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Impact of Robotics and Geospatial Technology Interventions on Youth STEM Learning and Attitudes

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Abstract

This study examined the impact of robotics and geospatial technologies interventions on middle school youth's learning of and attitudes toward science, technology, engineering, and mathematics (STEM). Two interventions were tested. The first was a 40-hour intensive robotics/GPS/GIS summer camp; the second was a 3-hour event modeled on the camp experiences and intended to provide an introduction to these technologies. Results showed that the longer intervention led to significantly greater learning than a control group not receiving the instruction, whereas the short-term intervention primarily impacted youth attitude and motivation. Although the short-term intervention did not have the learning advantages of a more intensive robotics camp, it can serve a key role in getting youth excited about technology and encouraging them to seek out additional opportunities to explore topics in greater detail, which can result in improved learning. (Keywords: Robotics, global positioning system, GPS, geographic information systems, GIS)

There is mounting evidence of the impact of structured informal learning environments on stimulating the interests of adults and children, influencing academic achievement, and expanding students' sense of science, technology, engineering, and mathematics (STEM) career options (Bell, Lewenstein, Shouse, & Feder, 2009). Informal learning environments can be leveraged to promote highly engaging and effective hands-on and inquiry-oriented STEM learning to support development of new skills that emphasize higher orders of thinking, creativity, design, and innovation in a technology-rich and interconnected world (National Academy of Engineering, 2005; Partnership for 21st Century Skills, 2004).

One promising approach to increase STEM attitudes, knowledge, skills, and workforce capacity is the use of robotics and geospatial technologies.

Robots have the potential to transform and enhance the learning process in education (Chambers & Carbonaro, 2003; Jonassen, 2000). Jonassen argues that computer technologies such as robotics can be used as "mind-tools," which involve students in using modern technologies to solve problems. Through hands-on experimentation, such technologies can help youth to translate abstract mathematics and science concepts into concrete real-world applications. Recent improvements in cost and operation of robotics make it possible for even relatively young children to engage in hands-on experimentation with robots. Further, children's fascination and identification with robots makes them naturally engaging and an ideal teaching/learning tool.

When considering spatial technologies such as geographic information systems (GIS) and global positioning systems (GPS), there is a growing potential for educational application, similar to robotics. Small handheld GPS receivers can obtain the data that GIS maps use. GPS is a system of satellites and ground-based receivers that provide geographic coordinates (latitude, longitude, and elevation) anywhere around the earth (Watson, Segarra, Lascano, Bronson, & Schubert, 2005). Although GPS is a relatively complex system, current user interfaces have continued to evolve, and many handheld receivers and their features are accessible to children as young as 9 years of age. Combined, the GPS and GIS technologies provide a powerful set of tools to collect, analyze, and interpret spatial information. Youth can benefit by learning to map areas in their communities. For example, they can map various landscape features (e.g., path routes, fire hydrants, trees) or even visualize data such as soil moisture measurements around the grounds of their school. Furthermore, youth can combine the geospatial concepts with mobile robotics to collect GPS environmental data through the use of sensors installed on a robot, and then use the data to create and analyze thematic GIS maps.

GPS and GIS have also become important tools in such operations as precision agriculture and natural resources management (Milla, Lorenzo, & Brown, 2005). GIS maps allow users to represent geographic features using points, lines, and polygons that, in turn, allow the analysis of relationships between features (Sampson, 1995). For example, examining the relationship between pests and crop growth helps producers apply chemicals at a variable rate, thereby reducing the overall amount of toxins released into the environment.

This quasi-experimental study was intended to substantiate the value of a summer camp focusing on robotics and geospatial technologies to improve youth self-efficacy and stimulate learning of STEM-related concepts. Another goal was to determine the effectiveness of a short intervention designed to increase the participants' interest in the technologies presented, as well as their interest in the more academic subjects of science and mathematics.

Theoretical and Empirical Support

The theoretical framework for using robotics and geospatial technologies in education is derived from the experiential learning model, which is similar in principle to problem-based learning, wherein students learn concepts and principles through authentic experiences and problem solving. In many instances, learning occurs in small groups with teachers as facilitators (Barrows, 1996). Research and theory suggest that youth can learn both content and critical thinking skills through their own experience in finding solutions to prescribed problems (Hmelo-Silver, 2004). Although the instruction includes procedural information, students are encouraged to transfer such knowledge to similar, but not identical, situations. Students who study in this manner become responsible for their own learning, seek out new knowledge, and are better prepared to generalize what they discover (Gurses, Acikyildiz, Dogar, & Sozbilir, 2007; Pressley, Hogan, Wharton-McDonald, Misretta, & Ettenberger, 1996). This approach can result in (a) better long-term content retention when compared to more traditional instruction (Dijbels, 2008; Norman & Schmidt, 1992), (b) higher motivation (Albanese & Mitchell, 1993), and (c) the development of problem-solving skills (Hmelo, Gotterer, & Bransford, 1997; Pedersen & Liu, 2002). Research also indicates that experiential education enhances social and academic development among children by encouraging social interaction and cooperative learning Junge, Manglallan, & Raskauskas, 2003; Slavin, 2000.)

