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The Ideal Science Student: Exploring the Relationship of Students' Perceptions to their Problem Solving Activity in a Robotics Context

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The purpose of this study is to examine the relationship of middle school students' perceptions of the ideal science student to their problem solving activity and conceptual understanding in the applied science area of robotics. Twenty-six 11 and 12 year-olds (22 boys) attending a summer camp for academically advanced students participated in the study. This correlational study utilizes survey and observational data. Students completed the ideal science student survey and individually engaged in a problem solving activity that was videotaped. Students were instructed to think-aloud during the problem solving session. The final programming solution students created was scored using a conceptual rubric. Two dominant perceptions of the ideal science student were identified, a traits-based view and a process-oriented view. Students with a traits-based view tended to use domain general strategies to solve the robotics problem. Whereas, students with a process-oriented view tended to use domain specific strategies, Chi-Square (1, n=24) = 4.608, p = .032. Students with the process-oriented view evidenced stronger conceptual understanding in their final program solutions as revealed by an ANOVA, F (1, 22) = 5.367, p = .03. Qualitative analysis of the data indicates that students with the process-oriented view modeled, verified and expanded their understanding of the use of specific tools in the environment. Implications of these findings for pre-service science teachers and the design of learning environments are discussed.

Research suggests that effective science education addresses not just knowledge and skills, but also the aspirations and perceptions students hold towards science learning (Aikenhead, 2001). Students, for example, need to aspire to learn science, not just to behave well in the science classroom, if they are to develop conceptually accurate understandings of science topics (Aikenhead). Our own work with middle school students showed that we can successfully require students to attend science classes, but we cannot guarantee their understanding about what is expected of them in order to be a successful learner (Author, 2003a; Author, 2003b). Indeed, the meaning students construct about learning expectations may end up being very different from what their teachers would like it to be (Author; Author; Kuhn, 2005). Moreover, while researchers have proposed a link between students' perceptions of themselves as science learners and their subsequent science learning (Alsop & Watts, 1997; Tyson, Venville, Harrison & Treagust, 1997), it is still unclear how these perceptions are related to their effort and approach in science learning.

The purpose of our study was to examine the relationship of student perceptions about what it means to be a science student and their approach to learning in the applied-science setting of robotics. Specifically, we sought to understand the relationship between students' perception of the ideal science student, their approaches to solving a robotics problem, and their achievement in so doing, as measured by their demonstrated conceptual understanding of certain computer science concepts related to robotics study. We selected the construct of the ideal science student because previous research has indicated that each of us develops a notion about what the 'ideal' person would be like in a given situation, and this ideal reflects our '… wishes or aspirations' (Strauman & Higgins, 1987, p. 1004). Therefore, asking students to reflect on their view of the ideal science student provides evidence of their own aspirations in this regard. And, these aspirations may affect their activity in learning science.

The Ideal Science Student Construct

When students were asked to describe the ideal science student, they were being prompted to reflect on two elements: the social category of science student and the attributes or behaviors an ideal member of this category would have. The latter element requires the student to make a value judgment. These judgments are dialogically constructed through interaction with their parents (Smith, 1982; Buchanan-Barrow & Barrett, 1996), and participation in school (Hatano & Wertsch, 2001), including interactions with teachers (Buchanan-Barrow & Barrett; Lunenberg & Volman, 1999; McRobbie & Tobin, 1996), other students (Cashmore & Goodnow, 1985) the classroom environment (Ames & Archer, 1988), and the overall school environment (Buchanan-Barrow & Barrett).

Ideal student research reports are few, and they primarily focus on identifying variations in perceptions of the ideal student (Cashmore & Goodnow, 1985; Author, 2003a; Ten Dam, 1995). The term 'ideal' is not defined singularly or even similarly by individuals residing in the same society (Barrett & Buchanan-Barrow, 2005). For instance, Author (2003a) found in a study of students' perceptions of the ideal student, that middle school students attending private schools (predominately white students with high achievement scores from upper middle class families) in a mid-sized, midwestern city in the United States perceived ideal students to have specific learning-oriented traits (e.g., explains and understands deeply, knows when one makes mistakes, etc.,), while students attending a public school in the same community (predominately underserved students with low achievement scores from families with few financial resources) perceived ideal students to have specific types of behavior in class (e.g., does not fight, sits still during lectures, etc.). Research suggests that these differences are due to the respective schools' culture (Gottlieb, 2007), differences between students' home culture and the school culture (Costa, 1995), teacher expectations (Rappaport & Rappaport, 1975), and race and class-based societal inequities (Anyon, 1980; Lareau, 2003).

Other researchers have found that student perceptions of the ideal student appear to differ based on age, country of origin, gender, and school type (Cashmore & Goodnow, 1985; Author, 2003a; Lunenberg & Volman, 1999; Ten Dam, 1995). In addition, Lunenberg and Volman found evidence of congruence between the perceptions of the ideal student and actual learning behavior in a higher education classroom. Students in their study viewed the ideal student as a passive receiver of knowledge from the teacher and they enacted this belief in class.

Ruff and Shoho (2005) reported a similar relationship of perceptions to activity in their case study of novice and expert elementary school principals. These researchers focused on the relationship of the principals' perception of her/his role as the instructional leader of the school to their daily activities and approaches to solving instructional problems at the school. They found that each of the participating principals had a different view of her/his role and that the principals' respective daily activities and problem solving approaches aligned with their individual perceptions.

While we see some evidence of the influence of perceptions on higher education learning activities, daily work activities, and problem solving in a professional setting, there remains little research regarding the relationship of perceptions about being a science student to problem solving in the K12 science classroom. However, there is reason to believe that such a relationship exists based not only on the ideal student and principal reports, but also in relation to implicit theories of personality research.

Implicit Theories of Personality

Dweck and Leggett (1988) articulated a social-cognitive view of personality seeking to explain the relationship of student motivation to achievement. This view posits students' implicit beliefs about the nature of intelligence as a strong predictor of the student's subsequent learning goal orientation, problem solving strategy selection, and achievement in the classroom. Dweck and Leggett discuss the fact that a generalization of their model may be used to explain 'properties of *people*, places, things, phenomena or the world' (p. 267, emphasis added). Therefore, literature regarding students' implicit beliefs of personality sheds light on how student perception of the ideal science student might affect student learning in the science classroom. Various researchers have empirically tested and found support for the main tenets of this theoretical model (Braten & Olaussen, 1998, Stipek & Gralinski, 1996). However, Vandewalle (1997) found significant but somewhat weak correlations between implicit beliefs and goal orientation, and Braten and Stromso (2004) found little correlation between implicit beliefs and goal orientation.

From this research it is clear that there is a relationship between students' implicit beliefs of personality and students' problem solving approaches; however, there is less support for the relationship of goal orientation to either construct. Our work, therefore, focuses on the relationship of students' implicit beliefs about the ideal science student and the relationship of these beliefs to problem solving approaches and outcomes in the applied science setting of robotics.

