Unequal Impacts of Augmented Reality on Learning and Collaboration During Robot Programming with Peers

IULIAN RADU, Harvard University, USA
VIVEK HV, Harvard University, USA
BERTRAND SCHNEIDER, Harvard University, USA

Augmented reality (AR) applications are growing in popularity in educational settings. While the effects of AR experiences on learning have been widely studied, there is relatively less research on understanding the impact of AR on the dynamics of co-located collaborative learning, specifically in the context of novices programming robots. Educational robotics are a powerful learning context because they engage students with problem solving, critical thinking, STEM (Science, Technology, Engineering, Mathematics) concepts, and collaboration skills. However, such collaborations can suffer due to students having unequal access to resources or dominant peers. In this research we investigate how augmented reality impacts learning and collaboration while peers engage in robot programming activities. We use a mixed methods approach to measure how participants are learning, manipulating resources, and engaging in problem solving activities with peers. We investigate how these behaviors are impacted by the presence of augmented reality visualizations, and by participants' proximity to resources. We find that augmented reality improved overall group learning and collaboration. Detailed analysis shows that AR strongly helps one participant more than the other, by improving their ability to learn and contribute while remaining engaged with the robot. Furthermore, augmented reality helps both participants maintain a common ground and balance contributions during problem solving activities. We discuss the implications of these results for designing AR and non-AR collaborative interfaces.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI) → Interaction paradigms → Mixed / augmented reality; • Applied computing → Education → Collaborative learning**

KEYWORDS: Augmented Reality; Collaborative Learning; Educational Robots

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1 INTRODUCTION

The medium of augmented reality (AR) is an increasingly available technology which overlays virtual content on real physical objects, providing learners with information that is otherwise difficult or impossible to access [1], [2]. The main assumption of this paper is that making invisible information visible has the potential to support learners in understanding complex concepts in STEM (Science, Technology, Engineering, Mathematics), especially in small collaborative groups.

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For example, previous work has shown that AR applications can aid the learning of invisible phenomena [3], [4] and facilitate collaboration by providing representations in situations where collaborators do not have easy access to computer displays [5], [6]. While the effects of AR experiences on learning have been empirically explored over the last decade, there is relatively less research on understanding the impact of AR on the dynamics of co-located collaboration, specifically in the context of novices programming robots. During robot programming tasks, users must work together to understand how a robot uses multiple sensors to detect its location in relation to the real world (ex: a proximity sensor that senses distance from the wall), and is guided by a program which makes decisions based on those sensors (ex: turn right if the proximity sensor value is above a certain threshold). Typically the sensor values are visible on a computer screen which is also used to program the robot. This creates an imbalance due to the fact that information about the robot, as well as the ability to control the robot, are localized on the computer screen; in this situation, one person tends to operate the computer while another manipulates the robot. One drawback is that the second person does not have easy access to the programming interface and the sensor values. The asymmetry of information is compounded in cases where one participant starts the task with more knowledge than the other, thus causing them to dominate the problem-solving process [7], [8].

In this research we investigate how augmented reality technology impacts collaborative learning in situations where peers engage in such robot programming activities. Computational literacy is a topic of global interest for educational institutions [9]. Defined as the ability to use computers and computational technologies to solve problems, at the core of computational literacy is the ability to understand and create computational programs [10], and is the gateway to teaching STEM topics to students of all ages . One popular method for exposing learners to computational literacy is to engage them in educational robotics. As early as 1980s, robots have been used as vehicles for engaging novices with computer programming concepts [11], [12]. When novices collaborate to program robots, they learn cognitive and social skills, by engaging with problem solving, negotiation, critical thinking, and collaboration [12]–[15]. However, when students engage in group-based programming of robots, collaboration difficulties can become present. Problems occur when the contribution of group members is unbalanced [15] and one person feels like they did a large share of the work, or feel like they were not adequately included in the activity. Reasons for such imbalance may be due to imbalance in team members' dominance of personalities [16] or unequal access to resources [8], [15]. Such imbalanced group collaborations can lead to student negative experiences engaging with the content and decreased learning [17], [18]

Of interest to the CSCW community is the effect of new mixed reality interfaces on small group work [19]. In this paper, we investigate whether augmented reality visualizations can improve collaborative learning and introduce balance in collaborators. by encouraging communicative grounding and reducing information seeking behaviors, leading to more balanced group collaborations.

2 RELATED WORK

A prevailing problem in collaborative learning contexts stems from inefficient team dynamics created by the imbalance between participants. Imbalanced contributions to problem-solving activities is caused by factors such as: participants having different ability to access information during the task, different personal characteristics related to dominance and comfort of sharing information, and different starting levels of prior knowledge [20], [21]. When such factors are present, the weaker participants contribute less and gradually become disconnected from the problem-solving process, leading to a "free rider" effect [22]. Research has shown that successful collaboration requires the pooling of unshared information which is otherwise accessible only to individual members of the group [23]. However previous literature also notes that sustaining mutual understanding, also known as "grounding", is a challenge when participants hold different information because they come from different disciplines or expertise [24]. Augmented reality technology may be helpful in situations where collaborators have different roles or imbalanced expertise.

Augmented reality is a digital medium that allows interactive superimpositions of digital content onto physical objects [25]. Virtual information is visible through a display such as an AR headset (ex: Microsoft Hololens), webcam-enabled computers, or mobile devices such as smartphones and tablets [1]. Research has shown that AR can improve student understanding of information that is either spatially complex [26] or invisible to the naked eye [27], provide practice for tacit knowledge [28], provides motivation for students to engage with content and peers [29]. These benefits occur due to a variety of design affordances for engaging learning processes such as using multiple interactive representations, reducing cognitive load, engaging kinesthetic learning, reducing risk and access to information [2], [30].

Augmented reality technology has been studied in the context of face to face co-located collaborations. AR applications contain affordances that can influence collaboration, such as allowing all collaborators to see task-relevant virtual information in the shared physical space as their peers. This has been shown to help groups of students to become motivated in engaging with the learning experience [31]. When the same information is available to all participants in a collocated space, participants can more easily achieve grounding [32]. Additionally, the shared virtual information has been found to aid nonverbal communication and improve teaching between participants who had the same roles [6], [33]. For activities that typically occur on computer screens, AR allows information to be brough out of a screen and overlaid at the location where participants undertake physical activities, creating overlap between the task space and the social communication space, leading to enhanced communication [19], [34]. Having virtual AR information shared between participants also encourages contributions from all participants, by creating additional opportunities to participate in the problem-solving activity [35] and reduce dominance in communication across participants [6]. In this research we expand on this work by investigating a situation where information in not equally accessible to both participants, and where they naturally take on different roles. More specifically, we look at a setting where one person is manipulating the robot and not seeing the information on the computer screen, while another is closer to the computer used to program the robot. We look at how the features of AR influence collaborative learning processes, and draw conclusions about enhancing these mechanisms through AR.