Educational robotics and geospatial technologies embody digital manipulation characteristics, allowing hands-on, mind-on, self-directed learning. Research supports the use of educational robotics to increase academic achievement in specific STEM concept areas closely aligned with formal education topics and coursework (Barker & Ansorge, 2007; Nourbakhsh et al., 2005; Rogers & Portsmore, 2004; Williams, Ma, Prejean, & Ford, 2007). Robotics also encourages student problem solving (Barnes, 2002; Mauch, 2001; Robinson, 2005; Rogers & Portsmore, 2004) and promotes cooperative learning (Beer, Hillel, Chiel, & Drushel, 1999; Nourbakhsh et al., 2005). Similarly, past research has shown that GIS can be used to teach project-based science, environmental education, and geography concepts to middle school students (McWilliams & Rooney, 1997). Similar to robotics, the use of GIS helps students to develop analytical and problem-solving skills (Wanner & Kerski, 1999). Some studies also underscore robotics' potential to engage females and underserved youth in STEM learning; for example, female students are more likely to appreciate learning with robots than with traditional STEM teaching techniques (Nourbakhsh et al., 2005; Rogers & Portsmore, 2004).

Beyond the potential to influence youth learning, educational robotics also represents a unique technology platform with the potential to excite youth and attract them into technology-related careers. The investigation of students' attitudes has a long history in learning research, with recognition that student affect within the learning process is closely related to student cognition, can moderate learners' conceptual change, and is often associated with behavior that is a precursor to learning and achievement outcomes (Alsop & Watts, 2003; Koballa & Glynn, 2007). The attitudinal dimension is particularly critical because of the need to attract young people to study and pursue careers in STEM fields (Bonvillian, 2002). Research has also shown that youths' goals for STEM learning, their self-efficacy, and the value that they assign to STEM tasks and activities are likely to influence their level of engagement (National Research Council, 2007). Studies show that robotics can generate a high degree of student interest and engagement in math and science careers (Barnes, 2002; Miller & Stein, 2000; Nourbakhsh, Hamner, Crowley, & Wilkinson, 2004; Nugent, Barker, Grandgenett, & Adamchuk, 2009; Robinson, 2005; Rogers & Portsmore, 2004).

Methods

The purpose of this research was to determine the impact of robotics and geospatial technologies instruction on youth STEM learning and attitudes. The study used a basic quasi- experimental two-group design to address the following research questions:

1. What is the impact of an intensive week-long robotics/geospatial technologies summer camp (full intervention) on youth STEM learning and attitudes? To answer this research question, the full intervention was compared to (a) a control group of similar duration who did not receive the robotics/geospatial intervention and (b) a three-hour introduction (short-term intervention) to the technologies.
2. What is the impact of the three-hour (short-term) intervention on youth STEM learning and attitudes? To further examine the impact of the short-term intervention, we made comparisons between pre- and postlearning and attitude scores.

Description of the Robotics Intervention

The robotics and GPS/GIS full intervention was targeted at middle school youth who spent 40 hours (one week) in a summer-camp setting. Youth activities included the building and programming of robots using the LEGO Mindstorms NXT robotics platform. The robotics kits consisted of 431 components, including axles, gears, servo motors, and light, sound, ultrasonic, touch, and rotational sensors. The education program also included activities with handheld GPS receivers and ArcMap (ESRI, Redlands, CA) GIS software. The participants used handheld GPS receivers to collect waypoints and tracks that were downloaded to the computer to construct GIS community mapping projects. Adult project staff led and university faculty organized camp activities. Staff delivered content and context in a short introductory lecture format followed by hands-on activities supported by structured worksheets for youth. Participants worked in pairs to complete the majority of robotics tasks, and small groups of three or four students were formed to complete certain more advanced challenges.

The researchers modeled the short-term intervention on the camp experiences but limited it to a three-hour duration. We set up the intervention in seven or eight learning stations, where students, in small groups of five or six, rotated through each learning station for approximately 20–25 minutes. Each station had an adult facilitator who ensured that the experience was well organized and that students were engaged. Each station also showcased a particular use of robotics or geospatial technologies in connection to a STEM concept. Several types of robots and a variety of settings were represented. For example, at one station, students attempted to drive a robot up a steeply inclined ramp to determine the angle at which the robot would slip on the ramp surface. Another learning station asked students to try to identify the minimum voltage generated by a potato battery needed to get a miniature robot to respond. In the GPS station, students tried to find two or three locations using GPS coordinates. The short-term intervention focused particularly on including brief intervention activities that were designed to be especially exciting and quickly engaging for students, in contrast to the long-term intervention, which included activities that were more time intensive and conceptually rich.

The control group consisted of the same students involved in the short-term intervention, which was also used as an instructional benefit for their participation in the earlier control group. We obtained control group data by having youth complete the instruments at two different time points prior to their exposure to the short-term intervention.

Participants

The full intervention treatment group consisted of 147 students participating in 2008 summer robotics camps. These camps were conducted across six Nebraska locations representing both urban and rural settings as well as diverse populations in both ethnicity (one location was 100% minority) and socioeconomic status. This treatment group was 76% male and 25% minority, with a mean age of 12.28 years.

There were a total of 141 students participating in the short-term intervention/control group. We recruited these students through Nebraska's Educational Service Units (ESU), a set of 19 state-funded educational support organizations. The ESUs sent e-mails to schools and curriculum leaders in an urban area inviting their participation in this research. Schools were asked to target a mix of student abilities, interests, gender, and ethnicities to reflect the school's general population of students. They were asked to avoid having only interested or high-ability students participate. The resulting group was 74% male and 20% minority and had a mean age of 11.39 years.