Problem-Solving, Science Education and Robotics

We focused on problem solving because it has been identified as an important aspect of science learning and scientific literacy (National Research Council, 1996). Problem solving is a constitutive element of scientific inquiry, as much scientific work has been, and continues to be, concerned with solving societal problems. Greeno (1991) proposes an environmental view of problem solving as one in which problem solving ability is characterized as an understanding of where to locate and how to use the resources with which one can reason to solve problems in a given domain. We based our theory of understanding (how people build knowledge) on this sociocultural idea of interaction with tools and resources in the environment. In our view, student understanding in a robotics context develops as a result of interaction within a system of distributed cognition (Cole & Engestrom, 1993). From this standpoint, it is argued that the ideas of others are reified in the tools and resources in the environment (Cole, 1996; D'Andrade, 1986). In other words, tools that help one to perform cognitive activities, such as calculation, are intelligent, and that intelligence is culturally-based and originated with the creators of the tool. When students interact with these tools, they enter into a dialogical relationship (Bakhtin, 1981) with these inventors – where the ideas of the inventors (present in the design of the tools) are made available to the students. Such interaction allows the students to begin to develop ideas about how to solve a particular robotics challenge by coming to understand how the tools function. And, through solving these robotics challenges students develop their conceptual understanding of computer programming. This latter idea is supported by previous research related to science education and problem solving. For example, Chang (2002) has argued that students who engaged in computer supported problem solving activities in an earth science curriculum were more likely to build knowledge of earth science than those who were given direct instruction of the relevant concepts.

We chose to conduct our study in the applied science domain of robotics because many students find robotics to be an engaging activity and the open-ended, robotics problem solving activities we presented to students fosters the development of the habits of mind typical of scientifically literate people (Author, 2008).

In sum, we argue that understanding student effort and approaches to learning in science is important to developing effective science learning environments. The ideal science student construct is presented here as a vehicle for probing students perceptions about learning in the science classroom.

As argued above, perceptions are socialized judgments that are dialogically constructed through interaction with parents, teachers, other students, the classroom environment and the school environment. Furthermore, there is empirical support for the idea that students' perceptions of personality are related to their effort in learning and, in particular, to the problem solving strategies they use. And, problem-solving activities in a system of distributed cognition provides students the opportunity to engage with the culturally-based, reified ideas present in the tools themselves, thereby stimulating the development of conceptual understanding in the domain of robotics; a domain that enables scientifically literate habits of mind.

Therefore, understanding the relationship of students' perceptions of the ideal science student as they relate to learning in science will help science educators and curriculum developers create meaningful science learning experiences for students that lead to strong learning outcomes. Our work seeks to contribute to this understanding. In so doing, we address three questions: (1) what are students' perceptions of the ideal science student and how do they vary?; (2) how are these perceptions related to their problem solving approaches in a science context?; and (3) how are these perceptions related to their conceptual understanding as evidenced in their problem solving activity and programmatic solution scores?

METHODS

Setting

The data for this study were collected in a summer camp program for gifted students in the United States (US). The summer camp program was offered to students who are termed academically advanced based on their standardized test scores. Specifically, the program accepted second through sixth grade students who have scored in the 95th percentile or above on nationally normed tests administered by their respective schools. Scores on state tests that were categorized as advanced, distinguished, honors, exceeds, etc., were also used to qualify a student for participation in the programs.

Posing a complex robotics problem to the participants was an important aspect of this study as it prompts the usage of inquiry-based habits of mind and several observable problem-solving strategies. This setting was selected because it provided the opportunity for students to engage in *intensive* robotics study. Unfortunately, in the US, intensive academic summer camp experiences are rarely provided to 'typical' students. We selected to work with the 'talented' students in order to conduct the study in the intensive setting.

The participants in the summer camp took part in a three-week long, intensive summer robotics session. The robotics class met five days a week from 8:45am to 4:30pm for three weeks. There were two three-week sessions. Twelve students attended the first session and fourteen students attended the second session.

Participants

Twenty-six 11 and 12 year-old students participated in the study (4 girls). All of the girls who applied to be in the summer camp robotics course were accepted. Unfortunately, far fewer girls were interested in studying robotics than boys. Other researchers have also documented girls' lack of interest in robotics (Turbak & Berg, 2002; Rusk, Berg, & Resnick, 2005). Fourteen of the participants in this study were European American (12 boys and two girls), nine were Asian American (eight boys and one girl), and three were bi-cultural students (two European American and Middle Eastern – one boy and one girl, and one European American and Native American boy). Twenty-five of the students spoke English as their primary language. The 26th student spoke English as a second language. This student was fluent in speaking, reading, and writing in English. Socio-economic status was not available; however, the camp was expensive and none of the students were receiving scholarship assistance.

The camp took place in Maryland, USA at a small liberal arts college. The campers arrived from states along the eastern seaboard (and one student attended from Belgium). Due to the fact that the students all attended different elementary schools in different districts and different states, it was not possible to observe the instructional strategies used by their respective teachers. The course was co-taught by the first author and another teacher. We primarily utilized a guided discovery (Mayer, 2004) approach in teaching the students robotics. In this approach, we provided minimal instruction, but we did structure activities within which students could explore and expand their knowledge of robotics. At the beginning of each camp session, the respective classes were asked if they had previous experience with Lego Mindstorms. While most of the students reported playing with Legos, none reported experience with robotics. Pseudonyms are used throughout this study. Parental consent for research participation was collected by the camp administrators. Student assent was sought by the researchers from the students. All of the students assented to be in the study.

Materials

The LEGO Mindstorms robotics kit and Robolab software were used in this project (see Author, 2008 for a complete description of these materials). Three sensing devices were used in the challenge including: the light sensor, the touch sensor and the rotation sensor. The light sensor is a device that measures the reflection of light off of a surface and displays the reading on the screen of the microcomputer formally titled the robotics command explorer (commonly known as and hereafter referred to as the RCX). Dark surfaces reflect less light and result in lower numeric readings. Light surfaces reflect more light and result in higher numeric readings. A touch sensor is a device that responds to physical contact with an object. The touch sensor has two states it may be in, activated or not activated. The rotation sensor counts the rotation of a wheel attached to a motor and the RCX.

Research Design

This correlational study utilizes survey and observational data. The data sources include two questionnaires completed by students on the first day of each session: a demographic survey and the ideal science student survey. During the last week of the respective summer sessions, each student also individually engaged in a problem solving activity that was videotaped; students were instructed to think-aloud during the problem solving session. These think-aloud data, along with the students' observed actions and their responses to the ideal science student survey formed the basis of our qualitative data collection.

The think-aloud technique requires the participant to verbalize his or her thoughts as he or she works through the problem solving challenge and is designed to reveal the reasoning processes of the participant. Numerous studies have shown that asking individuals to verbalize their thoughts while performing a task or solving a problem does not affect the outcome of the performance (Carp, 1972; Newell & Simon, 1972; Walker, 1982 all as cited in Ericsson & Simon, 1993). In our study, we were specifically interested in identifying the relationship between student reasoning processes and tool use manifested as problem solving strategies.

According to Erickson and Simon (1983) "When an investigator instructs a subject to think-aloud, some subjects may misunderstand the instruction and produce instead the more common social communication, explaining or describing the process to the experimenter" (p. xiv); therefore, the distinction between social communication and the think-aloud technique was explained to the participants. It was made clear that social interaction was not a goal of the process, participants were not meant to explain what they were doing to the researchers; rather, they were instructed to do their best to verbalize their thoughts as they occurred. Nevertheless, participants in this study produced both social communication and true think-aloud verbalizations. When students became quiet or engaged in social communication, the researchers gently prompted the students to either ‘keep talking’ or to ‘just say your thoughts’.