Previous research has shown that augmented reality can enhance human-robot interaction. Most studies have investigated single-user systems, where AR is typically used as a mechanism for improving the robot's ability to communicate its current or intended behavior through visualizations shown in the physical environment, such as virtual landmarks or motion trajectories [36], [37], or using AR as a mechanism for improving the communication from a human to robot during programming tasks, by allowing the human to refer to the real world instead of programming through code [38], [39]. These approaches typically lead users to feel the system is easier to use and more intuitive while improving efficiency and safety compared to traditional approaches [40] [41]. In the context of educational robotics with student users, research has shown that allowing students to program robots remotely while adding game-like elements to a robot maze can increase student engagement and learning [42], and that using robots to represent game characters in a projector-AR setting improved students' motivation and sense of authenticity for programming [43]. In collaborative programming of robots, a recent pilot study by Cheli et. al. [44] suggests that AR can encourage students to communicate more easily about sensor values, help students debug programs, and reduce barriers of entry for some students.

In the present work, we build upon this existing work by studying learning and collaborative processes in the context of participants interacting with an AR-enhanced robot. We study how AR visualizations of robot sensors influence participants' learning and behaviors. In this setting, participants' problem-solving abilities are imbalanced by factors such as unequal access to informational resources and unequal prior knowledge. Under such contexts, participants naturally take on specific roles, which influence their problem solving contributions and learning experience. While AR may increase collaboration and learning in this situation by providing participants with more shared information or improved ability to communicate with each other, AR may also hinder collaboration since participants can no longer see each other's eyes and facial expressions, or participants may use the information provided through AR technology to dominate the discussion. We investigate how the presence of AR technology influences participant roles, learning and collaboration.

3 STUDY DESIGN

In this study we investigated how augmented reality influences pairs of novices while engaging in programming a robot. We investigated the following research questions:

RQ1. Does augmented reality influence team **learning gains**?

RQ2. How does participant proximity to resources interact with augmented reality to influence participant **learning gains**?

RQ3. How do proximity to resources and presence of AR impact the **collaborative contributions** of participants?

RQ4. How do proximity to resources and presence of AR impact the **collaboration quality** and **equality of contributions**?

The research questions are investigated through a between-subjects design, with presence / absence of augmented reality visualizations as one independent variable, and participant placement as a second independent variable (described in section 4.2). Collaborative learning is measured through metrics of learning, collaborative problem solving behaviors, and resource manipulation behaviors. All experimental groups were tasked with the same activities, which required participants to program a robot to move around a maze while successfully performing certain behaviors (e.g. beep when sensing a magnet, turn when sensing a corner, back up when sensing a light).

4 METHODS

4.1 Participants and Procedure

Participants were recruited from the study pool of a university in the northeastern United States. Prerequisites for participating included: no prior computer programming experience, no corrective glasses, and participants had to have at least a high school degree. Of the participants who signed up for the study, 62.2% were full or part-time students. Participant ages ranged from 19 to 51 years old with a mean of 26.7 years, and 60% identified as female. For this study, 40 groups of participants were recruited.

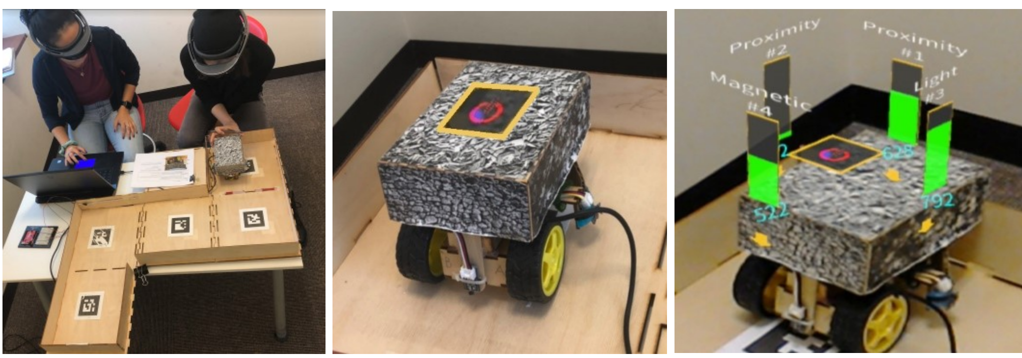


Figure 1. Participants interacting with robot and maze (left); The robot as it appears without AR holograms (middle); The robot seen through the AR headset, showing sensor types and real-time values (right)

At the start of the study, participants first signed an informed consent form, then introduced themselves to each other and were asked to choose who would be participant 1 and 2, without being informed what the numbers meant. Then participants individually completed a pre-test of programming knowledge, which contained 11 questions requiring participants to either complete or fix programs involving sensors, by applying understanding of sensor thresholds, directionality and identification. Participants had 15 minutes to complete the test on separate computers. Participants then moved to a room containing a robot, a wooden maze, and laptop, along with two seats for the participants. After being seated, participants were asked to solve a series of 6 challenges, all which required the robot to perform specific tasks in the maze. The maze contained embedded magnets in the floor, and flashing lights on some walls. The robot was constructed out of a GoGo Board, an open-sourced educational hardware device [45], and contained proximity sensors (to detect distance to walls on a side of the robot), a magnetic field sensor (to detect magnets in the floor), and light sensor (to detect flashing lights from the walls). Participants programmed the robot through a block-based programming interface on a PC computer screen and were able to move the robot manually around the physical maze.

In each challenge, participants were asked to complete programs that operate the robot successfully under a time limit. Participants were told the robot start position and its expected behavior. They were provided with an incomplete program. In order to fix the program, participants had to manipulate the robot, and use the mouse and keyboard on the computer to modify the IF statements in order to ensure that the program was reacting to the correct sensor, the correct sensor value, or the proper directionality. These features were common for all experimental conditions. After some of the challenges, all participants watched videos explaining the computational concepts involved in solving the previous challenge (e.g. how to find sensor thresholds; how If statements work), lasting roughly 5 minutes total. The 6 challenges could be completed in 20 minutes.

Afterwards, participants moved back to the intake room, and were given 15 minutes to complete a post-test containing equivalent questions to the pre-questionnaire.

4.2 Study Conditions

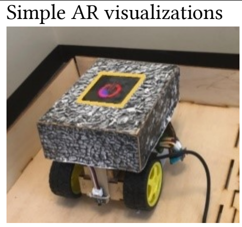
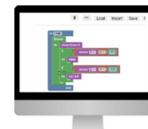
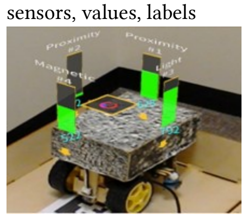
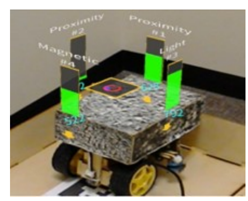
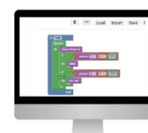
Participants were separated according to two variables: presence of augmented reality, and participant placement.