Instrumentation

The content learning instrument we used for this study was a 37-item, paper-and-pencil, multiple-choice assessment covering mathematics (including fractions and ratios), geospatial concepts (coordinate estimation based on location), engineering (such as gears and sensors), and computer programming (such as looping and condition statements). Two experts from Carnegie Mellon University's Robotics Academy and two engineers from the University of Nebraska—Lincoln Department of Biological Systems Engineering reviewed and helped to validate the assessment instrument's content. The same instrument was used as the pre and posttest. A Cronbach's alpha reliability coefficient of .80 was reported for the administration of the posttest.

The project staff also developed the attitude instrument, consisting of 33 Likert scale items and modeled after the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, Garcia, & McKeachie, l991). Items were on a 5-point scale ranging from strongly disagree (1) to strongly agree (5). The questionnaire included two subsections focusing on motivation and the use of learning strategies. The motivation component included questions measuring youth self-efficacy in robotics and GPS/GIS. Self-efficacy was derived from Bandura's (1977) theory centered on one's belief in their ability to cope with a task. Self-efficacy has also been shown to be correlated with achievement outcomes (Sorge, 2007) and motivation to learn (Pintrich, Smith, Garcia, & McKeachie, 1993). The self-efficacy scales focused on youth's self-appraisal of their confidence in performing certain robotics and GPS/GIS tasks, such as "I am certain that I can build a LEGO robot by following design instructions." By focusing on performance tasks, these scales complemented the multiple-choice content test, which assessed general comprehension and knowledge.

The motivation section also included questions on students' perceived value of mathematics, science, GPS/GIS technologies, and robotics. These task value scales measured youth's evaluation of the importance, usefulness, and interest of a particular task. Research has shown that an early interest in STEM topics is a predicator for later learning and/or eventual career interests and choices (DeBacker & Nelson, 1999; Organisation for Economic Co-operation and Development, 2007). Sample items included: "It is important for me to learn how to conduct a scientific investigation," and "I like learning new technologies like GIS."

The learning strategies section of the assessment focused on problem solving and teamwork, which were targeted outcomes for the summer camps. The problem-solving scale measured the degree to which youth use specific problem-solving approaches to successfully accomplish the robotics tasks. Our observations of youth in previous robotics camps had shown that they sometimes appeared to use a variety of problem-solving approaches, including trial and error, with little preplanning and problem analysis. Sample

Table 1. Diagram of Research Design

Short-term/control group intervention	0_1	0_2	X	0_3
Full intervention	0_1		X	0_2

survey items included: "I use a step by step process to solve problems," and "I make a plan before I start to solve a problem." The teamwork scale was included because a stated goal of the summer camps was to encourage teamwork and get youth to work with their peers to solve problems. An underlying premise was that working with peers could help youth learn the STEM content faster and accomplish tasks they could not accomplish on their own. A sample item included: "I like being part of a team that is trying to solve problems."

The researchers factor-analyzed the attitude instrument using the two constructs of motivation and learning strategies (Nugent, Barker, Toland, Grandgenett, & Adamchuk, 2009). We conducted a confirmatory factor analysis because it allows a strong test of the theoretical structure of an instrument and also takes into account the measurement error. The motivation construct conformed to the recommended fit criteria of Standardized Root Mean Squared Residual (SRMR), Root Mean Square Error of Estimation (RMSEA), and Comparative Fit Index (CFI). The learning construct was close to meeting acceptable fit criteria for the same indices. The overall Cronbach alpha reliability, computed from data collected at the 2008 camps, was .95, with individual scale alphas running from .64 to .88.

Procedures

Youth in the full intervention completed the learning and attitudinal instruments on the first day of camp, prior to participating in any of the educational activities. They completed the post instruments at the conclusion of the week-long camp. Students selected for the short-term/control group also took the pretest and posttest a week apart, without any intervention, and then participated in the later three-hour educational robotics exploration event, provided as an educational benefit for the earlier control group participation. The youth completed the questionnaires a third time at the conclusion of the session.

Research Design

Table 1 diagrams the basic experimental design for the research study. The short-term/control group was administered the content and attitude questionnaire twice, with a time lapse of one week between administrations (O_1 and O_2), prior to receiving the three-hour intervention (X). O_1 and O_2 data were used for the control condition. Youth also completed the instruments after the intervention (O_3). This data was used for the short-term condition (O_1 and O_3).

To answer the first research question examining the impact of full intervention, the researchers used a quasi-experimental research design with a between-group comparison between the treatment group (full intervention) and either the control or short-term intervention group. Pre- and postobservations for the short-term intervention are represented as O_1 and O_3; for the full intervention they were O_1 and O_2. For the second research question, examining the effect of the short-term intervention, we used a single group pre-post design (O_1 and O_3).