In addition to the surveys and the think-aloud observations, we also collected the students final problem solution. This solution was scored using a conceptual rubric (described below).

Instruments

Ideal science student survey. The ideal science student survey is an open-ended instrument that asks students to write five sentences or list five qualities of an ideal science student. The design of the instrument responds to a major criticism of the forced-choice nature of survey instruments used in research related to the social-cognitive view of personality (the theoretical basis of the ideal science student research) which leaves out the student voice (Quihuis, Bempechat, Jimenez and Boulay, 2002; Schunk, 1995)

The ideal science student survey is based on the ideal student survey which was first developed and used by Author (2003a). We used this instrument in a study with 280 students in the United States and China. We asked students to list the five qualities of the ideal student. Results from this study indicated that students had either a predominately learning-oriented or a predominately behavior-oriented view of the ideal student. In the Chinese context, all of the students evidenced a predominately learning-oriented view. This finding is in accordance with Li’s (2001) findings related to Chinese people’s cultural models of learning which emphasize knowledge seeking and achievement.

Two researchers independently coded all ideal student data from this initial study. To test for inter-rater reliability, the coding of all responses was analyzed with Cohen’s (1960) kappa (k = .88). Cohen’s kappa is a more stringent measure of reliability in the case of categorical/qualitative data as it also attempts to account for the probability that coders reached the same conclusion through chance.

As a manipulation to test for construct validity of the initial survey instrument and coder rating of ideal characteristics, students were asked what they believed the consequences of certain actions were (namely not completing homework and not behaving in class). In other words, we sought confirmation of student understanding of the construct through examining the consistency of their views. Significant ($p < .001$) negative correlations were found between not completing homework and deep learning, and between not behaving in class and valuing good behaviors. Students, then, not only were able to articulate ideals as answers to researchers' questions, but also believed that there were outcomes associated with such beliefs. This manipulation check provides evidence of the construct validity of the survey.

Problem solving challenge. The individual problem solving sessions were conducted from the eighth to the thirteenth day of the sessions. All of the relevant programming content needed by the students to solve the challenge had been covered by day five of the course. This content included the proper use of the three sensing devices and knowledge of procedural flow (loops, forks and split tasks). The problem solving session consisted of solving a robotics challenge that required minimal building. A partially constructed robotic vehicle was provided to the students; they completed the construction by adding the appropriate sensors, wheels and structural supports.

The students were individually asked to write a program that would cause the vehicle to follow an angled black line on a paper track, when the vehicle bumped into an object at the end of the track it should back up for six inches, make a 360 degree turn and stop. Appendix A is a reproduction of the paper track used in the problem solving session. There were three programmatic components to the challenge: the first was the line following task; the second was the back up six inches on contact task; and the third was the 360-degree turn task.

The problem solving task environment included the written robotics challenge, the Lego Mindstorms kit which included the RCX, the sensors, a paper track with a six inch/15 centimeter ruler inscribed on it, and the Robolab software program. The following instructions were given to each student: 'Please read the challenge. You may solve the challenge in any way you like. As you are solving the challenge, please say out loud what you are thinking.' There was no time limit imposed on the problem solving sessions. Each student worked individually and no one received help from other students.

We responded to student questions during the course of the problem solving challenge. Many questions regarded the use of certain materials. For instance, some students asked if they could use certain sensors. Our reply to this was ‘you can use all of the materials we have.’ When students asked for specific help in solving the challenge, they were directed to ‘keep thinking about ways to solve the challenge’. All problem-solving sessions were videotaped. At the end of the session, the final Robolab screen was printed out and saved. This artifact served as the record of the students’ programmatic solution to the problem.

Computer science conceptual scoring rubric. Students’ scores on their programmatic solutions were used as a measure of their problem solving ability and conceptual development. These solutions were scored using a conceptual rubric (Appendix B). Students were awarded points for their solution based on the correct utilization of specific icons, which denoted understanding of specific computer science concepts and their relevance to the problem solving challenge. The scoring rubric may be applied objectively, as it is based on the presence or absence of specific icons, and the correct usage of icons in the program. Correct usage is defined as proper placement and correct modification of an icon in the program.

Points were allocated based on judgment of the difficulty and complexity of each concept. Two experts in the use of Robolab and the LEGO Mindstorms kit provided feedback on the first draft of the conceptual rubric; changes were made to the scoring system based on this feedback. Content validity of the conceptual rubric was achieved when both experts independently reviewed the rubric and agreed that the scoring system reflected the difficulty and complexity of understanding and applying the concepts involved in the robotics challenge. The experts were professional educators who both worked for a non-profit educational organization devoted to bringing robotics curriculum to public school settings. Both experts had been involved in developing robotics curriculum and teaching the curriculum to teachers and students. In addition, both experts had advanced degrees in the area of educational technology and extensive professional backgrounds in the field of computer programming.

The computer science concepts inherent in the challenge were input/process/output, procedural flow, and infinite looping. The first concept input/process/output is operationalized in Robolab through the use of the sensors. The sensors take in data that trigger programmed events based on the data value. The second concept, procedural flow, refers to the order in which different elements of a program are executed. Procedural flow may be managed in Robolab using a task split icon or if/then forks. The third concept, infinite looping, is represented in Robolab through the use of directional or looping icons. Next, we discuss each of the concepts as they were embedded in the challenge, and the point values assigned for the programmatic application of the concepts.

Input/process/output. Utilizing environmental feedback to control the motion of the robot in the line-following task was the most challenging aspect of the robotics problem given to the students. There were four different approaches students could take to solve the line-following task; the approaches are presented in descending order of conceptual sophistication.

The first approach consisted of programming the robot to detect both the right and the left edge of the black line on the paper track. In this approach two sensors are continuously reading both the black line and the white field surrounding it and making adjustments to the movement of the robot accordingly. This program relies on both the correct variable modification to the light sensor icons and accurate physical placement of two light sensors on the front of the robot. The successful execution of this approach was awarded three points. A second and slightly less complex approach to solving the line following task was to program the robot to sense either the right or the left edge of the black line against the white field. In this solution, one sensor continuously reads the edge and tracks the movement of the robot along this edge. Accurate execution of this approach was awarded two points. A third approach to solving the line-following task relied on reacting once to a change in light value. For example, the robot was programmed to turn when it reads a brighter value (indicating the white field). This approach does not provide for a continuously adjusting light sensor program. The success of this programming approach relied heavily on the physical placement of the robot on the paper track. One point was given for this approach. Figure 1 provides a visual illustration of these three approaches to solving the line following task.