Presence of Augmented Reality: In this research we are interested in understanding the effects of AR visualizations on collaborative learning. We manipulate the presentation of information through AR technology, while controlling for the effect of novelty of AR technology, since novelty has been found to be a significant effect simply from participants wearing AR devices or seeing basic AR augmentations [46]. Participant groups were randomly assigned to one of two experimental conditions, both of which required participants to wear AR headsets, but which varied on the presence of augmented reality features, summarized in Table 1.

In the **"NonAR" condition,** participants wore a Microsoft Hololens AR headset, and saw a simple visualization overlaid on the robot, which showed a rectangular area that changed color from red to green if the robot's program was running or not. This basic exposure to AR technology was done in both experimental conditions, to control for the motivational effects from wearing an AR headset observed in previous literature. For participants in this condition, information about robot sensors was provided on the computer screen through an application window. Sensor information was displayed through an interface that showed sensor values as bar charts associated with each sensor ID (Table 1). Even though this condition contains basic exposure to AR technology, we label this the "NonAR" condition since it does not contain significant augmented reality visualization.

In the **"Augmented Reality" condition**, both participants similarly wore a Microsoft Hololens headset which overlaid the simple on/off visualizations on top of the robot. Participants in this group did not have access to the computer application showing sensor values, but instead saw sensor information visualized through AR on top of the robot. The AR visualizations included (1) bar charts next to each physical sensor, showing sensor values as bars; (2) text labels above each physical sensor, indicating the sensor ID number (ex: 1,2,3,4); (3) text labels above each sensor, indicating what is the purpose of each sensor (ex: proximity, magnetic, light); (4) whenever the program contained IF statements associated to a sensor threshold, the bar chart visualization changed its color from green to red when the sensor was meeting the threshold condition, and (5) all the AR visualizations associated with a sensor were enabled or disabled depending on the task (ex: in an experimental task that did not include the light sensor, the light sensor AR visualizations were disabled). Thus, the two experimental conditions differed in that AR participants had information about sensors in a way that was expected to be easier to access (since it was accessible on the robot, and since participants were reminded of the function of each sensor through AR labels), and less cognitively demanding (since the sensor information was spatially associated with the corresponding sensor, and since information dynamically changed its color and visibility depending on the task).

Table 1. Differences between the NonAR and AR conditions, in terms of what participants wear, what they see on the robot, and what they see on the computer.

Condition	Headset	View of the robot	View of sensors values	Programming
NonAR	Hololens device	Simple AR visualizations 	On computer screen 	On computer 
AR	Hololens device	AR visualizations of sensors, values, labels 	On robot 	On computer 

Participant placement: Both participants were seated at the end of a table which contained a wooden maze, a computer, and a worksheet (Figure 1). The computer was slightly closer to the participant on the left, and the maze was slightly closer to the participant on the right; however, all these resources were accessible to both participants. The participant seating was allocated using a participant identifier (1 or 2). Participants were not given any information about what the identifier meant, but as a first group decision activity they were told "One of you must be participant 1 and the other participant 2. Please take a moment to decide who will be which." This choice was designed as a first team activity to create a sense of control in participants. Once participants selected a number they were told where to sit, and were asked to work together to solve the tasks. For the purpose of this paper, participants will be labeled as "Left Participant" (#1) who is closer to the computer and "Right Participant" (#2) who is closer to the robot (Figure 2).

Figure 2. Camera images showing that participants could access both resources. Left Participant accessing the robot (left, middle) and Right Participant accessing the computer (right).

4.3 Dependent Measures

Through pre-post tests and qualitative observations, we measured participants' learning, movement, and collaboration contributions.

Learning Gains: We measured participants' learning through pre- and post-tests containing programming questions. The test questions (illustrated in Figure 3) presented situations involving robots using sensors to make decisions, and required participants to understand the logic of using sensor values in programs. Programs involved and required participants to select proper sensors in order to achieve a task, choose the proper sensor values, and write directional if-else statements to solve tasks. Participants' learning was measured using relative learning gains based on pre- and post-tests. Relative learning gains is a measure of the relative improvement that occurred between pre-post test scores, calculated as the ratio between actual improvement and the total amount of possible improvement: (post score − pre score) / (max achievable score − pre score). This metric accounts for the knowledge that each participant has coming into the study, and the fact that a participant's score will not increase as much when they already know a lot.

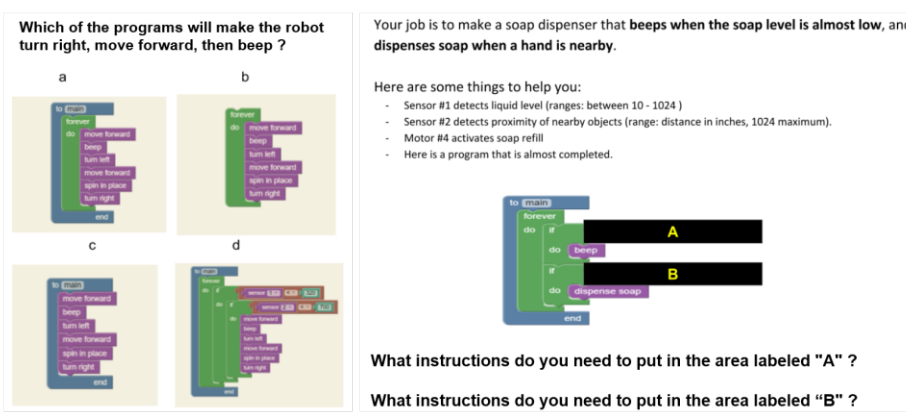


Figure 3. Examples of two questions included in the pre- and post- learning test.

Manipulation of Resources (Robot and Computer): Each participant's hand movements were observed and indicated how often they manipulated the robot (i.e. picking up and moving the robot), and how often they manipulated the computer (i.e. changing the computer program). Both metrics were assigned by observing videos from all study sessions, and ranking participants on an ordinal scale of 0-2 according to amount of time spent manipulating the resources (Table 2).

Table 2. Codes assigned to the metrics of Robot Manipulation, or Computer Manipulation.