Data Analysis

The data analysis we used to answer the first research question, involving comparisons of full intervention with both a control group and short-term intervention group, was an Analysis of Covariance (ANCOVA), with the independent variable being type of intervention and the dependent variables being student learning (total score on content assessment) and STEM attitudes (overall mean score on attitude survey). We used pretest scores on both the learning and attitudinal instruments (short-term/control O_1 and full intervention O_1) as covariates. For comparisons involving the full treatment and control group, posttest scores were observations made at point 2 (O_2) for the control group and point 2 (O_2) for the treatment group. For comparisons involving the full intervention and short-term intervention, posttest scores were O_1 and O_3 for the short-term intervention and O_1 and O_2 for the full intervention. To conduct ANCOVA analyses, homogeneity of slopes assumption must be met. For any analyses that violated this assumption, we conducted a split plot ANOVA, with time (pre-post) being used as the within factor and intervention (full intervention versus control) serving as the between variable.

The third research question, examining the impact of the short-term intervention in increasing student learning and attitudes from pre (O_1) to post (O_3), used a dependent t test.

Results

Comparison between Full Intervention and Control Group

Learning results. We observed a violation of the homogeneity of slopes assumption between the covariate (pretest scores on the learning instrument) and the dependent variable (posttest scores on the learning instrument), so we could not use an ANCOVA. As an alternative, we conducted a split plot ANOVA with time (pre-post) as the within factor and intervention (full intervention versus control) as the between variable. We observed a significant time by treatment interaction (Wilk's $\Lambda = .72$, $F[1, 268] = 102.20$, $p < .0001$). The graph (Figure 1) of the interaction clearly shows the significant increase in scores for the full intervention treatment group, whereas the control group scores were relatively unchanged.

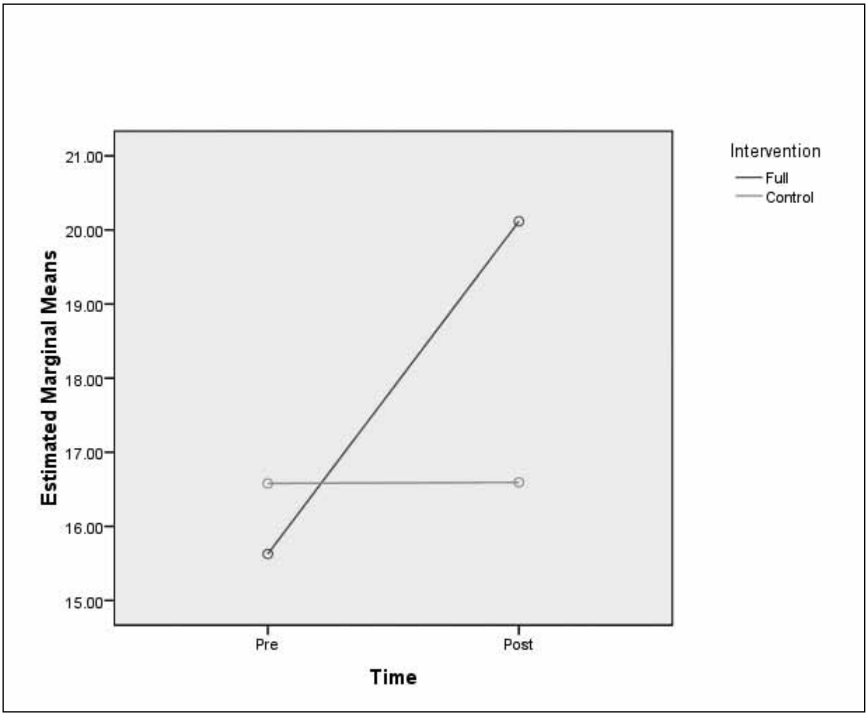

Figure 1. Line graph of the time by intervention interaction for content assessment scores.

Table 2. ANCOVA Results for the Content Scale Scores

Scale	Post Means		*F*	Effect Size η2	Significance
	Treatment	Control			
Engineering	5.34	5.01	8.21	.05	.01
Programming	5.85	4.11	115.73	.30	.0001
Geospatial	1.32	.98	10.24	.04	.01

To provide more insight into the results, we ran ANCOVAs for each of the four scale scores. The homogeneity of slopes assumption was met for the engineering, computer programming, and geospatial scales, and the ANCOVAs showed significantly higher scores for the full intervention treatment group as compared to the control group (see Table 2).

We conducted a split plot ANOVA for the mathematics scale. There was a significant time by treatment interaction (Wilk's $\Lambda = .88$, $F[1, 261] = 35.29$, $p < .001$). A graph of the interaction shows the dramatic increase for the full intervention group (see Figure 2, p. 400).

Results also showed that while males in the full intervention treatment group scored significantly higher than females on both the pre and post content assessments, both gender groups had significant pre-post increases (males: $t[105] = 13.92$, $p < .0001$, females: $t[32] = 4.18$, $p < .0001$).

