dimensions. As shown in Table 3, all 11 items were rated at the Highest level, with item means ranging from 4.57 to 4.90. The participant-level composite satisfaction score was $M = 4.68$ ($SD = 0.48$), and the questionnaire demonstrated excellent internal consistency (Cronbach's $\alpha = .958$). Perceived Benefits had the highest dimension mean ($M = 4.77$), followed by Learning Activities ($M = 4.67$), Content ($M = 4.64$), and Motivation ($M = 4.60$). The highest-rated item was the applicability of knowledge to real contexts ($M = 4.90$), followed by the value of hands-on practice compared with lecture-only instruction ($M = 4.77$).

Table 3.

Student Satisfaction by Item and Dimension (n = 30)

Item	Mean	SD	Level
1. Content (mean = 4.64)			
1.1 Learning materials used clear language	4.63	0.56	Highest
1.2 Content was appropriate for the allotted time	4.60	0.67	Highest
1.3 Instructional media improved understanding	4.70	0.53	Highest

Item	Mean	SD	Level
2. Learning Activities (mean = 4.67)			
2.1 The practice environment was appropriate	4.57	0.68	Highest
2.2 Activities promoted collaborative learning	4.73	0.52	Highest
2.3 Activities reduced learning boredom	4.70	0.59	Highest
3. Motivation (mean = 4.60)			
3.1 Activities motivated skill development	4.57	0.63	Highest
3.2 I participated enthusiastically	4.63	0.67	Highest
4. Benefits (mean = 4.77)			
4.1 Knowledge was applicable to real contexts	4.90	0.31	Highest
4.2 Hands-on practice was preferable to lecture-only instruction	4.77	0.43	Highest
4.3 Practice improved troubleshooting ability	4.63	0.61	Highest
Overall Mean	4.68	0.48	Highest

The consistently high ratings indicate strong perceived relevance and acceptance of the learning activities. Ratings for collaborative learning ($M = 4.73$) and reduced boredom ($M = 4.70$) also suggest that students valued the active and social features of the session. These findings represent self-reported perceptions and should not be interpreted as independent evidence of learning effectiveness.

Discussion

The primary analysis showed a statistically significant increase in achievement for the full sample, although the effect size was small to moderate and the class-average normalized gain was low. This pattern is consistent with the expectation that a structured, contextualized activity can help students connect image-processing concepts with observable system behavior (Bybee et al., 2006; Freeman et al., 2014; Luo et al., 2023). The robot demonstration provided a concrete reference for the calibration and localization tasks, but the one-group design does not establish that the observed change was caused by the intervention alone.

The exploratory subgroups displayed contrasting patterns: scores increased in the lower-pretest half and did not significantly change in the higher-pretest half. Several explanations are plausible, including restricted room for improvement at higher baseline scores, differences between the two content-matched test forms, and regression to the mean. Because the groups were created from the same baseline measure used to characterize change, regression to the mean is a particular concern (Barnett et al., 2005). The

subgroup findings should therefore be treated as descriptive signals for future differentiated instruction, not as evidence that the intervention was selectively effective for one ability group.

The findings offer several practical implications. First, a single robot can provide an authentic Engage-phase context while students complete most activities on readily available webcams, reducing hardware demands. Second, the high satisfaction ratings - especially for real-world applicability and hands-on practice - indicate that students perceived the session as relevant and engaging. Third, collaborative activity emerged as a valued feature and could be strengthened in future implementations through explicit roles such as camera operator, programmer, and systems analyst. Finally, the two-round IOC process improved alignment between the achievement items and their behavioral objectives: after revision, all items met the predefined criterion. This evidence supports content congruence, but further psychometric evidence, including reliability, item difficulty, discrimination, and equivalence of the two test forms, is still required.

■ Conclusion

Following the service robot-contextualized 5E IBL session, students' posttest scores were significantly higher than their pretest scores, $t(29) = 2.16$, $p = .039$, with $d_z = 0.39$ and a low class-average normalized gain ($g = 0.19$). Student satisfaction was at the Highest level ($M = 4.68$, $SD = 0.48$), and the satisfaction questionnaire demonstrated excellent internal consistency ($\alpha = .958$). After expert review, all achievement-test items met the predefined IOC criterion (0.67-1.00). These findings provide preliminary classroom-level evidence that the instructional sequence was feasible, well accepted, and associated with short-term achievement gains. Causal effectiveness cannot be established because the study lacked a comparison group and was implemented during a single 3-hour session.