Movement code	Meaning
0	Movement was not present or very infrequent
1	Movement was present but during less than half of the activities
2	Movement was present during more than half of the activities

Problem Solving Contributions: We performed qualitative video analysis to understand what kinds of contributions participants make to the problem solving process. A coding scheme was constructed through iterative bottom-up coding, to assess the degree of contribution made by each participant. Inter-rater reliability was assessed using two independent researchers coding 20% of the videos, and reached a Cohen kappa of 0.7 which implies good agreement [47]. Participant contribution was measured for every 15 seconds of video footage, by assigning each participant one of the contribution codes in Table 3. The segment length of 15 seconds was chosen because that was found to be an appropriate amount of time for a contribution to be made and usually did not involve multiple contributions.

Table 3. Codes used for categorizing participant contributions.

Code	Description
Non-Task (NT)	Participant is involved in an action or statement that is not directly related to building the solution for the specific task. Examples: Moving seat; Adjusting Hololens device.
Task-related non-critical (TR)	Participant is involved in an activity that is not a critical leap between problem and solution. These represent actions and statements performed with trivial cognition - activities that are required and can be considered as expected responses in a collaborative environment. Examples: Passive agreements ("Yes", "Okay"); Moving robot as response to peer action; Expressing frustration ("I don't know what else we can do"); Confirming ("Do you want me to do it?")
Seeking Information (SI)	Participant requests information, or acts to gain information unavailable to them. Examples: Looks at paper worksheet; Looks at computer screen; Asking "What is the sensor value now?"
Grounding (GR)	Participant contributes an action or dialogue to create a common understanding with teammates. These can be through contribution of repeating goals and/or directions, repeating information from previous activities, or asking/stating clarifications. They were counted when provided voluntarily, not in response to seeking information. Examples: Clarification of task goals ("They asked us to turn right here"); Repeating information ("There's a magnet here"); Pointing at sensor and saying sensor value; Reporting system state ("I heard the beep")
Action: Trial and Error (TE)	Participant contributes actions or statements that are random guesses and/or trial-and-error approaches, that do not depend on the outcome of the previous activity. Examples: Without having talked about values says "Let's just try 200"; Try a random guess, fail, try a lower value, succeed partially and then repeat without clear understanding why success is happening.
Action: Hypothesis Driven (HD)	Participants contributes actions or statements are based on a hypothesis made through understanding the system and requirements of the solution. This usually represents suggestions made through sound logic irrespective of the outcome of the previous activity. Examples: Suggesting action based on previous observation "I think we should move it there because…"; Asking explicitly for action "It got higher, why don't we just move it closer"
Suggesting Actions (TE|HD)	Aggregated metric indicating suggestions for actions. Contains occurrences of either Trial and Error, and Hypothesis Driven actions.
Collaboration Contributions (GR|TE|HD)	Aggregated metric indicating contributions through grounding information or through action suggestions. Contains occurrences of either Grounding, Trial and Error, and Hypothesis Driven actions.

If a participant made multiple types of contributions during the same 15 second interval, then multiple codes were recorded. This process allowed us to measure the types and amount of contributions made by each participant. In the analysis we report these as % of time segments these were observed from each participant during a session. Additionally, we calculated two aggregated measures, amount of Suggested Actions and amount of Collaboration Contributions, as described in Table 3. Finally, we calculated the overall imbalance between participants, by calculating differences in contributions from each participant over the course of each session; measuring the absolute value to indicate overall strength of imbalance between participants.

4.4 Data and Analysis

This study included 40 groups of dyads, with 20 groups in the AR condition and 20 groups in the Non-AR condition. For analysis of learning gains and participant movements, data from all sessions was used. We chose a subset of 12 out of the total 40 groups to perform the coding of participants' problem solving contributions. The groups for this analysis were selected according to the following criteria: (a) each of the two study conditions (AR vs. NonAR) are equally represented; (b) half the groups in each condition represent contexts where the difference in participants' pre-test programming knowledge was relatively equal (within 1 standard deviation of the mean difference) indicating similar starting knowledge, while half represent groups where participants were imbalanced (pre-test knowledge differences were beyond 1 standard deviation) indicating one of the participants was more knowledgeable; and (c) within each of those conditions, half the groups represent high learning gains after the activity (in the top 25%), while half represent low learning gains (in the bottom 25%). For the scope of the current paper we omit the analysis of differences between high-vs-low learning gains, or high-vs-low starting imbalance. The 12 analyzed sessions ranged between 27-33 minutes, with the variation due to participants finishing tasks early or requiring more technical assistance.

We statistically analyzed differences in metrics between the conditions of AR presence (AR vs Non-AR) and between the two participants. For the learning gains metrics, the data met the parametric test assumptions of normality and homogeneity of variance, and we performed ANOVA to measure group differences and interaction effects. For metrics of participant movement and problem solving contributions, the data was ordinal or did not meet parametric assumptions, thus we performed nonparametric Mann–Whitney–Wilcoxon tests. We note that the data used for problem solving contributions represent a small sample, and statistical tests had low power for this reason, thus we focus our analysis on descriptive statistics and qualitative descriptions.

5 RESULTS

5.1 RQ1. Does augmented reality influence team learning gains?

We analyzed learning in all groups based on relative learning gains between the pre- and post-tests as described in Section 4. In this section we report overall differences in learning between AR and NonAR conditions, and the next section will discuss learning for each participant.

Figure 4. Relative learning gains for both participants under each of the two experimental conditions (percentage scale 0-1). N=40. Bars=std. error. *=sig. p<0.05.

Learning of AR groups was significantly higher ($F_{1,79}$=5.37, p=0.023) by almost two times more than compared to NonAR groups. Descriptive statistics show that participants who had AR visualizations tend to learn better about all the topics: sensor values, sensor identification, and sensor directions. An explanation for this is that, in the NonAR condition, groups do not have as easy access to sensor information condition, and to gain it they must look at the computer or talk to their peers; whereas in AR this information is readily available while they maintain mutual attention on the robot's state. Furthermore, under the AR condition, groups receive rapid feedback while they manipulate the robot, and this feedback may speed their ability to engage in cycles of learning and generation of hypothesis driven actions [48].

Figure 5. Participant placement in relation to the computer and robot.

5.2 RQ2. How does participant proximity to resources interact with augmented reality to influence participant learning gains?

In the previous research question, we found that group learning scores were significantly higher in the AR conditions. In this section we analyze learning scores further by analyzing the effect on each participant. The participant closer to the computer is labeled as the Left Participant, while the participant closer to the robot is labeled as the Right participant (matching the view in Figure 5).

An interaction effect was detected between participant placement and presence of augmented reality in relation to overall learning gains ($F_{1,79}$=4.52, p=0.037). When analyzing each individual participant, we find that the learning of the Right Participant, who was seated farther from the computer, was significantly influenced by the presence of AR. Overall learning scores for the Right Participants were significantly higher in the AR condition than the NonAR condition ($p<0.01$) by roughly 3 times (Figure 6 right). In contrast, for the Left Participants, closest to the computer, their overall learning scores were relatively equal between AR and NonAR conditions and not significantly different (Figure 6 left), although descriptive statistics indicate the AR condition may be causing some improvements in understanding sensor values and identifying sensors.