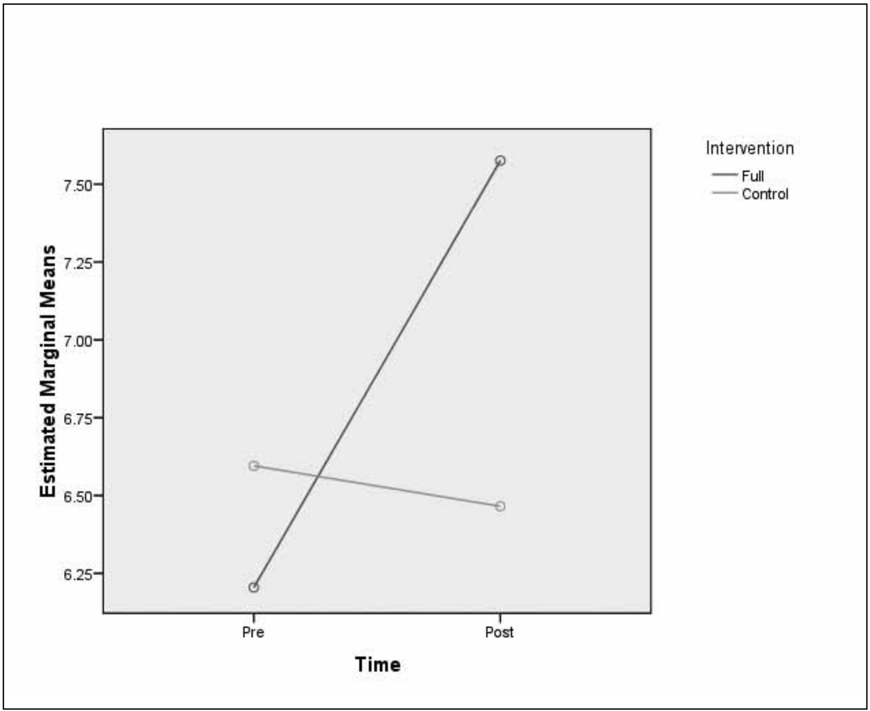

Figure 2. Graph of the time by intervention interaction for the mathematics scores.

Attitudinal results. A preliminary analysis evaluating the homogeneity-of-slopes assumption for the ANCOVA analysis indicated that the relationship between the covariate (pre attitude scores) and the dependent variable (post attitude scores) did not differ significantly as a function of the independent variable, $F(1,255) = .28$, $p = .60$. The ANCOVA was significant ($F[1, 256] = 10.45$, MSE = 1.074, $p < .001$, partial $\eta 2 = .04$). The results indicated that the robotics full intervention group scored significantly higher on the post attitudinal assessment than the control group (full intervention M = 4.23, SD = .53; control M = 4.12, SD = .46). Follow-up examinations of the individual scale scores indicated that most of this difference could be explained by the increases in self-efficacy regarding robotics and GPS/GIS. Split plot ANOVAs showed significant time by treatment interactions for both outcomes (robotics: Wilk's $\Lambda = .92$, $F[1, 249] = 20.21$, $p < .0001$; GPS/GIS: Wilk's $\Lambda = .92$, $F[1, 249] = 20.84$, $p < .0001$). A graph (Figure 3) of the interactions clearly shows the significant increase in scores for the full intervention group, whereas the control group scores remained relatively unchanged.

Comparison of Full- and Short-Term Intervention

A series of ANCOVA analyses looking at both total and scale scores were run comparing the full- and short-term interventions (see Table 3, p. 402).

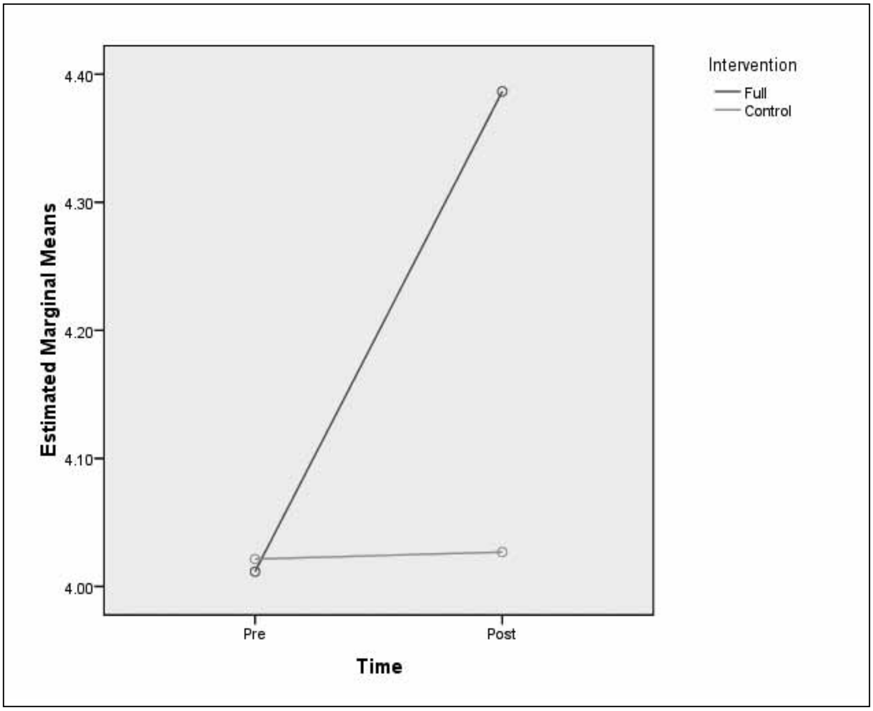

Figure 3. GPS/GIS (left) and robotics (right) self-efficacy scores for full intervention versus control group.

There were violations of the homogeneity of slopes ANCOVA assumption for the robotics task value and self-efficacy scales, as well as the cognitive measure, so we conducted split plot analyses for these three outcomes.

Learning results. An examination of the total cognitive scores in Table 3 shows that the youth in the full intervention scored significantly higher than the short-term intervention, providing additional support for the effectiveness of the summer camps in impacting student learning.