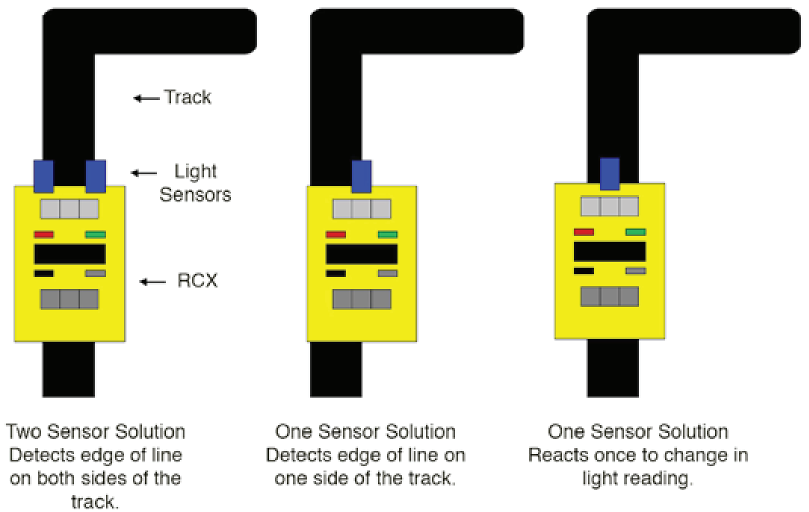

Figure 1. Line Following Task Solutions

The fourth approach is to have the robot move forward when it senses the black line. This approach indicated that a student was not accurately conceiving of the proper use of the light sensor in solving this problem. Programming the light sensor to move forward when it senses the black line only does not take into account what the robot should do when it detects a brighter light value. This approach was given zero points.

The input/process/output computer science concept was also inherent in the second section of the challenge: upon contact, back up for six inches. There are two approaches to solving this element of the challenge. The optimal approach was to use a rotation sensor to measure the six-inch distance. The rotation sensor tracks the rotations of the wheel attached to the motors. This sensor is immune to variables that would affect a timing based solution such as fluctuations in battery power or the interference of dust particles on the paper track. To successfully program the rotation sensor, one needs to derive the distance the RCX would travel with one rotation of the wheel and use this number to calculate the proper modifying variable needed to travel six inches. Two points were given to students who successfully employed the rotation sensor in this task. A second approach to solving this task is to use a timing element to program the robot to back up for six inches. Points were not awarded for this approach because no evidence of conceptual understanding of the input/process/output nature of the rotation sensor was demonstrated.

Procedural flow and infinite loops. We address the second and third computer science concepts embedded in the challenge – procedural flow and infinite loops – together, as the two were intertwined in the solution to the challenge. To reiterate, the challenge requires the students to program the robot to complete three tasks in sequence, first the line following task, then the back up six inches task, and finally the 360-degree turn task. The strongest solution to the problem includes control elements that allow for the activation, looping, and deactivation of portions of the challenge.

There were three primary approaches to organizing the flow of the program. One approach was to use a task split with two branches. A task split is an icon that allows one to write parallel lines of code that run simultaneously. In one branch of the task, it is possible to write the line following program, using infinite loops to indicate that the program should execute repeatedly. This allows the algorithm to run continuously until the robot makes its way to the end of the black line. The second branch of the task split may then be programmed to perform the touch sensor triggered elements of the challenge. In this branch, the first programmatic element is the touch sensor icon; this is followed by a stop task icon set to stop the first branch of the task split. This configuration stops the line following program once the touch sensor is activated, and it allows for the smooth functioning of the touch sensor triggered tasks. This approach was awarded two points. Figure 2 depicts a student program that utilizes this approach.

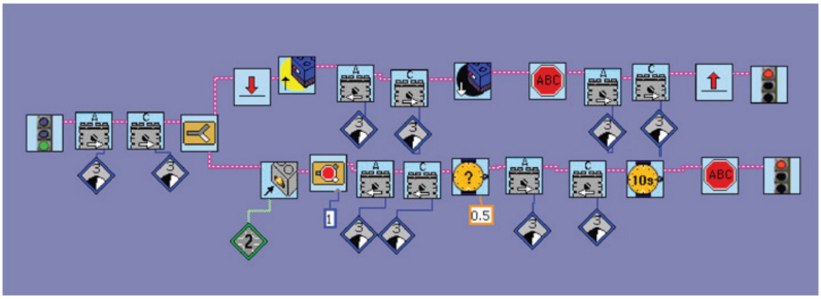

Figure 2. Procedural Flow/Infinite Looping Example

A second approach that utilizes these concepts was quite similar to the first approach except that the stop task icon is not in place. Therefore, this approach allows the line following algorithm to operate in parallel with the touch sensor program. This solution is problematic in that with an active light sensor program, the robot will continue to respond to environmental input from the light sensor, potentially disrupting the smooth flow of the touch sensor triggered elements. Therefore, this approach was awarded one point.

The third approach to procedural flow utilizes none of the control icons. Rather, this approach simply utilizes one line of code that was executed in a linear fashion. This approach relied exclusively on timing elements in writing the program. Therefore, a student who utilized this approach exhibited no conceptual understanding of procedural flow or iterative mechanisms. This approach was awarded zero points. This rubric was used for analysis purposes only. Students attending the summer camp were not given grades or point scores on their robotics work. Their learning in this environment was for enrichment only.

Data Analysis

Ideal science student coding scheme. Strauss and Corbin (1998) note that in coding data, one may begin with a set of codes derived from previous research. The coding of the ideal science student survey data collected in this study began with the codes derived from the initial ideal student study discussed above. So, we started with codes that focused on a learning orientation and those that focused on a behavior orientation. However, Chi, (1997) argues that the granularity of codes should be derived from the data set itself. Therefore, in iteratively analyzing the data, we refined the initial categories to better describe the data from the current study. We did this through an iterative process of reading, re-reading and discussing the responses, refining the codes as necessary. The final coding scheme is presented below. Once the authors had refined the codes, two graduate students were trained on their use with the data. These students then independently coded all of the data. We then came together and compared the two sets of coded data. All coding disagreements were resolved through discussion between the coders and the first author. Inter-rater reliability was calculated using Cohen's kappa, agreement was achieved at $k = .86$.

Group classification. To further classify the survey data, we turned to the implicit beliefs work of Bempechat, London, and Dweck (1991) who found that students generally used either traits-based or process terms as evidence to support their attributional judgments of intelligence. Students in our study who gave mostly personal traits-based responses were considered to have a traits-based view of the ideal science student. Students who provided a richer and fuller view of the ideal science student, which included not only personal traits, but also learning strategy and performance aspects, behavioral aspects, and motivation, interest and effort aspects were considered to have a process-oriented view of the ideal science student (these categories are described in detail in the results section below).

We systematized the classification of the students into one of these two groups by developing a metric that could be applied to each case. This metric takes into account the depth and breadth of responses. The metric used for determining classification in the traits-based view was as follows: (1) sixty percent of responses to the ideal science student survey must be categorized as a personal trait response; and (2) all responses must fit into just two categories overall, the personal traits category and one other category.

The metric developed for classifying students as having a process-oriented view of the ideal science student is as follows: (1) the responses must fall into a majority of the possible categories (at least three of the four response categories) – (a) learning strategies and performance, (b) classroom order and discipline, (c) motivation, interest and effort, and (d) personal traits. Our analysis was guided by this classification system which allowed us to distinguish between more narrowly focused views of the ideal science student and those that were more inclusive of a diversity of traits and activities.

Problem solving strategies used. Descriptive logs of student activity during problem solving were created through multiple viewings of the videotapes. The unit of analysis was shift in activity (Chi, 1997). A shift in activity refers to turning attention from one element or task in the challenge to another element or task. Examples of a shift in activity are: (1) switching from writing the program to accessing the Robolab context-sensitive help system; (2) turning from writing the program to building the robot; (3) shifting from running the program to measuring the quality of light in the room, etc. The activity log serves as a sequential record of the students' activities during problem solving. All verbalizations were also transcribed.