When analyzing within each NonAR vs. AR condition, we find that in the AR condition, the Right Participant had significantly higher overall learning than compared to their peer ($p=0.015$). In the NonAR condition there were no significant differences in learning between participants.

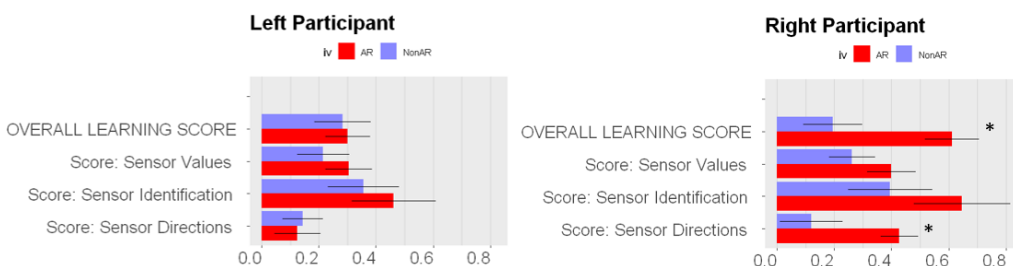


Figure 6. Relative learning gains under the two experimental conditions, for the Left Participant closer to the computer (left) and the Right Participant farther from the computer (right). N=40. Bars=std. error. *=sig. $p<0.05$.

These results show that the presence of AR visualizations has an asymmetric effect on participants, whereby the presence of AR strongly affected the learning of the Right Participant who typically manipulates the robot, but does not significantly influence the learning of their peer who typically manipulates the computer. The reasons for this imbalanced increase in learning may be due to increased availability of information provided through AR which may be specifically useful to the robot manipulator participant, the ease of feedback of information available while manipulating the robot, and/or increases in ability to collaborate between partners, as will be discussed in RQ3.

5.3 RQ3. How do proximity to resources and presence of AR impact the collaborative contributions of participants?

In this section we analyze participant behaviors based on observations of manipulation of resources, gathered from the whole dataset (N=40 dyads), and based on details of verbal communication, gathered from video analysis (N=12 dyads). We first present results comparing both participants within each AR condition, to illustrate the roles participants play within each condition. Then, we analyze whether each participant is influenced by the presence of AR, to illustrate how AR impacts participant contributions.

Analyzing both AR and NonAR conditions together (Figure 7 left), we find that the Right Participant who is closer to the robot was manipulating the robot significantly more than their peer ($W=240$, $p<0.01$), while the Left Participant closer to the computer is manipulating the computer significantly more ($W=1170$, $p<0.01$). Descriptive statistics indicate that the Right

Participant is making slightly more problem-solving contributions, and tends to be seeking information more than their peer.

When comparing participants within only the NonAR condition (Figure 7 middle), we find that the Right Participant moved the robot significantly more than their peer (W=33.5, p<0.01), and programs the computer significantly less (W=338, p<0.01). The analysis of talking behaviors shows this participant spends significantly more time seeking information from their peer (W=3.5, p=0.017), and descriptive statistics indicate the participant spends more time grounding the conversation, and making less overall action suggestions and contributions than their peer. In contrast, the Left Participant, closer to the computer, spends significantly less time moving the robot and significantly more time manipulating the computer, seems to be making more suggestions for action, spends less time grounding and seeking information. This indicates that in this configuration, the participant closer to the computer has a role that tends to drive the computer interaction, while the other participant is a more passive worker who manipulates the robot with less contributions. This effect will be illustrated through a case study in Table 4, and is similar to what is found in studies of peer programming where participants dominate the resources close to them [49].

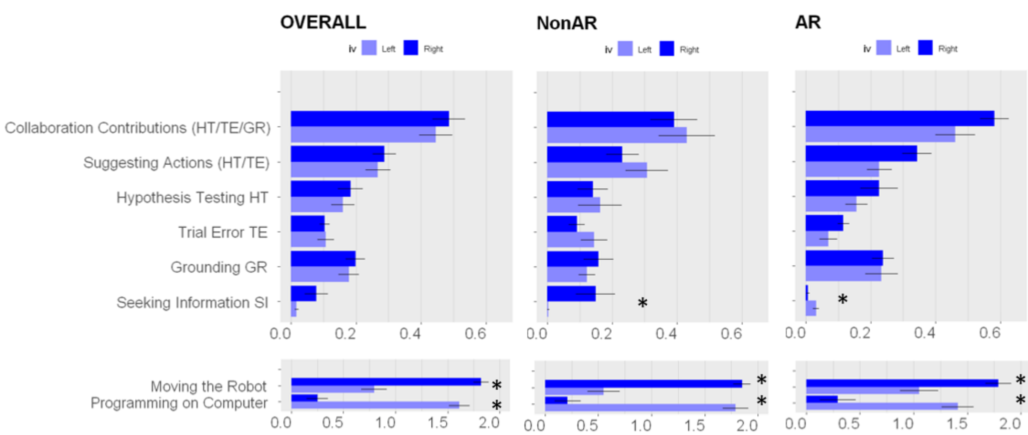


Figure 7. Differences between participants overall (Left), in the NonAR condition (Middle), and AR condition (Right), in types of conversation behaviors (top; percentage scale: 0-1; N=12) and resource manipulation (bottom; ordinal scale 0-2; N=40). Bars=std. error. *=sig. p<0.05.

In the AR conditions (Figure 7 right) we see similar behaviors in participant use of resources, whereby the Right Participant farther from the computer tends to manipulate the robot significantly more than their peer (W=84.5, p<0.01) although the Left Participant appears to engage with the robot more than in the NonAR condition. Furthermore, similar to the NonAR condition the Left Participant manipulates the computer significantly more than their peer (W=251, p<0.01). However, the descriptive statistics show that verbal contributions from each participant are different than in the NonAR conditions, as the Right Participant farther from the computer makes more suggestions for action and more overall contributions than their peer, and engages in less information seeking behaviors. This indicates that under the AR condition, the Right Participant farther from the computer is a more active driver of the conversation, while remaining in charge of manipulating the robot. This change in verbal behavior will be illustrated in a case study in Table 4.

Table 4. Quotes from participants showing dominance from P2 in NonAR condition (left), and dominance from P1 in AR condition (right). L=Left Participant closer to computer; R=Right Participant farther from computer.