Attitudinal results. An examination of the attitudinal scores revealed that the short-term intervention group displayed significantly higher scores than the full intervention (camp) group on all but the GPS/GIS self-efficacy scale (no significant difference) and the robotics self-efficacy scale, where the full intervention group scored higher.

Short-term Intervention Pre- and Post-Learning and Attitudinal Comparisons

Pre-post learning results. A dependent t test showed that, although there was a slight increase in content test scores (pre M = 16.57, post M = 16.81), the increase was not significant ($t[131] = .91$, $p = .36$). Results indicated that the short-term intervention did not significantly impact learning.

Pre-post attitudinal results. The dependent t test comparing overall at-

Table 3. Total and Scale Score Comparison for Full- and Short-Term Interventions

Outcome	Full (Post) Mean	*N*	Short-Term (Post) Mean	*N*	*F*	Effect Size Partial η2	Significance
Total Attitude (5-point scale)	4.23	134	4.34	124	7.49	.03	$p < .01$
Task Value							
Science	4.20	134	4.33	124	5.89	.02	$p < .05$
Mathematics	4.15	134	4.43	124	4.72	.02	$p < .05$
Robotics	4.41	134	4.55	124	12.86	.05	$p < .0001$
GPS/GIS	4.11	134	4.27	124	7.32	.03	$p < .01$
Self-Efficacy							
Robotics	4.59	130	4.34	123	130.86	.34	$p < .0001$
GPS/GIS	4.39	130	4.40	123	.01	.00	$p = .93$
Teamwork	4.08	130	4.40	123	8.37	.03	$p< .01$
Problem Approach	3.96	134	4.26	123	8.30	.03	$p< .01$
Cognitive	20.12	137	16.81	132	126.43	.32	$p < .0001$

titude scores showed that there was a significant increase in attitudes for the youth experiencing the short-term intervention ($t[123] = 6.92, p < .0001, d = .62$). The mean attitude score increased from 4.09 (pre) to 4.34 (post). To provide more insight into these increases additional dependent t tests were run for each of the attitude scale scores. All of the scales showed a significant increase (see Table 4).

Discussion

Students participating in the week-long intervention clearly increased their STEM learning, as measured by a content test covering topics in computer programming, mathematics, geospatial technologies, and engineering. Scores for youth in this condition were significantly higher than those for both the control group and short-term intervention. The full intervention also led to greater self-efficacy for youth ability to perform robotics tasks. Forty hours of summer camp educational activities gave youth significantly greater confidence in their abilities than did the three-hour intervention. As this result focused on performance tasks, it complements findings from the content test that assessed general comprehension and knowledge. Both the cognitive and self-efficacy results suggest that an intensive, 40-hour robotics instructional program can directly support the learning of challenging STEM concepts and processes. This capability for informal educational activities to directly support academic achievement is encouraging and illustrates the complementary potential of formal and informal education.

In contrast, the short-term intervention had no impact on student learning. It would appear that three hours of robotics and geospatial activities, no matter how interesting, engaging, and well facilitated, do not provide

Table 4. Pre-Post Attitudinal Impacts for Short-Term Intervention

Attitudinal Measure (5-pt. scales)	Means		t(121)	Effect size d	Significance
	Pre	Post			
Task Value				.	
Science	4.06	4.33	6.69	.61	.0001
Mathematics	4.26	4.43	3.80	.35	.0001
Robotics	4.38	4.55	3.38	.31	.001
GPS/GIS	4.03	4.27	4.25	.39	.0001
Self-Efficacy					
Robotics	3.81	4.33	7.94	.72	.0001
GPS/GIS	4.02	4.40	6.04	.55	.0001
Problem Approach	4.00	4.26	6.07	.55	.0001
Teamwork	4.23	4.40	3.70	.34	.0001

enough time to cover topics with sufficient depth and structure to promote student understanding. Students are introduced to certain STEM topics, but the time constraints do not allow the full exploration of concepts and processes necessary to promote learning.

Although the short-term intervention did not have an impact on student learning, it clearly had an impact on student attitudes. Students' attitudes toward science, mathematics, robotics, and GPS/GIS all increased from pre to post, as did their self-efficacy with robotics and GPS/GIS. The study obtained further insight from the comparisons between the short-term and full intervention. Students in the short-term intervention had significantly higher perceptions of the value of science, mathematics, robotics, and GPS/GIS than did the full intervention group.

This result is likely due to the fact that the activities in the short-term intervention were specifically selected and designed to be highly engaging and motivating, with limited cognitive load. The short-term nature of the intervention also meant that the individual activities could not contain extensive mathematics background material or the needed calculations to perform the tasks. Similarly, the activities could not illustrate the complete scientific inquiry or engineering design processes, which may have led to a relatively superficial content focus. Additionally, these activities could not require extensive knowledge of the programming protocols for controlling the robot. This emphasis on the affective, as opposed to cognitive, domain appeared to contribute to the more positive views of youth in the short-term intervention. In short, youth did not have to "work as hard" to successfully complete the activities, which may have resulted in more positive attitudes.

Students in the short-term intervention also increased their self-reported problem-solving skills and teamwork and scored higher on these constructs than did the youth in the full intervention. Again, we hypothesize that the relatively superficial nature of the short-term activities led to perceived goal achievement with little effort. Team-based activities in the short-term intervention afforded youth rapid team-based success without the typical challenges (e.g., planning, time management, resource allocation, roles) associated with investigations presented to the long-term intervention group. Moreover, youth resolved relatively minor issues with little need for background knowledge in the short-term intervention and may have attributed this success to newly acquired problem-solving skills.