Strategy classification. We used Jonassen's (2000) problem solving typology to classify student strategy usage. As Jonassen notes, domain specific strategies are ones that derive from and are specific to a given domain[1]. Robotics is a tool intensive activity; therefore, most of the domain specific strategies deployed in a robotics environment regard use of the available tools. Domain general strategies are those that may be used in any domain.

Coding of the problem solving activity logs. The observed domain specific and domain general strategies were then used to code each student activity log. A graduate student with expertise in Robolab and Lego Mindstorms was trained on the use of the strategy codes with these data; the first author and the graduate student coded the problem solving activity logs. Inter-rater reliability was established at $k = .94$. All disagreements on codes were resolved through discussion. The total number of domain specific vs. domain general strategies used by each student was calculated, this ratio was then used to designate students as being more likely to use domain specific or domain general strategies.

Qualitative data analysis. The transcribed think-aloud videotaped data was analyzed using a modified interaction analysis approach (Jordan & Henderson, 1995). Using the coded logs as a guide, the incidences of student use of problem solving strategies were analyzed as regards the physical and verbal activity students were engaging in at the time. This interaction analysis allowed us to look more deeply at how students grappled with solving the problem and, in so doing, developed their conceptual understanding. Our interpretation of student activity as evidenced in the videotapes is provided below.

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1 As all of the students were involved in writing an algorithm for the RCX to run, we seek to avoid confusion by not utilizing the commonly used problem solving terms of heuristic (general strategies) and algorithmic (specific strategies). For the sake of clarity, we prefer Jonassen's (2000) terms of domain specific and domain general strategies.

RESULTS

Research Question #1-Perceptions of the Ideal Science Student

The ideal science student survey responses were used to answer research question number one: what are students' perceptions of the ideal science student and how do they vary? Four categories of response to the ideal science student survey were identified: (1) learning strategies and performance; (2) classroom order and discipline; (3) motivation, interest and effort; and (4) personal traits. The first category, learning strategies and performance, refers to responses that focus on external and outcome oriented academic aspects of classroom behavior. The second category, classroom order and discipline, refers to responses that focus on external, non-academic, orderly student behavior in the classroom. The third category, motivation, interest, and effort refers to responses related to student internal motivation and interest in science, and their external effort in the science classroom. The fourth category contains responses that refer to internal personality traits that a student may possess. Table 1 displays the types of responses given in each category. Figure 3 shows percent of total responses received in each category.

Table 1
Ideal Science Student Category Responses

Personal Traits	Learning Strategies and Performance	Motivation, Interest, and Effort	Classroom Order and Discipline
Smart	Listens	Likes science	Behaves
Intelligent	Listens to the teacher	Gives best effort	Obeys
Creative	Observes	Hard working	Doesn't disobey
Imaginative	Participates	Interested	Doesn't fool around
Responsible	Voices opinion	Likes touching anything	Doesn't disturb others
Reliable	Prepares completely for all assessments	Wants to learn more about science	
Cool	Ready for class		
Friendly	Good at math		
Nice	Good at science		
Neat	Good grades		

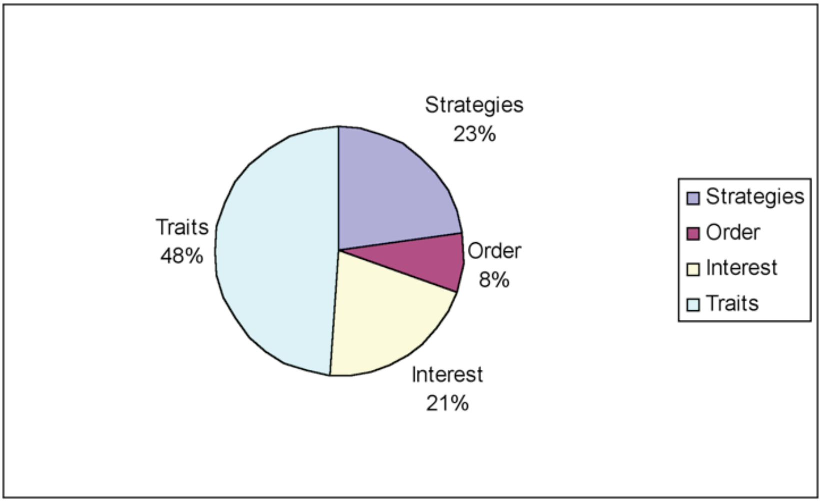

Figure 3. Ideal Science Student Percent Total Response by Category

Group classification. Using the group classification metric described above, ten students were classified as having a traits-based view. Table 2 displays the percentage of total response by category of the students in this classification. Table 3 presents two illustrative examples of actual survey responses drawn directly from the data.

Table 2

Percentage of Responses by Category for Traits Classification

Number of Students	Personal Traits	Motivation, Interest, and Effort	Classroom Order and Discipline	Learning Strategies and Performance
3	100%			
3	60%	40%		
2	80%			20%
1	80%		20%	
1	80%	20%		

Table 3
Samples of Survey Responses - Traits Classification

Student #1		**Student #2**	
Response	*Code*	*Response*	*Code*
Smart	Trait	Smart	Trait
Curious	Trait	Creative	Trait
Flexible	Trait	Clever	Trait
Inventive	Trait	Willing to Learn	Mot., Int., & Effort
Friendly	Trait	Loves Science	Mot., Int., & Effort

Fourteen students were classified as having a process-oriented view. Table 4 displays the percentage of total response by category of the students in this classification. Table 5 provides two examples of response drawn from the actual data.

Table 4
Percentage of Responses by Category for Process Classification

Number of Students	**Per-sonal Traits**	**Motivation, Interest, and Effort**	**Classroom Order and Discipline**	**Learning Strategies and Performance**
3		20%	20%	60%
2	20%	60%		20%
1	20%		20%	60%
1	20%	40%	20%	20%
1	20%	40%		40%
1	40%	20%		40%
1	20%	20%	40%	20%
1	60%	20%		20%
1	60%		20%	20%
1	20%	20%		60%
1	40%	20%	20%	20%

Table 5
Samples of Survey Responses - Process Classification

Student #3		Student #4	
Response	*Code*	*Response*	*Code*
Good listener	Learn Strat/Perf	Likes science	Mot., Int., & Effort
Asks for help if needs it	Learn Strat/Perf	Likes math	Mot., Int., & Effort
Never late for class	Classroom Order/ Disc	Good in school	Learn Strat/Perf
Participates	Learn Strat/Perf	Can remember a lot	Trait
Gives best effort	Mot., Int., & Effort	Likes touching anything	Mot., Int., & Effort

Two of the 26 students fit into neither of the classifications. Both of these students were male; one is Asian American, the other European American. Of these two students, one had primarily classroom order and discipline responses and the other student had mostly motivation, interest and effort responses. These two students were dropped from further analysis.

Research Question #2-Perceptions and Problem Solving Approaches

In order to answer research question number two - how are these perceptions of the ideal science student related to their problem solving approaches in a science context? - we analyzed overall student problem solving activity to identify strategies used and we then coded the individual problem solving logs with these strategies. We performed a chi-square analysis of group membership and problem solving strategy usage to further investigate the association between perception and problem solving approach.