Non AR Session	**AR Session**
L: so let's look at sensor 4 which is when the magnet goes off. so right now when it's pretty far it's at 9. <moves robot closer to magnet> and then.. wait why doesn't it work.. oh wait I don't see it.. oh, sensor 4. can you bring it back? R: <moves robot back across magnet, then looks at computer> L: does it go up when it goes closer to the magnet ? <looks at computer> R: well... magnet's right here <looking at computer while moving robot> so magnet doesn't affect it much L: so <looking at computer> greater than 500, because it's at 526 <types on computer>	R: so let's try and see the magnet [task] L: the magnet is... R: <moves closer from magnet, looking at robot> L: it's at 546 R: <moves robot farther from magnet> and then if I put it right here L: 518 R: <moves robot slightly, still looking at robot> L: 530 R: <moves robot slightly> so like.. 535... <moves robot slightly> 530 maybe ? L: <types on computer>
L: So [for the new task] to back up... can you bring it close to the light ? R: <moves robot close to light> L: oh we've done that before. when it's close to the light.. so it jumps up to 1015 and when it's not on the light it's at 715. so id' say we need to have it greater than 1000 ? R: <looks at computer> maybe 1100 ? L: well that works.. but sometimes it doesn't shoot up to 1000. sometimes it just shoots up to 900.	R: [new task] and then back up when it senses a light. that was this one of here <points to light>. <moves robot closer to light, while watching robot> let's look... so when the light comes on, it's at 1024. so i think like 1000 should be fine. L: yeah
L: and then this one [new task] turning right is hardest one, so can you bring it close to the wall ? R: <moves robot> L: ok so i would say when it's greater than 50 R: <looking at computer while moving robot> maybe 70 L: ok can you move it to the beginning? R: <moves robot>	R: [new task] so the last one is when it's close to the front wall L: <moves robot close to wall, watching robot> so I'll put it here. the value's at 58 right now, right ? R: yeah L: <moves robot farther> I'll put it here R: 42 L: <moves robot closer, watching robot> here <moves robot slightly> again... so maybe do like 50, so it's kindof more than 50 R: <types on computer>

The transcripts in Table 4 illustrate the similarities and differences between NonAR and AR conditions. In these examples participants are solving a challenge that involves multiple subtasks (e.g. they must program the robot to beep when it passes a magnet, turn when it passes a wall corner, and back up when it senses a blinking light is on). In both examples, P1 does most of the robot manipulation and P2 most of the robot programming. The examples show differences between conditions. In the NonAR example (Table 4 Left), although both participants spend lots of time looking at sensor information on the computer, the P2 participant does most of the suggestions, brings information based on previous information (ex: about the range of values for the light sensor), and drives most the problem solving and programming, while P1 is more passively following orders while seeking information from the computer. In contrast, Table 4 Right shows an AR condition, where P2 still performs the computer programming, but P1 has an active role by doing most of the problem solving, engaging in rapid cycles of exploration through movement of the robot across the sensor thresholds while watching the robot. These examples show that, although in both AR and NonAR conditions participants engage in unbalanced manipulation of robot and computer, in the AR condition the participant manipulating the robot can be more actively engaged.

Based on these results, we conclude that the physical proximity to resources influences the physical actions of participants, since under both NonAR and AR conditions the participant closer to the computer tends to do most of the computer manipulation, and the participant closer to the robot tends to do most of the physical manipulation. However, the presence of AR appears to have an effect on the verbal contributions of each participant, whereby the Right Participant farther from the computer becomes more active in the problem solving process. To investigate further, we analyze the effect of AR on each participant. As an overview, the contributions of both participants under AR and NonAR conditions is shown in (Figure 8 left). No statistical differences were found when analyzing differences between conditions. Descriptive statistics indicate that the presence of AR changes participants' manipulation of resources by increasing the engagement with the robot and slightly decreasing engagement with computer, and that it changes the problem-solving process by decreasing the amount of time participants spend seeking information, increasing the amount of grounding, increasing amount of hypothesis driven activities, slightly decreasing trial and error, and overall increasing collaborative contributions.

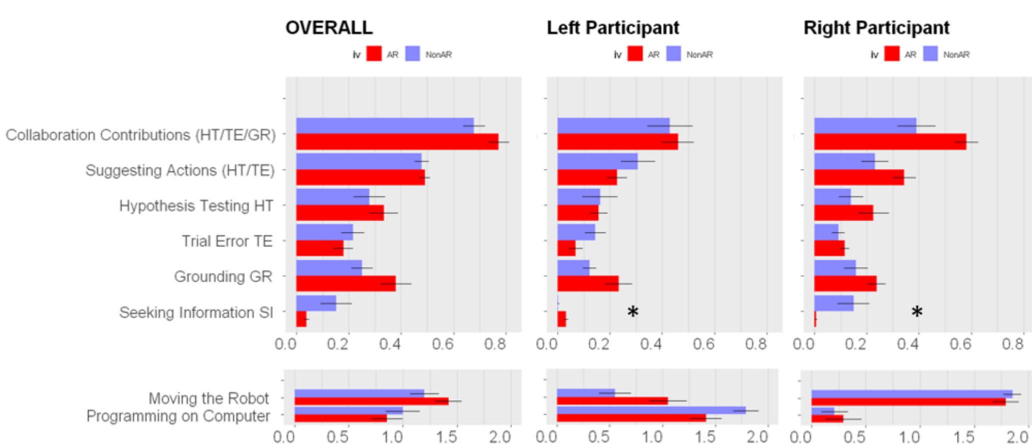


Figure 8. Types of conversation behaviors (left: between both participants; middle: Left Participant; right: Right Participant) in types of conversation behaviors (top; percentage scale: 0-1; N=12) and resource manipulation (bottom; ordinal scale 0-2; N=40). Bars=std. error. *=sig. p<0.05.

Observing each participant individually, we find that the presence of augmented reality influences the types of contributions each participant makes. For the Right Participant who typically manipulates the robot (Figure 8 right), the descriptive statistics show that AR strongly increased their amount of hypothesis driven actions and grounding, increased their collaboration contributions and suggestions of actions (nonsignificant W=30, p=0.06), and significantly decreased the amount of time spent seeking information (W=4, p=0.03), while their manipulation of robot and computer remain roughly unchanged. These findings suggest that with AR this participant remains in the role of manipulating the robot, but is now able to more effectively contribute to the problem solving process.

In contrast, for the Left Participant who typically manipulates the computer (Figure 8 middle), descriptive statistics show that under AR conditions this participant increased their manipulation of the robot and slightly decreased manipulation of the computer, while they decreased their amount of suggestions for actions, reduced the amount of trial and error, while increasing overall contributions and behaviors related to grounding with their peer, and significantly increased seeking information behaviors (W=32.5, p=0.02). A possible explanation for these findings is that under AR conditions, although this participant has the same information available as in NonAR conditions, they may be engaging with their peer more in robot manipulation, and allowing for their peer to provide information and make suggestions for the problem solving process, thus leading to a more balanced collaboration.