These results point to the value of summer camps for improving participants' self-efficacy with robotics and GPS and for teaching related STEM concepts. Results also show that a shorter intervention, intended as a vehicle to promote interest in robotics and geospatial technologies, can concurrently increase student interest in the academic subjects related to science and mathematics. Future research is needed to determine if students in the short-term intervention pursued additional robotics and geospatial activities, and whether improved STEM attitudes and knowledge in the long-term intervention translates into pursuit of STEM-related courses and opportunities during middle and high school education, as well as choice of STEM-related majors in college. Although this study documented the immediate impacts, further research is needed to document the long-term impact of these interventions.

Summary

An intensive week-long educational camp focusing on robotics combined with geospatial technologies appears to promote hands-on, creative, self-directed learning, providing an ideal platform for concepts to be introduced to support youth success with building, testing, and refining their robotics/geospatial projects. In addition, such STEM-related summer camps offer a chance for youth to become more deeply involved in STEM activities and concepts than what might be possible in more formal educational settings or short-term workshops, where the typical time constraints make extended involvement with a particular STEM application more difficult. Short-term robotics interventions appear to be highly successful in impacting student STEM attitudes and getting students excited about robotics and geospatial technologies (and STEM in general). Although such activities do not have the learning advantages of a more intensive robotics camp, they can serve a key motivational role to encourage youth to seek out additional opportunities to explore topics in greater detail. This finding illustrates the value of short, engaging events to increase student interest in STEM-related subjects. Such events have the potential to encourage students to seek out additional opportunities and to explore such topics, which can later contribute to improved STEM learning.

Author Notes

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References

Albanese, M. A., & Mitchell, S. (1993). Problem-based learning: A review of literature on its outcomes and implementation issues. *Academic Medicine, 68*, 52–81.

Alsop, S., & Watts, M. (2003). Science education and affect. *International Journal of Science Education, 25*, 1043–1047.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychology Review, 84*, 191–215.

Barker, B., & Ansorge, J. (2007). Robotics as means to increase achievement scores in an informal learning environment. *Journal of Research on Technology Education, 39*, 229–243.

Barnes, D. J. (2002). Teaching introductory java through LEGO Mindstorms models. In SIGCSE (Ed.), *Technical Symposium on Computer Science Education*. Covington, Kentucky.

Barrows, H. S. (1996). Problem-based learning in medicine and beyond: A brief overview. *New Directions for Teaching and Learning, 68*, 85–92.

Beer, R., Hillel, J., Chiel, J., & Drushel, R. (1999). Using robotics to teach science and engineering. *Communications of the ACM, 42*, 85–92.

Bell, P., Lewenstein, B., Shouse, A., & Feder, M. (2009). *Learning science in informal environments.* Washington, D.C.: National Academies Press.

Bonvillian, W. B. (2002). Science at a crossroads. *FASEB Journal, 16*, 915–921.

Chambers, J., & Carbonaro, M. (2003). Designing, developing, and implementing a course on LEGO robotics for technology teachers education. *Journal of Technology and Teacher Education, 11*, 209–241.

Council, N. R. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future.* Washington, D.C.: The National Academies Press.

DeBacker, T. K., & Nelson, R. M. (1999). Variations on an expectancy-value model of motivation in science. *Contemporary Educational Psychology, 24*, 71–94.

Deen, M. Y., Bailey, S. J., & Parker, L. (2001). *View life skills.* Retrieved on April 28, 2010, from http://www2.montana.edu/lifeskills/viewlife.asp

Dijbels, D. (2008, October). *Effectiveness of problem-based learning.* Retrieved October 9, 2009, from http://ww7.nationalacademiesorg/bose/Gijbels_ComissionedPaper.pdf

Education Week. (2008). *Technology counts—STEM: The push to improve science, technology, engineering, and mathematics.* Bethesda, MD: Editorial Projects in Education. Retrieved on April 28, 2010, from http://www.edweek.org/ew/articles/2008/03/27/30intro.h27.html

Gurses, A., Acikyildiz, M., Dogar, C., & Mustafa, S. (2007). An investigation into the effectiveness of problem-based learning in a physical chemistry laboratory course. *Research in Science & Technology Education, 25*, 99–113.

Hmelo, C. E., Gotterer, G. S., & Bransford, J. D. (1997). Theory-driven approach to assessing the cognitive effects of PBL. *Instructional Science, 25*, 387–408.

Hmelo-Silver, C. (2004). Problem-based learning: What and how do students learn? *Educational Psychology Review, 16*, 235–266.

Jonassen, D. H. (2000). *Computers as mindtools for schools: Engaging critical thinking* (2nd ed.). Upper Saddle River, NJ: Merrill.

Junge, S., Manglallan, S., & Raskauskas, J. (2003). Building life skills through afterschool participation in experiential and cooperative learning. *Child Study Journal, 33*, 165–174.

Koballa, J. E., & Glynn, S. (2007). Attitudinal and motivational constructs in science learning. In S. Abell & N. G. Lederman (Eds.), *Handbook of research in science education* (pp. 75–102). Mahwah, NJ: Erlbaum.

