THE EFFECT OF COMPUTATIONAL ACTION ON STUDENTS' COMPUTATIONAL IDENTITY AND SELF-EFFICACY

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Abstract

Recent education policies in the U.S. and globally have pushed for computer science and artificial intelligence (A.I.) instruction for young people in K-12 grade bands. At the same time, student outcomes in these initiatives have varied widely depending on implementation. At stake is whether such programs can motivate students not only to succeed in the classroom but to advance beyond introductory classes and develop satisfying professional pathways. The computational action framework, proposed by Tissenbaum, Sheldon, and Abelson in 2018, offers a way of scaffolding young people in creating technology projects that address real issues in their communities, rather than "just coding." This paper presents the computational action process, a curriculum and set of tools based on the original framework, and the results of a human-subject research study on the computational action process with U.S. and international students aged 11 to 18. Analyses of pre-post surveys on the Likert scale show that after the intervention, students showed an increase in computation skill and identity, an increase in confidence in their ability to make a prosocial impact, and an increase in their confidence in solving ambiguous problems on their own. Students' responses post-intervention demonstrated more impact-driven, community-oriented thinking. These promising results indicate that the computational action process can be a helpful addition to computer science and A.I. education programs to motivate student learners.

Keywords: Constructionism, artificial intelligence, computational thinking, K12 Computer Science.

1 INTRODUCTION

A recent global policy trend to establish formal computer science instruction in schools has resulted in successful student outcomes as well as stagnation, depending on the location, standards, and methodology [1, 2]. In the US, robust policies for K-12 computer science education are now in over 24 states. However, gains in broader participation have been modest and varied by location and content. For example, growing participation among underrepresented groups in introductory computer science classes has not accompanied increased participation in elective coursework or interest in pursuing computer science careers. Outside the US, there is evidence that nations and school systems that began deepening their efforts into compulsory public computer science education have experienced varied results, especially in cases where the focus is on the acquisition of programming fundamentals in contrast to teaching the subject in a societal context and with student-defined design goals [1, 3].

This paper presents the computational action process — a set of curricula and toolkit for K-12 students — and the results of a human-subject research study with 101 U.S. and international students ages 11 to 18. The computational action process is an engineering design process for middle and high school students tailored to computer science and A.I. education. The process presented in this paper draws heavily from existing engineering design processes but frames practices for K-12 students within the computer science domain. Pre-post survey results show that after learning the computational action process, students showed significant increases in computation skill, self-efficacy, and identification as programmers. Students also demonstrated an improved understanding of the impact of technology on people and society.

1.1 Framework

The computational action framework, first proposed by Tissenbaum, Sheldon, and Abelson in 2018 [4], grows out of constructionism, especially Turkle and Papert's project to extend and critique Piaget's constructivism [5, 6]. In practice, constructionism invites an emotive element to student learning by providing a "personally meaningful" experience such that "forming a new relationship with knowledge is as important as forming new representations of knowledge [7]." This framework has influenced several aspects of the computational action process, including:

- Students define their own personally meaningful goals instead of working toward a pre-determined "solution"
- Students are encouraged to produce divergent prototypes
- Students are meant to tailor the process to their needs

The computational action process also takes structural elements from common engineering design processes adopted by educators to emulate professional practices. In the current work, we posit that an emphasis on user research benefits student motivation and engineering identity formation by making the activity more meaningfully connected to a student's community. For historically underrepresented groups in the computing fields, computational action has been designed as a vehicle for asset-based strategies in the classroom. Castaneda and Mejia have provided evidence that engaging students in problem-finding based on real needs they see in their communities positively affects the formation of their identity as engineers and their motivation to continue in the field [8]. Many elements of the computational action toolkit, described in Section 2, were developed to scaffold students in authentic engineering design practices.

The current research sought to measure correlations between the intervention and students' perceptions of identity as engineers and their self-efficacy. Perceptions of identity — related to one's skills and personal values — have been shown to inform one's expectation of success in accomplishing tasks [9]. Perceived ability or self-efficacy, according to Bandura, bears upon a student's sense of agency and mastery [10]. Self-efficacy scales [11] have been shown to effectively measure a student's confidence in their ability to perform tasks. Through these measures, we hope to establish a correlation with an increase in a student's perceived ability to find, understand, and create solutions for ambiguous design problems.