Figure 9. Difference between participants' contributions at the end of each session (absolute value, scale 0-1; N=12). Bars=std. error.

5.4 RQ4. How do proximity to resources and presence of AR impact the collaboration quality and equality of contributions?

The increased amount of contributions from participants in AR conditions may contribute to more balance between participants as they engage in problem solving activities. To investigate the notion of balanced participation, we calculated the difference between participants' contributions over time. For each study session, we compared the difference in amount of collaboration contributions made by each participant, calculated as an absolute value. Figure 9 shows the results. This metric is high when one of the participants made more contributions than the other during a session. NonAR conditions exhibited higher imbalance by twice as much (nonsignificant W=6, p=0.06). Imbalance in participant contributions over time is shown in Figure 10, which shows that in NonAR groups the imbalance between participants tends to increase over time. This data indicates that with AR participants tend to remain more synchronized in their contributions over time.

Table 4 illustrates examples of imbalance, where one participant dominates in a NonAR session, and where participants are balanced in an AR session. In both cases, participants are solving activities investigating the sensor thresholds for light sensors, proximity sensors, and magnet sensors.

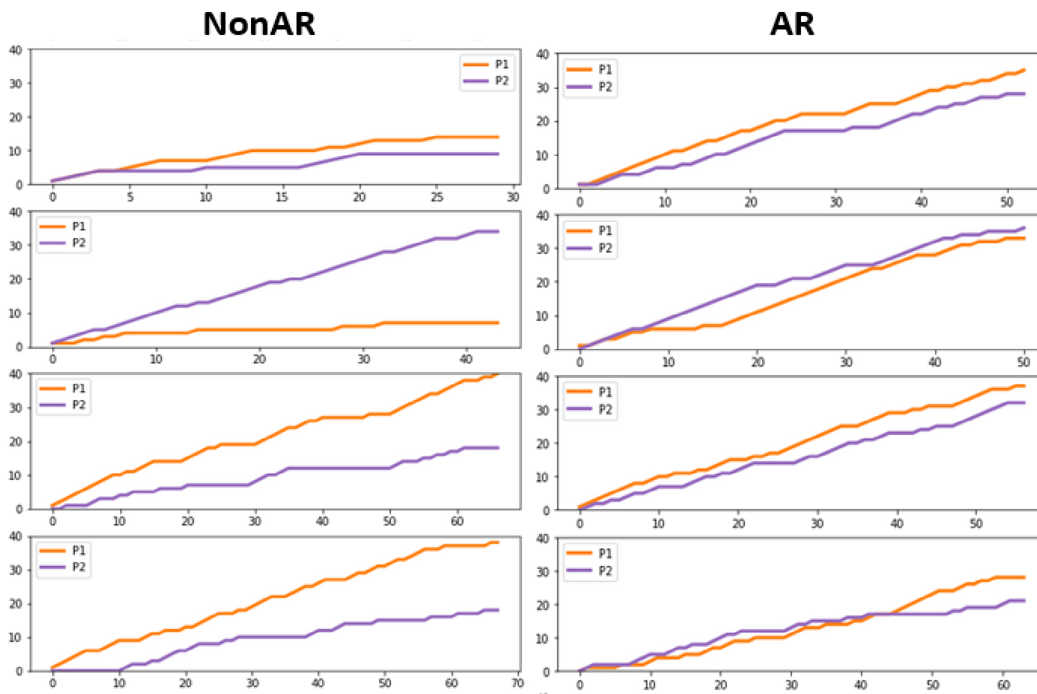


Figure 10. Examples of changes in participants' cumulative contributions over time (measured in 15 second units), in four NonAR sessions (left) and four AR sessions (right).

In the NonAR case (**Error! Not a valid bookmark self-reference.** Left) P2 does the majority of the robot manipulation and problem solving, while P1 is following along but spends their time looking at the computer screen and just contributing through confirmations rather than actions or new suggestions. In contrast, in the AR case (**Error! Not a valid bookmark self-reference.** Right) both participants are actively looking at the robot and solving the tasks together. Participants appear highly synchronized while they watch the sensor values on the robot, fluidly taking turns to move the robot, frequently finishing each other's sentences, and communicating through more acknowledgements and pointing gestures rather than explicitly stating complete new ideas. These examples illustrate how in the AR condition both participants can remain on the same page during the problem solving process.

6 DISCUSSION AND FUTURE WORK

Our results show that the presence of augmented reality content modified group communication and problem solving behaviors. Participants under the AR condition maintained more balance in their communication compared to NonAR groups, and this effect appeared to be influenced by the robot manipulator participant's increased ability to make meaningful contributions to the discussion. The change in collaboration was associated with an increase in grounding communication from both participants, and is likely due to the increased amount of shared information easily available to both participants under AR conditions, allowing enabling each participant to think about the problem individually while also remaining on the same page during the collaboration. This indicates that AR applications have potential to improve group dynamics, especially in situations where access to resources and information is traditionally imbalanced, by facilitating equity of collaboration.

Table 5. Quotes from participants showing imbalance in NonAR condition (left), and balance in AR (right). L=Left Participant closer to computer; R=Right Participant farther from computer.

NonAR Session	**AR Session**
L: should we take a look at the sensors?.. so sensor 3 is the light sensor <moves robot closer to light> I want it here... so I see... 1024 R: is it ? <looks at computer> ah 1024 L: so.. <moves robot farther from light, look at computer> so sensor 3 is greater than.. should we say 1000? R: <looks at computer> mm-hm L: [new task] and then sensor 2 [proximity sensor] <moves robot close to wall> let's see if there difference between here... R: I don't remember which one is 2 L: I think it's on this side <points to side where proximity sensor is> R: mmhm L: <moves robot past turning point, looks at computer> so that's 6 R: <looks at computer> 6 L: <moves robot before turning point, looks at computer> and that's.. 45 R: <looking at computer> 45 L: <moves robot slightly past turning point> and here R: <looking at computer> 26 L: <looks at computer> 26 <moves robot past turning point> and here in the open... so pretty much less than 10 R: 10 L: should we give it a try ? R: sure.	R: let's figure the light <moves robot close to start point> L: so when the light is off it's at 20, and when it's on it's at... R: <uninteligible> <points with finger at light sensor> L: it's at 800 sorry.. it's at 800 and when it's on it's 822.. R: <moves robot closer to light> does it need to be like.. L: <points to start place on maze> R: <moves robot> ok <both watch robot> it's at ... L: 890... R: 895... so when it's greater than 890... so when it moves closer it's gonna be higher right ? <moves robot closer to light> L: yeah R: <after light turns off> so it's low L: yeah, so 890 is the threshold <types on computer> like that... R: [new task] and then ... sensor 2 is the proximity L: <pointing at corner> so we want it to turn left when it's... R: <moves robot past the corner of the wall> <points at robot> so it's 14 and.. <moves to before the turning point> so it's ... L: um.. <makes hand motion to move farther from wall> further because it's driving R: so it... <moves robot farther from wall> L: so I'd say if it's less... R: less than... 14 maybe <moves robot past corner> L: let's get it to the start, maybe <moves robot to start point> <moves robot close to corner> mm.. maybe it should be started there <moves robot back to start> R: yeah so it should be... L: yeah so it should start... so it's 35... so it should be less than 35 R: yeah.. let's check... L: so maybe less than 30 so it doesn't start turning before R: <moves past corner, both look at robot, then moves back to start> yeah L: <types on computer and runs program>