Lemke, M., Sam, A., Pahike, E., Partelow, L., Miller, D., Williams, D., et al. (2004). *International outcomes of learning in mathematics literacy and problem solving: PISA 2003 results from the U.S. perspective.* Washington, D.C.: U.S. Department of Education, National Center for Education Statistics.

Mauch, E. (2001). Using technological innovation to improve the problem-solving skills of middle school students. *The Clearing House, 75*, 211–213.

McWilliams, H., & Rooney, P. (1997, March). *Mapping our city: Learning to use spatial data in the middle school science classroom.* Paper presented at the meeting of the American Educational Research Association, Chicago, IL. (ERIC Document Reproduction Service No. ED407264)

Milla, K., Lorenzo, A., & Brown, C. (2005). GIS, GPS, and remote sensing technologies in extension services: Where to start, what to know. *Journal of Extension, 43.* Retrieved on April 28, 2010, from http://www.joe.org/joe/2005june/a6.shtml

Miller, D. P., & Stein, C. (2000). So that's what pi is for and other educational epiphanies from hands-on robotics. In A. Druin & J. Hendler (Eds.), *Robots for kids: Exploring new technologies for learning experiences* (pp. 219–243). San Francisco: Morgan Kaufmann.

National Academy of Engineering. (2005). *Engineering research and America's future: Meeting the challenges of a global economy.* Washington, D.C.: National Academies Press.

National Governors Association (n.d.). *Building a science, technology, engineering and math agenda.* Retrieved on April 28, 2010, from http://www.nga.org/Files/pdf/0707INNOVATIONFINAL.PDF

National Research Council. (2007). *Taking science to school.* Washington, D.C.: National Academy of Sciences.

Norman, G. R., & Schmidt, H. G. (1992). The psychological basis of problem-based learning: A review of the evidence. *Academic Medicine, 67*, 557–565.

Nourbakhsh, I. R., Crowley, K., Bhave, A., Hamner, E., Hsiu, T., Perez-Bergquist, A., et al. (2005). The robotic autonomy mobile robotics course: Robot design, curriculum design and educational assessment. *Autonomous Robots, 18*, 103–127. Retrieved on April 28, 2010, from http://www.springerlink.com/content/m5m6k53511h08511/fulltext.pdf

Nourbakhsh, I., Hamner, E., Crowley, K., & Wilkinson, K. (2004). *Formal measures of learning in a secondary school mobile robotics course.* Paper presented at the International Conference on Robotics and Automation, New Orleans, LA.

Nugent, G., Barker, B., Toland, M., Grandgenett, N., & Adamchuk, V. I. (2009). Measuring the impact of robotics and geospatial technologies on youth science, technology, engineering, and mathematics attitudes. In C. Fulford & G. Siemens (Eds.), *Proceedings of the World Conference on Educational Multimedia, Hypermedia, and Telecommunications* (pp. 3331–3340). Chesapeake, VA: Association for the Advancement of Computing in Education.

Organisation for Economic Co-Operation and Development. (2007). *Education at a glance 2007: OECD indicators.* Paris, France: Author.

Partnership for 21st Century Skills. (n.d.). Retrieved October 9, 2009, from www.21stCenturySkills.org

Pedersen, S., & Liu, M. (2002). The transfer of problem-solving skills from a problem-based learning environment: The effect of modeling an expert's cognitive processes. *Journal of Research on Technology in Education, 35*, 303–320.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ).* Ann Arbor, MI: University of Michigan, National Center for Research to Improve Postsecondary Teaching and Learning.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). *Educational and Psychological Measurement, 53*, 801–814.

Pressley, M., Hogan, K., Wharton-McDonald, R., Misretta, J., & Ettenberger, S. (1996). The challenges of instructional scaffolding: The challenges of instruction that supports students thinking. *Learning Disabilities Research and Practice, 11*, 138–146.

Robinson, M. (2005). Robotics-driven activities: Can they improve middle school science learning. *Bulletin of Science, Technology & Society, 25*, 73–84.

Rogers, C., & Portsmore, M. (2004). Bringing engineering to elementary school. J*ournal of STEM Education, 5*, 17–28.

Sampson, S. A. (1995). Determining need for a geographic information system (GIS). *Journal of Extension, 35*. Retrieved on April 28, 2010, from http://www.joe.org/joe/1995october/tt2.html

Slavin, R. (2000). *Educational psychology: Theory and practice* (6th Ed.). Englewood Cliffs, NJ: Allyn and Bacon.

Sorge, C. (2007). What happens: Relationship of age and gender with science attitudes from elementary to middle school. *Science Educator, 16*, 33–37.

Wanner, S., & Kerski, J. (1999, July). *The effectiveness of GIS in high school education.* Paper presented at the 1999 ESRI Users Conference, San Diego, CA. Retrieved on April 28, 2010, from http://proceedings.esri.com/library/userconf/proc99/proceed/papers/pap203/p203.htm

Watson, S., Segarra, E., Lascano, R., Bronson, K., & Schubert, A. (2005). Guidelines for recommending precision agriculture in southern crops. *Journal of Extension, 43*. Retrieved on April 28, 2010, from http://www.joe.org/joe/2005april/rb7.shtml

Williams, D., Ma, Y., Prejean, L., & Ford, M. J. (2007). Acquisition of physics content knowledge and scientific inquiry skills in a robotics summer camp. *Journal of Research on Technology in Education, 40*, 201–216.

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