Problem solving strategy classification. The domain specific strategies identified from the videotape activity logs were: (1) measure with ruler on the track; (2) take readings with the sensors; (3) plan through simulation of the movement of the robot; (4) use the Robolab context-sensitive help; and (5) make structural adjustments to the robotic device with Lego pieces. Four of these five strategies are self-explanatory. The strategy of planning through simulating the movement of the robot refers to the observed student activity of reading the challenge, picking up the RCX, affixing a light sensor, and then manually moving the RCX over the black line on the paper track while simultaneously reasoning aloud about the factors involved in programming the robot to follow the black line.

The domain general strategies used by students in this study were: (1) guess and check; (2) sub-goal analysis; (3) ask questions; and (4) take notes. Three of these four strategies are self-evident. Sub-goal analysis refers to breaking down the problem into smaller chunks or sub-goals that can be solved individually to arrive at an overall solution. Illustrative examples of the use of each of these strategies, drawn from the student activity log, are presented in table 6. Table 7 displays the percentage of students who used each strategy during the problem solving session.

Table 6

Illustrative Examples of Student Problem Solving Strategies

Activity	**Verbalizations**
Domain Specific Strategy: Measuring with the Ruler on the Track	
Mike takes a measurement with the rotation sensor, using the ruler on the track to measure 6 inches.	Let's see about six inches. So if we are going backwards, about 15. Let's see…
Domain Specific Strategy: Taking Light Readings with the Light Sensor	
Neil takes a light reading for black and white.	So the black line is about 40 and the white's like 50. Great so now I have to put that in.
Domain Specific Strategy: Plan Through Simulation of the Movement of the Robot	
Roger moves the robot on the track and reasons verbally about the movement of the robot.	Detects greater than 39, which is the black line, it should...Then that would means that it sensed the white line, the white, then it should turn, umm. It should turn right until it finds the black line again.
Domain Specific Strategy: Using the Context Sensitive Help	
Karen opens and reads the context sensitive help about the rotation sensor.	Wait, the rotation sensor senses in either direction, so it could be negative anyway. Ok, so six inches is negative 22.
Domain Specific Strategy: Making Structural Adjustments with Lego Pieces	
Ethan begins to replace the tires on the robot exchanging the little tires for the wide tires.	OK, I will just replace the tires and see if that will fix it.
Domain General Strategy: Guessing and Checking	
Cal adds motors a and c reverse after the touch sensor, followed by a wait for 2 seconds. He then adds motor a forward and motor c reverse followed by a wait for 2 seconds icon and an all motors stop icon. He then adds motor a reverse and motor c forward after the wait for light icon.	When it hits something…it will go backwards for, I'll try two seconds for now and then it should stop. And then if it senses light I'll make it turn left. So that means A, I'll try…I'm not sure if it will turn that way or that way, so I'm just testing for now.

Table 6 continued

Activity	Verbalizations
Domain General Strategy: Sub-Goal Analysis	
Tyrell decides to write a tester program to make the robot move for one second. He adds motors A and C forward, followed by a wait for one second icon, followed by an all motors stop icon.	Tester program! It wanted to go…both motors go forward and then they should almost…until, for... one second, then all motors stop, program ends.
Domain General Strategy: Asking Questions	
Nancy asks a question.	N: I have a question. Will it start on the track, or will I have to drive it up to the track? R: Start it on the track. N: OK.
Domain General Strategy: Taking Notes	
Vanessa re-opens the main program and writes a note on the screen with the new measurement (30 seconds at power level 1, 360 degree turn).	I write little notes so I make sure I don't forget it later.

Table 7
Frequency of Strategy Usage for All Participants

Strategy	Type	% of students
Measure with ruler	Domain Specific	54.17
Take readings with sensors	Domain Specific	70.83
Plan through simulation	Domain Specific	33.33
Use of context help	Domain Specific	54.17
Structural adjustments	Domain Specific	45.83
Sub-goal analysis	Domain General	54.17
Guess and check	Domain General	91.67
Ask questions	Domain General	79.17
Take notes	Domain General	8.33

Student perceptions and strategy usage. A chi square test of independence was conducted to examine the association of group membership to strategy type most frequently used during problem solving, domain specific or domain general. A significant association was found, x^2 (1, n=24) = 4.608, p = .032. The stricter Fisher's exact test for sparse tables was reported at p = .047. Students with a process-oriented view are more likely to use domain specific strategies than students with a traits-based view. The contingency table for this test is presented in table 8.

Table 8

Strategy Usage by Social Mental Model Group

	Traits Model	Process Model	Total
Domain General	8	5	13
Domain Specific	2	9	11
Total	10	14	24

Research Question #3-Perceptions, Conceptual Understanding and Solution Scores

In order to answer research question number three - how are these perceptions related to their conceptual understanding as evidenced in their problem solving activity and programmatic solution scores? - we used the conceptual rubric to score programmatic solutions and then compared the two groups on achievement outcomes using analysis of variance. We then conducted micro-interactional analysis of students' activity while solving the robotics problem. This analysis aims to illuminate the relationship of tool use to conceptual development.

Student perceptions and problem solving ability. The range of possible scores on the programmatic solution was zero to seven points. Students' programmatic solution scores were tabulated using the conceptual rubric described in the methods section and presented in appendix B. The mean and standard deviation for the traits group was M = 1.30, *s.d.* = 1.49, and the process-oriented group M = 3.07, *s.d* .= 2.06. A one-way ANOVA revealed that the difference in the group mean scores is significant, $F(1, 22) = 5.367$, $p = .03$. A large effect size was found, $\eta^2 = .196$, the observed power was .601. Students with a process-oriented view obtained significantly higher solution scores than did the traits-based students.

Since students were allowed to take as much time as needed to complete the robotics challenge, we performed an analysis of covariance (ANCOVA) to control for the effects of time on task. The main effect for view group was affirmed, F (1, 21) = 4.321, $p = .05$, the effect size was $\eta^2 = .171$, and the observed power was .509.

We should like to note here that the observed power of both the ANOVA and the ANCOVA in the group comparisons of programmatic solution was relatively low. This means that the risk of a type II error (failure to reject a false null hypothesis) is increased. While the null hypothesis (no difference between groups) was rejected in this case, it is still important that these findings be validated with a larger group of participants to verify the quantitative results.

Qualitative Data Analysis - Tool Use and Conceptual Development

Based on the results of the study we sought to further examine the relationship of tool use to conceptual development. Using interaction analysis (Jordan & Henderson, 1995), we focused on the physical and verbal activities students engaged in as they solved the problem. From this analysis of the data, we were able to more clearly characterize the activity students engaged in that may have affected their conceptual development. Specifically, we identified two activities that we believe may be important to their conceptual development: modeling of their own understanding as well as verifying and expanding their current understanding. We address each theme in turn.

Modeling understanding. As previously mentioned, the three computer science concepts subsumed in the robotics challenge were input/process/output, procedural flow and infinite looping. The most difficult aspect of the challenge was the line following task which concerns the input/process/output concept. One means of reasoning about this concept in regards to the line following task was to use the 'simulating the movement of the robot' strategy. As noted above, this strategy includes manually rolling the light sensor equipped robot along the provided track while thinking about how the light sensor should be programmed to accurately perform the task. Table 9 presents an excerpt from a student who utilized the strategy. The left column details the student's physical activity, the right column presents the student's concurrent verbalizations.