■ Research Limitations and Recommendations

Research Limitations

The findings should be interpreted within the scope of this classroom-based study. The one-group pretest-posttest design, involving 30 students in a single 3-hour intervention, provides initial insights into short-term learning outcomes in a specific instructional context. Without a comparison group, however, the contribution of the intervention cannot be separated from testing effects, maturation, differences in test-form difficulty, or other contextual influences. The two achievement-test forms were aligned in content coverage, while their statistical equivalence remains to be empirically established. Examining these properties in future research would strengthen the assessment evidence. The satisfaction questionnaire demonstrated high internal consistency in this cohort ($\alpha = .958$), providing a useful basis for further

evaluation with larger and more diverse samples. The pretest-based subgroup findings offer an exploratory perspective on differences in learning gains and should be interpreted with consideration of regression to the mean. As the study focused on immediate outcomes, long-term retention was not assessed; incorporating delayed posttests would extend understanding of the durability of learning. Overall, the findings provide context-specific evidence relevant to similar educational settings and a foundation for further research using comparison groups, validated parallel test forms, and longer follow-up periods.

Recommendations

Future studies should use a comparison or randomized design, include larger and multi-institution samples, report reliability and item-analysis evidence for both achievement-test forms, and include a delayed posttest. Differentiated group roles may help distribute cognitive load and support equitable participation. Future research should also examine deeper robot integration across multiple 5E phases and analyze whether prior knowledge, programming experience, collaboration, or instructor scaffolding moderates learning outcomes using prespecified statistical models.

References

- Barnett, A. G., van der Pols, J. C., & Dobson, A. J. (2005). Regression to the mean: What it is and how to deal with it. *International Journal of Epidemiology*, 34(1), 215-220. <https://doi.org/10.1093/ije/dyh299>
- Bybee, R. W., Taylor, J. A., Gardner, A., Van Scotter, P., Powell, J. C., Westbrook, A., & Landes, N. (2006). The BSCS 5E instructional model: Origins and effectiveness. BSCS Science Learning.
- Chen, H., Zhuang, J., Liu, B., Wang, L., & Zhang, L. (2023). Camera calibration method based on circular array calibration board. *Systems Science & Control Engineering*, 11(1), Article 2233562. <https://doi.org/10.1080/21642583.2023.2233562>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Esteva, A., Chou, K., Yeung, S., Naik, N., Madani, A., Mottaghi, A., Liu, Y., Topol, E., Dean, J., & Socher, R. (2021). Deep learning-enabled medical computer vision. *npj Digital Medicine*, 4, Article 5. <https://doi.org/10.1038/s41746-020-00376-2>
- Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, 111(23), 8410-8415. <https://doi.org/10.1073/pnas.1319030111>
- Guerrero-Osuna, H. A., Nava-Pintor, J. A., Olvera-Olvera, C. A., Ibarra-Perez, T., Carrasco-Navarro, R., & Luque-Vega, L. F. (2023). Educational mechatronics training system based on computer vision for mobile robots. *Sustainability*, 15(2), Article 1386. <https://doi.org/10.3390/su15021386>

- Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics*, 66(1), 64-74. <https://doi.org/10.1119/1.18809>
- Kim, J.-W., Choi, J.-Y., Ha, E.-J., & Choi, J.-H. (2023). Human pose estimation using MediaPipe Pose and optimization method based on a humanoid model. *Applied Sciences*, 13(4), Article 2700. <https://doi.org/10.3390/app13042700>
- Luo, T., Arcaute, K., & Muljana, P. S. (2023). Integrating inquiry-based learning into engineering education: A case study. *Innovations in Education and Teaching International*, 60(6), 836-847. <https://doi.org/10.1080/14703297.2022.2130393>
- Munawar, H. S., Ullah, F., Heravi, A., Thaheem, M. J., & Maqsoom, A. (2022). Inspecting buildings using drones and computer vision: A machine learning approach to detect cracks and damages. *Drones*, 6(1). <https://doi.org/10.3390/drones6010005>
- Rovinelli, R. J., & Hambleton, R. K. (1977). On the use of content specialists in the assessment of criterion-referenced test item validity. *Tijdschrift voor Onderwijsresearch*, 2(2), 49-60.
- Szeliski, R. (2022). *Computer vision: Algorithms and applications* (2nd ed.). Springer. <https://doi.org/10.1007/978-3-030-34372-9>
- World Economic Forum. (2025). *The future of jobs report 2025*. World Economic Forum.
- Zhou, L., Zhang, L., & Konz, N. (2023). Computer vision techniques in manufacturing. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 53(1), 105-117. <https://doi.org/10.1109/TSMC.2022.3166397>