1.2 Related Work

Research in "self-transcendent goals" provides good evidence for a mechanism between prosocial design goals and task persistence [12]. The work of Yeager, *et al.* demonstrates links between student reflection on a task's "purpose for learning" — including benefiting other people, an ideal, or a social justice cause — and persistence over time, deeper learning behavior, and higher test scores for 2,000 high school seniors and college students taking math and science. A key context for the development of the computational action process is the prevalence of newly established, low-barrier computational infrastructure in the educational and professional computing fields, such as abstracted coding tools, publicly available machine learning models, and sophisticated, low-cost mobile devices. An additional influence has been the many interventions by the Technovation organization in teaching girls to code and use AI tools to pursue solutions to ambiguous design problems [13]. Technovation's curriculum helps girls name personally relevant design goals and use low-barrier coding and AI tools.

1.3 The Computational Action Process

The computational action process presented in this paper was created to address the criteria of computational identity and self-efficacy posited in the computational action framework [4]. The components of the process were also influenced by industry-standard engineering design practices and tailored to meet K-12 standard expectations. An overview of the computational action process and its topics appear in Table 1.

The first topic of the computational action process facilitates students in discovering a project idea that is both a real problem in their community and a topic of genuine personal interest to figure out and solve. Topic one is introduced using a combination of the United Nations Sustainable Development Goals (UN SDG) and a mind-map brainstorming tool, providing steps to turn a general UN SDG into specific project ideas students feel passionate to work on. The second topic teaches students why user research is important, offering concrete steps to conduct user and community research through user research and persona-building tools. The third topic introduces students to the impact matrix, a tool that prompts students to weigh the tradeoffs of their designs. These materials potentially allow students to enhance connections to meaningful and authentic practice. The third topic also scaffolds students in designing interfaces with user feedback by testing sketches, creating wireframes, and testing prototypes of potential designs — all while foregrounding the people affected by the design. App Inventor (*www.appinventor.mit.edu*), a blocks-based app programming tool popular among K-12 students, is introduced as a tool for students to prototype and implement their designs. The fourth topic gives students real-world tools to support teamwork and project management. The fifth and last topic reinforces the process's cyclical nature, aiming to inspire students to make future iterations and plan for a long-lasting impact by communicating their project to others, seeking continued feedback, and redesigning along various points of the process they identify.

Table 1. The computational action process topics, toolkit, and learning objectives.

Topics	***Toolkit***	***Learning Objectives***
Defining a real-world problem	Individual brainstorming (mind map) Group brainstorming tool	Students learn how to find a real problem in their community Students learn about UN Sustainable Development Goals Students practice brainstorming with mind maps
Understanding users and communities	User research tool User personas tool Collaborative analysis	Students learn why user research is important Students practice open-ended user questions Students create user personas to summarize learnings Students analyze solutions using collaborative analysis
Designing responsibly with users and communities	Impact matrix Features tool	Students learn about stakeholders and values Students learn about the ethical impact of their idea Students discuss positives and negatives in impact matrix Students practice sketching and wireframing their projects
Teamwork, implementation	Teamwork task table Project management tool	Students learn tools to organize implementation tasks Students practice creating team roles and coding together
Making a long-lasting impact	Project summary matrix Project timeline plan	Students learn to communicate about their project or app Students learn about getting iterative user feedback

Figure 1. Example slides from the five-topic computational action curricula and toolkit.

Each topic of the computational action process has a "I do, we do, you do" structure, which takes the form of (1) introduction of the topic, (2) review of an example further illustrating the topic, (3) student engagement in a guided discussion or group activity, and (4) self-guided student use of the corresponding tool(s) in the toolkit. A few examples of the materials appear in Fig. 1. The full computational action toolkit is available at: bit.ly/3JLz2tn.

2 METHODOLOGY

The research questions we investigated were: (1) What interventions enable students to make a socially responsible impact in their community? and (2) Is the computational action process effective in empowering students to make a good impact using technology? The workshops for this study were set up to teach the five computational action topics and encourage students to complete the tools in the toolkit. Students were asked to complete a pre-post questionnaire, described in Section 3.1. One hundred one (101) participants between the ages of 11 to 18 were recruited from mailing lists of U.S. and international students associated with the Technovation Challenge, the MIT Solv(Ed) program, and a K-12 program local to the Boston area. The study was designed with two cohorts: cohort 1 consisted of students who had been previously introduced to coding and elements of engineering design processes, and cohort 2 consisted of students who had not been in these types of programs. Other variables between the two cohorts were kept constant as much as possible. The study protocol was approved by the Institute Review Board (IRB) associated with the researchers' institution. Participants from both cohorts participated in a three- to four-hour computational action workshop, which served as the study intervention.