In this excerpt, Larry uses the light sensor equipped robot and the track to reason about the problem. He discusses how the light sensor works to 'sense' whether the track surface is white or black and he physically manipulates the robot to consider what action the robot should be programmed to take when it senses a change in color from black to white. Previously, all of the students learned about the functioning of the light sensor. In this session, Larry was physically modeling for himself how the light sensor works. He was also developing some ideas related to how he will program the robot. For example, he was considering programming the robot to back up and turn to the right for 1/10th of a second each time the light sensor sees the white surface of the track. He considered looping this part of the program so that the robot will negotiate the angled turn of the track by incrementally making a right hand turn.

Table 9
Modeling Understanding: Reasoning with the Robot and the Track

Larry	
Activity	**Verbalizations**
Larry rolls the robot along the black line on the track and moves the robot back and forth at the turn, where the black turns to white.	Ok it can go forward until this senses light, then back up a bit, back up a bit. Maybe if I fill a container, just maybe. Okay so, this part is obvious, it has to go forward and when it hits the point where it no longer senses blackness, it's got to back up until it senses blackness.
Larry continues to roll the robot over the angled black line as he reasons aloud about how the robot will perform the algorithm.	Then how about it turns right for about a 10th of a second and then it does that algorithm again and again and again. Eventually, that is, you started here goes forward until it senses white, goes back until it senses black turns a bit, forward 'til it senses white, goes back 'til it senses black turns a little, goes forward…think that will work? Let's try it.

Jonathan also simulated the movement of the robot to help him reason about how to program it correctly. However, rather than placing the robot on the track, Jonathan used his fingers to simulate the black line on the track (Table 10).

Jonathan is also physically modeling his understanding of how the light sensor works and using this to reason about how the light sensor program should be written. His programming strategy is a bit different from Larry's in that he is using two light sensors. In Jonathan's approach, the light sensors was used to keep track of the white field on either side of the black line and, in this way the robot will stay directly on the black line as it turns to the right. Simulating the movement of the robot seems to have served to both reinforce student understanding of the light sensor (input/process/output concept), and it allowed them to reason about how the program should be written in order for the robot to perform the task correctly.

Table 10
Modeling Understanding: Reasoning with the Robot and Fingers

Jonathan	
Activity	**Verbalizations**
Jonathan picks up the robot with two light sensors attached to it and places his fingers vertically between the two light sensors (so his hand is serving as the black line in this explanation). He moves the robot one direction and then the other as he reasons about the movement of the robot.	Ummm, I'm going to have the ummm two light sensors each be in their own task, ummm. Like if this light sensor were to detect the black line, then the robot would turn a little like that. If the light sensor were to detect the black line, the robot would turn like that. And then in the meantime it would just be going forward. So, OK.

Verifying and expanding understanding. Students used the context sensitive help to verify or expand their respective understandings of how to use various icons in writing their program. Many of the 13 students who used this resource used it to read more about how to program the sensors. A few students also used it to read more about how to start and stop tasks and how to use the if/then light sensor forks. The students, therefore, were developing their understanding of the input/process/output concept and the procedural flow concept. In addition to this, two students browsed the help section, apparently searching for new ways to do things. Table 11 is an excerpt drawn from the data that exemplifies the students' use of the context sensitive help.

In this example, Karen used the rotation sensor to get a reading of how many rotations[2] of the wheel it will take to travel six inches. She moved the robot in a backward motion along the length of the six inch ruler inscribed on the track. The reading she obtained is displayed as a negative number on the RCX. Karen decided to check this reading against the information about the rotation sensor in the context sensitive help. With this effort, Karen both verified and expanded her understanding of how the rotation sensor functioned.

While students used many strategies to help them solve the problem, the two strategies detailed here were the ones that seemed to provide opportunities for students to further develop their conceptual understanding of the computer science concepts inherent in the challenge. By physically modeling the functioning of the light sensor, students were able to concretely rea-

2 Rotations are counted in 16ths, so 16/16 = one rotation of the wheel.

son about how it should be programmed. As aforementioned, programming the light sensor to follow the black line on the track was the most difficult aspect of the challenge. Also, by utilizing the context sensitive help, students were able to verify and expand their understanding of the functioning of the various sensors and the procedural flow icons.

Table 11
Verifying and Expanding Understanding: Using the Context Sensitive Help

Karen	
Activity	**Verbalizations**
Karen moves the robot alongside the ruler and takes the rotation sensor reading from the display on the RCX.	So, negative 22.
Karen re-opens her main program and adds the readings and measurements. She modifies the rotation sensor icon with (-22) in the reverse six inches section of the program.	Negative 22…negative 22 is six inches.
Karen opens and reads the context sensitive help about the rotation sensor to make sure the readings can go in either direction (negative or positive -- since her reading had come up negative 22).	Wait, the rotation sensor (inaudible) in either direction, so it could be negative anyway. Ok, so six inches is negative 22.

DISCUSSION

The purpose of this study was to explore variations in students' perceptions of the ideal science student and to examine the relationship of these variations to problem solving strategy use and achievement in a robotics environment. Two predominant perceptions of the ideal science student emerged from analysis of the data, a traits-based view and a process-oriented view. Students with a traits-based view gave responses that focused primarily on personal traits such as intelligent, responsible, creative, organized, and neat. These traits may also be characterized as internal traits. Students with the process-oriented view presented a richer and fuller perception of the ideal science student as an active learner, a hard worker, one whom enjoys science, is smart and is a good group worker. These attributes evidence an external focus. In the meantime, two students' perceptions of the ideal science student did not fall into either the traits-based or process-oriented classifications. One student had a view that emphasized motivation, interest and effort and the other student had a view that emphasized following the behavioral rules set by the teacher in the classroom. Therefore, there are at least four, and likely more, views of the ideal science student held by individual students, though in this study the traits-based view and the process-oriented view were predominant.

Nine problem solving strategies were utilized by the students, including five domain specific strategies (measure with ruler on the track, take readings with the sensors, plan through simulation of the movement of the robot, use of Robolab context help, and make structural adjustments to the robotic device with Lego pieces); and four domain general strategies (subgoal analysis, guess and check, ask questions, and take notes). Chi-square analysis revealed that strategy usage is associated with students' views. The traits-based group relied more on domain general strategies, and the process-oriented group utilized more domain specific strategies. Furthermore, an ANOVA comparison of the programmatic solution scores of the two groups showed a significant difference. Students with a process-oriented view developed conceptually stronger solutions to the robotics challenge than did students with a traits-based view.

In considering why students with the process-oriented view provided conceptually stronger solutions, we focus on their use of tool-intensive, domain specific strategies. The tools in the environment offer advantages in solving the challenge through the concept of distributed cognition. Students in the process-oriented group made excellent use of the provided tools and, by extension, the intelligence inscribed in the tools themselves. The differences in strategy usage point to the process-oriented students' ability to take advantage of the distributed cognition aspects of the task environment.