The presence of augmented reality content changed the learning of participants. Team learning improved under AR conditions, but this effect was in large part due to the robot manipulator participant learning much more than the computer participant. This effect in increasing learning may be due to multiple reasons. One reason is that the robot manipulator under AR conditions has easier access to sensor information than in NonAR conditions, since the information is overlaid on the robot they are manipulating. Additionally, by having the improved information availability through AR as the participant is manipulating the robot, this participant was able to engage in faster feedback cycles of action and reflection while they solved problems by manipulating the robot. These reasons, coupled with the improved collaboration that occurs in AR, may explain the increased learning experienced by this participant. Future work is needed to separate how these factors are influencing the learning of such participants.

On the other hand, the participants closer to the computer did not show strong learning effects from the presence of augmented reality, even though under the AR condition they showed changes in their collaboration behaviors and increased manipulation of the robot. For this participant, in both AR and NonAR conditions, they had easy access to the robot program and the sensor information, but in AR the sensor information was aligned with the sensors on the robot. The lack of learning effect from AR indicates that the aligned placement of sensor information (i.e. on a computer screen or on the robot itself) does not seem to matter for this participant's ability to learn. Additionally, the fact that this participant moved the robot in the AR condition without corresponding increase in learning gains may indicate that, for this person, manipulating the robot did not significantly influence learning. An alternative explanation is that this person's learning was positively influenced by these factors, but was also negatively influenced by the changes in collaboration, namely the increased contributions from the other participant, which may have relaxed the computer participant's need to think as deeply as in the NonAR conditions. Future work is needed to investigate specifically why this person's learning is not influenced by AR, and whether the more balanced collaboration from AR may be causing detrimental effects on learning. Furthermore, future work can investigate time-based analysis of how collaborator contributions evolve over time during a session, and how AR technology and user roles influences such activities.

These results point to broader implications for AR and non-AR collaborative environments. First, these findings indicate that the AR system can be helpful to improve learning and collaborative problem solving in contexts where participants have unequal access to information (such as in physical contexts where participants are near specialized resources) or have different roles with respect to manipulating resources (such as in a team where one person's role is to manipulate objects while another focuses on information analysis). We found that AR increased the amount of information commonly available to participants by displaying the same information to both people, thus likely increasing their ability to ground communication, increase peer awareness and balance contributions. The system presented information at the place of action, and sensor information was aligned with the robot sensors rather than on a separate display. We hypothesize that it provided participants with rapid feedback as they manipulated the robot, reduced cognitive load, and enabled faster cycles of action and reflection, thus contributing to increased collaborative problem solving efficiency and faster turn-taking behaviors. From an individual perspective, the system provided the previously disadvantaged participant (farther from the robot) with easier access to information, as now they did not have to reply on their peer. This likely increased the agency of this participant and accounts for the improvements in learning gains and ability to make significant contributions.

Second, it is worth mentioning that some of these effects on collaboration can be achieved without AR technology. Replacing the laptop screen with a large computer monitor easily visible to all participants would equalize access to information and likely increase learning and contributions from the previously disadvantaged participant. However, unlike with AR, participants would need to connect the information on the computer screen to the actual physical sensors located on the moving robot, potentially leading to increased cognitive load and difficulties remembering which sensor represents which information. Another approach is to attach sensor information on the robot itself through small displays attached to the robot. While this approach would be limited due to the small size of displays and portability, it would allow information to be localized on the robot similar to AR, reducing the cognitive effort of mapping information representations. However, this approach would likely introduce an accessibility problem. Unlike AR, the displays would be easily visible only when the person looks at the robot up close from the appropriate angle. Another approach is to project information on the robot from a top-down projector, which would equalize access to and localize the information. However, it would only be applicable to 2D sensor information and may suffer from occlusion when one participant blocks the view of the other. Future work should investigate how these lower-cost approaches influence the processes of collaborative learning, compared to augmented reality approaches such as the one investigated in this research.

We acknowledge that this research has limitations. The access to sensor values in the NonAR condition was limited by the location and size of the laptop display. Future work is needed to investigate the effect of using other approaches to share this information, such as discussed in the previous paragraph. Although these approaches are not traditionally used, they would allow researchers to understand whether the increased information availability, a feature provided through our AR system, can be implemented with lower cost technologies and yielding the same effects. Another limitation is that participants chose their own identifiers, a task done before knowing anything about the activity. In the future this aspect will be randomized. In our study this can introduce a bias from dominant participants (e.g., people who choose #1 might be more dominant); however, this is representative of real-world work situations where people self-assign to different roles, and we did not observe that dominant participants selected one particular identifier (e.g. participants either self-selected themselves to be #1 or #2, or suggested that their participant be #1). Another limitation is during the qualitative coding process, it was not fully possible to hide the study conditions. Thus, the researcher who assigned codes to the participant discussions, could determine the condition by observing participant behaviors, since to see sensor values they either used the computer (in NonAR) or not (in AR conditions). Furthermore, another limitation is that our experimental room size limited participants' movement around the maze; future work is needed to understand how participants would behave if the same task was performed in a different space configuration. Finally, the analysis of our study data is limited by the datapoints available. The data used for the analysis of learning was from all 40 sessions, but for the collaboration metrics we only used a subset of sessions (12 out of 40) for qualitative coding; this leads to decreased ability to find statistical differences between conditions. Although the reported observations are likely to apply more generally, further analysis is needed to determine how generalizable the findings are, and what nuances occur in a larger dataset.

7 CONCLUSIONS

We conducted a mixed methods analysis of collaborators engaging in a problem solving of robot programming activities, in conditions where collaborators either used or did not use augmented reality technology as a systemic aid. Overall, our observations suggest that the use of augmented reality in a collaborative problem solving environment has a positive impact on group learning and collaboration. Detailed analysis showed that AR significantly helped one participant more than the other, allowing them to gain deeper understanding of learning content and contribute to the team collaboration. Furthermore, augmented reality helped both participants remain balanced in their contributions during the problem solving activities. These findings suggest that the application of AR in problem solving environments could promote balanced collaboration in environments with unequal access to resources, and support group learning more generally.

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