Table 2. The pre-post survey instrument used in the research study. Responses are on the Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Question Type	Question Number	Question
Computational Identity	1	I see myself as a computer programmer
Learning Motivation	2	I want to learn things that will help me make a positive impact on the world
Learning Motivation	3	I want to become an educated citizen that can contribute to society
Learning Motivation	4	I want to expand my computer programming knowledge
Learning Motivation	5	I want to learn computer programming to earn more money
Computation Skill	6	I do well on computing tasks such as app programming
Computation Skill	7	I would rate my computer programming skills (including app programming) as:
Self-efficacy, Computational Action Skill	8	I know how to find and define a real problem
Computational Action Skill	9	I know how to figure out what users and communities need
Computational Action Skill	10	I know how to design technology with an ethical framework in mind
Computational Action Skill	11	I know how to work on a team
Self-efficacy	12	I know how to make a lasting impact in my community or in the world
Self-efficacy	13	I am confident in my ability to design and create solutions using technology, rather than working toward a "right" answer someone else gives me

2.1 Data Collection

Participants in both cohorts received the same pre-post questionnaire, and all scored on the Likert scale from 1 (strongly disagree) to 5 (strongly agree). For question 7, the Likert scale was slightly modified from 1 (very beginner) to 5 (very advanced). The survey questions appear in Table 2.

2.2 Data Analysis

The analysis of quantitative survey data was done using tests corresponding to the data distribution (whether normal or not normally distributed). Paired tests compared pre-post data from the same de-identified individuals. For paired results, data that followed normal distribution were analyzed using paired t-tests; otherwise, non-normally distributed data were analyzed using the Wilcoxon signed-rank test. A p-value of 0.05 determined whether results were significant.

3 RESULTS

3.1 Quantitative Results

Analysis of quantitative data from pre-post surveys shows that after the computational action workshop, students felt more confident in their ability to code, solve ambiguous problems, and make an impact, and they were more knowledgeable about the ways to make an impact responsibly with technology. Students demonstrated this increase in computational ability and self-efficacy regardless of previous level of coding or engineering and design experience. The results appear in Figs. 2 and 3.

3.1.1 Computational Identity

Cohort 1 pre-post paired results for computational identity (Q1: "I see myself as a computer programmer") showed an increase post-intervention (Pre/Post: $\bar{x}$ =3.000,3.522; p=0.001; t(25)=-3.761). There was no change for cohort 2 students.