It is important to recognize that students in the process-oriented group occupied an expanded learning space; as they actively engaged with the use of the tools in the environment, so did they increase their knowledge of and ability to use the tools. Indeed, existing research into science education and problem solving has shown that a student's knowledge base is an important aspect of successful problem solution (Reid & Yang, 2002; Shin, Jonassen & McGee, 2003). Students who used the context-sensitive help utility actively expanded their knowledge base as they solved the problem. The notion of an expanded learning space aligns well with the process-oriented view of the ideal science student inasmuch as the process-oriented view evidences a broad, external focus.

However, the qualitative data analysis points out that it is not just the use of the tools, but *how* the tools were used that may have made a difference in students conceptual development as evidenced in their programmatic solution scores. For example, students in the process-oriented group who utilized the 'simulating the movement of the robot' strategy appear to increase their understanding of robotics through physically modeling the functioning of the light sensor. This activity allowed these students to concretely reason about how the light sensor should be programmed. Indeed, students with both the process-oriented view and the traits-based view used the light sensor to get the necessary light readings to program the light sensor. But, the process-oriented students who enacted the 'simulating the movement of the robot' strategy also used the light sensor as an object to think with (Perkins, 1986). By physically modeling the functioning of the light sensor, the students gave themselves extra dimensions for reasoning about the problem. Rather than relying solely on whatever internal representation of the light sensor they may have already constructed, the students used the physical and visual dimensions of their problem solving environment to aid in their reasoning. This concrete 'thinking with' the tools may have allowed these students to develop a stronger conceptual understanding of the problem and possible solutions to the problem. It is interesting to note that none of the students with a traits-based view of the ideal science student enacted this particular strategy.

LIMITATIONS

While this study responds to McGinnis and Stefanich's (2007) call for more research regarding the relationship between talented learners and the types of outcomes these students may achieve in specific science learning programs, as previously noted, the participants do not constitute a representative sample of the 'typical' United States middle school population. The students were primarily male (22 out of 26), primarily white (22 out of 26) and none were on scholarship. Therefore, it is not possible to generalize these findings beyond the groups represented in the study. Future studies featuring a more representative sample of participants are warranted. Nevertheless, the findings in this study confirm that students' perceptions of the ideal science student vary and that this variation is correlated to both problem solving strategy utilization and subsequent achievement in a robotics environment.

IMPLICATIONS

In sum, our study contributes to the theoretical understanding of how students' values about what it means to be an ideal science student are related to student problem solving and conceptual development in a science context. We have demonstrated that students hold at least two perceptions of the ideal science student and these perceptions are correlated to their problem solving strategy usage and conceptual understanding in an open-ended inquiry activity. These findings have important implications for teacher education, and the design of learning environments.

It is possible that teachers' perceptions of the ideal science student are also related to their problem solving. The main problem teachers should be engaged with solving is how to help students learn. If a teacher has a transmission belief in learning enacted through lecture, demonstration and telling, this teacher may not see student learning as a problem to be solved and/or may not share a view of problem solving as locating and utilizing tools in the environment. Such a teacher may not provide a classroom environment that includes a wealth of physical and social resources for learning. Therefore, a transmission learning classroom may put learners with a process-oriented view at a distinct disadvantage. Indeed, Thomas, Pederson, and Finson (2001) report teachers' beliefs about themselves as science teachers influence the type of classroom environment they create. Therefore, science teacher educators may wish to urge their pre-service students to reflect on their own perceptions of the ideal science student and to consider how this view is related to their perception of learning. These pre-service teachers may then develop a deeper understanding of how the environment they create in the classroom may have a differential impact on students with varying perceptions of the ideal science student. Understanding the scope of students' perceptions and the relationship of these perceptions to the context for learning science will aid science educators in addressing the science culture 'fit' issue raised by Taconis and Kessels, (2008).

As regards the design of learning environments, this study suggests that utilization of physical and social resources leads to stronger conceptual understanding of a given topic. Others have argued that the use of tools in science is an important element of developing scientific understanding (Roth, 2001; Crismond, 2001). An excellent learning environment should take into account the multiple perceptions that various students may hold. Learning environments should provide a robust palette of tools that include resources for student expression of ideas, access to informational resources, and communications pathways and tools for student interaction with one another, the teacher, and outside experts. Additionally, teachers and learning environment designers should think about ways to invite students to utilize the tools in the environment. Specific structural elements that strongly emphasize the affordances of the tools should be identified and integrated into the pedagogical design. These structural elements may include pathways through the learning environment, or the use of scaffolds at opportune moments when a student is studying in the environment.

Future studies should focus on two areas. First, what is the range of perceptions of the ideal science student? In this study, we have identified at least four. It will be useful to understand the breadth, depth and interconnectedness of these perceptions and their relationship to learning in the classroom context. Second, are these perceptions context or task dependent? For example, Gottlieb, (2007) has found that people's epistemological beliefs are sensitive to the context and the particular kind of knowledge in question. This may also be the case for students' perceptions of the ideal science student. For instance, students may have a process-oriented view in one domain and a traits-based view in another. These studies should be carried out with representative samples of students in order to generalize the results more widely than we are able to do with this study. Such future research will be helpful in the effort to create effective science learning environments and experiences for all students.

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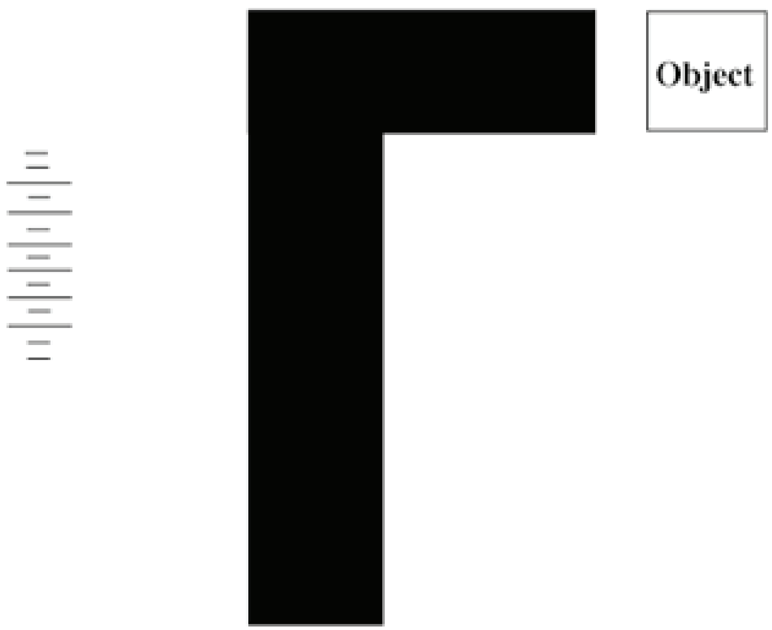
APPENDIX A

Drawing of Track used in the Robotics Challenge



APPENDIX B

Conceptual Rubric for Scoring Final Program Solution

Conceptual Scoring of Solutions:			
Computer Science Concept	***Points***	***Points***	***Points***
Input/Process/Output Does the program sense both edges of the black line?	3		
Does the program sense one edge of the black line?		2	
Does the program sense the white or black area only?			1
Procedural Flow and Looping Does the program loop the line following program, and stop this program when the touch sensor is activated?		2	
Does the program loop the line following program?			1
Input/Process/Output Does the program correctly utilize a rotation sensor in the second task?		2	