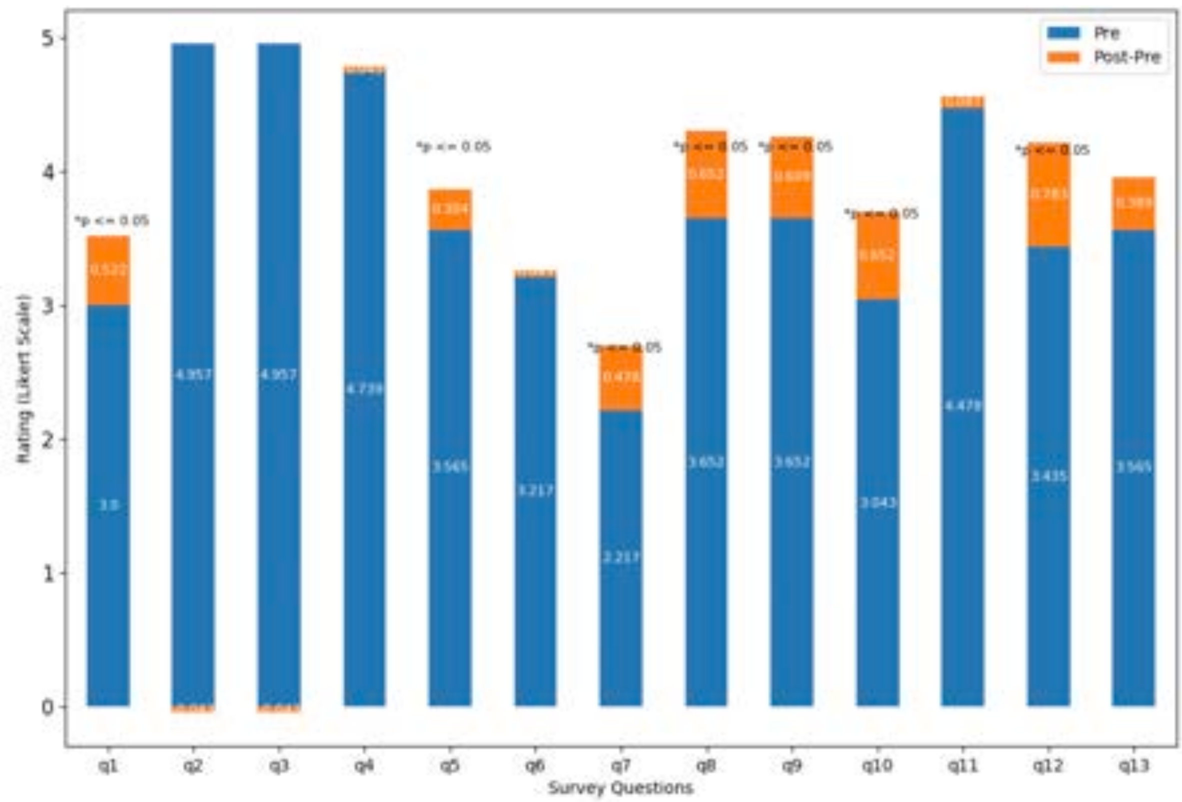

Figure 2. The plot of cohort 1 pre-post paired results.

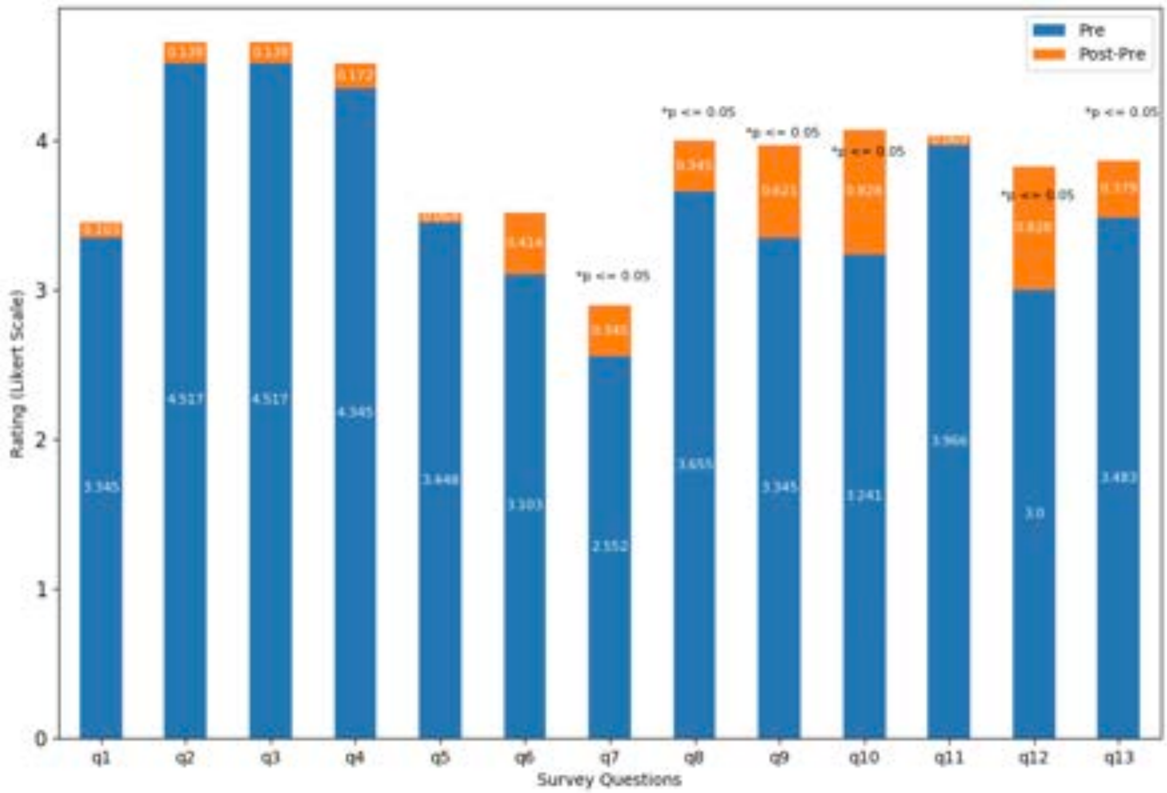

Figure 3. The plot of cohort 2 pre-post paired results.

3.1.2 Computation Skill

Students were asked to rate their computation skills on the Likert scale from 1 ("very beginner") to 5 ("very advanced"). Students from cohort 1 showed an increase post-intervention (Q7 Pre/Post: $\bar{x}$=2.217,2.696; p=0.0356; W(25)=17). Students from cohort 2 also showed an increase post-intervention (Q7 Pre/Post: $\bar{x}$=2.552,2.897; p=0.0479; t(38)=-2.069).

3.1.3 Self-Efficacy

Three questions measured self-efficacy (Q8: “I know how to find and define a real problem;” Q12: “I know how to make a lasting impact in my community or in the world;” and Q13: “I am confident in my ability to design and create solutions using technology, rather than working toward a ’right’ answer someone else gives me”). For Q12, both cohort 1 and cohort 2 students showed an increase in perception of ability to make a lasting impact (Cohort 1 Pre/Post: $\bar{x}$=3.435, 4.217; p=0.0026; W(25)=12; Cohort 2 Pre/Post: $\bar{x}$=3.000,3.827; p=0.002; W(38)=12.5). Students in cohort 2 also demonstrated increased self-efficacy post-intervention (Q13 Pre/Post: $\bar{x}$=3.483,3.862; p=0.0124; W(38)=13). The analysis of results from cohort 1 students for Q13 did not show a significant change.

3.1.4 Computational Action Skills

Computational action skills were measured by questions 8-11 in the survey. Both cohorts 1 and 2 demonstrated significant increases in their responses to Q8, Q9, and Q10 (Q8 is also a measurement of self-efficacy). Students from cohort 1 showed an increase post-intervention for knowing computational action skills (Q8 Pre/Post: $\bar{x}$=3.652,4.304; p=0.000275; W(25)=0; Q9 Pre/Post: $\bar{x}$=3.652,4.261; p=0.0086; W(25)=12.5; Q10 Pre/Post: $\bar{x}$=3.043,3.696; p= 0.00428; t(25)=-3.185). Students from cohort 2 also showed an increase post-intervention (Q8 Pre/Post: $\bar{x}$=3.655,4.000; p=0.0479; t(38)=-2.069; Q9 Pre/Post: $\bar{x}$=3.345,3.965; p=0.0048; W(38)=34; Q10 Pre/Post: $\bar{x}$=3.241,4.069; p=0.0002; t(38)=-4.296).

3.1.5 Learning Motivation

Post-intervention, students in cohort 1 agreed more strongly with external motivation (Q5: "I want to learn computer programming to earn more money.") (Pre/Post: $\bar{x}$=3.565,3.869; p=0.0497; t(25)=-

2.0765). There were no other significant changes from either cohort for the three learning motivation questions.

3.2 Qualitative Results

Students in cohort 2 responded to questions on what making an impact in the context of technology means to them with short, written answers. We performed an inductive analysis of the responses to identify themes and codes related to pro-social motivations and self-efficacy. Two researchers iteratively developed the codes, then convened to discuss the code results. The qualitative results from these questions provide another means of assessing the intervention's effect on student self-efficacy in pro-social impacts with technology.

3.2.1 Pre-Intervention Responses

79% of students in cohort 2 answered the pre-survey question ("What does making an impact in your community mean to you?"). Most responses described a range of motivations, including helping people in their own community, helping people generally, or accruing personal benefits ("making your mark"). A minority of responses expressed ambivalence about the possible impacts they could create with technology.

Table 3. Themes resulting from the qualitative survey questions asked pre- and post-intervention (% of students).

Pre-Workshop responses to the question: ***"What does making an impact in your community mean to you?"***
Themes: • Helping others (63%) • Leaving a personal legacy (23%) • Ambivalent about technology's impact (10%) • Don't know (4%)
Post-Workshop responses to the question: ***"After this class, how do you now think about making an impact in your community?"***
Themes: • Increase in self-efficacy involving technology (71%) • Unknown change in self-efficacy (13%) • Decrease in self-efficacy involving technology (11%) • No change in self-efficacy (5%)

3.2.2 Post-Intervention Responses

64% of cohort 2 participants answered the post-intervention survey question. Their answers were generally longer and more detailed than in the pre-survey. A large majority of responses (71%) reported an increase in characteristics associated with self-efficacy. In addition, another sizeable group (13%) expressed positive attitudes about impacting their community, but answers were too ambiguous to attribute to an increase in self-efficacy from the intervention (*e.g.*, P26 wrote: "It is important.") A summary of responses associated with both increases and decreases in self-efficacy is in Table 4.

Where students showed an increase in self-efficacy involving technology, they most often reported a greater awareness of user needs when designing, as with P3: "I'm thinking about identifying more problems and how users will respond to the app." In connection with user needs, P23 noted that co-designing solutions is a benefit of the intervention: "Collaboration with other people to make an impact is part of that impact." Students such as P9 also cited the benefits of breaking down a problem into specific steps: "By thinking of an idea that seems needed and then finding a way to implement it." Other students described a feeling of greater motivation for unspecified reasons, such as P4: “I have a lot more motivation, and it feels fun.” Students showing a decrease in self-efficacy involving technology expressed being overwhelmed by too many considerations. P30 wrote: “I now think its a lot harder than I originally thought. Creating an app is pretty difficult.” The data also show ways the intervention did not work for certain students, prompting ideas for future design of computational action curricula.

Table 4. Codes for the themes related to increased or decreased self-efficacy of helping others in post-workshop responses (% of students).

Theme: Increase in self-efficacy involving technology	• Conveyed the positive impact of designing with users/communities in mind (26%) • Provided specific steps which made my engineering goals feel easier (24%) • Increased motivation to take on engineering design (18%) • Increased awareness of harms and benefits in a useful way (3%)
Theme: Decrease in self-efficacy involving technology	• Made engineering and design seem hard and full of pitfalls (8%) • Decreased interest in using this formulation of engineering design (3%)
Theme: Unknown change in self-efficacy	• Unknown change in self-efficacy (13%)
Theme: No change in self-efficacy	• No change in self-efficacy (5%)

4 DISCUSSION

The computational action curriculum and toolkit presented in this paper were created to enable a novel engineering design process for A.I. and programming education for young people. Students in the research study were asked to complete pre- and post-intervention surveys so that the effectiveness of the process could be measured. The quantitative pre-post paired results show that the students, who were of middle school and high school ages, both domestic and international, showed an increase in computational identity, computation skill, and self-efficacy. In other words, they felt more confident in their programming skill; more able to identify a problem, understand user and community needs, and design socially responsible solutions; more empowered to make something to address a real problem; and more confident in their ability to do this on their own, rather than being told what to do. Regardless of students’ previous coding and engineering design experiences, this increase was significant across both cohorts.

The increases in identity, knowledge, and self-efficacy were also evident from students’ qualitative responses to survey questions. In written feedback, most students felt that they gained skills to tangibly make an impact and will continue to use computational action for future coding projects. Students felt that learning the process helped them see that making an impact is achievable, and now they know the steps to go about it. Some students qualified this impression of ease by also commenting on the “harder” work that they now realize should go into a coding project: namely, that they will now consider potential negative side effects, interview users, and collect data to inform their project ideas. Overall, students associated their introduction to the computation action process with an increase in self-efficacy manifested in several ways: new understandings of the kinds of possible impacts, knowledge of specific steps to achieve them with technology, and new ways of evaluating designs authentically for better results. This is good support for the effectiveness of the computational action process. Analysis of students’ responses shows that students are highly capable of creating, on their own, impressive work that embodies computational action. They can define real-world issues, hone in on a problem that affects their community and is also motivating for themselves, create user research questions and gather data, use this data to discuss meaningful positive and negative impacts of technology, and design and implement functional applications that address these issues.

4.1 Future Work

The research and results described in this paper make a promising start for future work of incorporating the computational action process into longer out-of-school programs or formal middle and high school curricula in which students implement end-to-end coding and AI projects. Future work aims to integrate the material and toolkit more with coding environments and to differentiate the material for various grade bands.

Students came into the computational action workshops with a range of backgrounds and experiences with programming. Future versions of materials can benefit from technical sections that fork for beginner, intermediate, and advanced programming experience. Students of different grade bands can also benefit from curricula and tools that are better targeted for their education levels. The current computational action curriculum emphasizes play and bold color, and introduces programming in App Inventor to assume little or no experience with coding. The third and fourth topics in particular can be fine-tuned depending on age and coding experience. A set of beginner/elementary school, intermediate/middle school, and advanced/high school compilation of computational action curriculum and tools can likely be more effective for the different grade bands.

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