Exploring the Influence of Hour of Code on Students' CS Interest and Perceptions

Jessica Yauney[†]
Technology
Brigham Young University
Provo, UT, USA
jessica.yauney@gmail.com

ABSTRACT

As the focus on computer science (CS) in K-12 classrooms grows, many teachers are turning to "Hour of Code" (HoC) programs. Created in 2013, they invite teachers to spend one hour working on pre-developed CS activities with their students. Some research with university students has supported the HoC initiative. However, little work has been done with K-12 students (the primary audience) regarding the effects of HoC. This study reports findings from computer science education research with over 1000 students who engaged in HoC activities. Students reported their interest and perceptions of CS before and after completing HoC activities. While stated goals generally focus on exposing students to computer science and computational thinking, it is also important to determine if the intended impact of these activities is being reached.

CCS CONCEPTS

• K-12 Education • Computing Literacy • Computer Science Education • Computer-Assisted Instruction

KEYWORDS

Hour of Code, Computer Science Education, Programming Curriculum, Motivation, Broadening Participation

1 Problem & Motivation

Countless passionate educators, policymakers, and other leaders have devoted themselves to improving computer science education. They seek to expand access and increase students' interest in computer science (CS) for various reasons. CS is a growing career field where demand has continued to outpace supply (New Data: AP Computer Science Principles Course Bringing More Diverse Set of Students Into Computer Science Pipeline, 2020) so increased participation in CS would provide societal economic good. CS is also a field where increased diversity is a priority. As such, "Hour of Code" (HoC) was created in 2013 to increase student exposure to computer science instruction. Over $90 million (Code.org 2018 Annual Report, 2019) and millions of classroom hours per year (Code.org 2018 Annual Report, 2019), are spent building and completing HoC activities.

2 Background & Related Work

Research in CS education has explored a wide variety of programs and instructional approaches, with a focus on determining their effectiveness in promoting learning and engagement. Studies have investigated the use of game-based learning (Papastergiou, 2009), and online learning platforms. Additional research has looked at the impact of teacher professional development programs (Voogt et al., 2017) and the use of educational technologies such as robotics (Benitti, 2012) and programming languages (Kelleher & Pausch, 2005). While these research initiatives have contributed to our understanding of effective teaching strategies, Hour of Code, has had an even greater impact, reaching over 100 million students in more than 180 countries since its launch in 2013 (Code.org, n.d.).

HoC's main goals include increasing awareness and interest in computer science(Majumdar, 2018). HoC provides a variety of different one-hour activities designed to guide students through CS learning without requiring a teacher to have technical expertise. These activities have a variety of themes, difficulty levels, and programming languages.

In-house data collection without peer review has shown that participation in HoC activities improves students' attitudes toward, and interest in, computer science (Phillips & Brooks, 2017). However, little evaluation has been done regarding the effectiveness of this initiative. Of 64 papers identified to focus on Hour of Code, only 12 papers completed research experiments looking at the outcomes of HoC with the majority of these focusing on non-K12 audiences (Yauney, 2021). Some research has begun looking at the amount of knowledge students gain through their participation in HoC activities. However, their results suggested that students did not gain programming skills (Du & Wimmer, 2013). Research experiments at the K-12 level look at student engagement and success in Minecraft and Frozen-themed activities (Majherová, 2017) high school students perceptions of self-efficacy and their interest in a computer science career (Mallios & Vassilakopoulos, 2015) and students' reported motivations for interacting with HoC (Nikou & Economides, 2014).

3 Uniqueness of the Approach

Interventions were performed and data was collected from 687 students in 72 classes with twenty 7th grade teachers at fourteen schools across four school districts in the Western United States. All teachers invited to participate in this research were instructors teaching a required middle school STEM course, so their classes were representative of the wider school population. The course where this intervention was inserted covers multiple STEM topics. Teachers are required to expose students to computer science but have historically done so in a variety of ways. Hour of Code was selected as the intervention for this study because it is the most common tool previously used by teachers in this area but also one of the most common options for computer science instruction internationally. It also is particularly useful because it requires such limited teacher knowledge and training. While access to specialized computer science instructors varies, many locations including these districts rely heavily on teachers without specific CS training to provide computer science instruction (Yauney, 2022). In order to improve consistency of implementation one researcher implemented all HoC activities as a guest in the teachers' classrooms. This researchers in addition to current research is a professional software developer, former high school CS teacher and teacher trainer. While the findings may not be immediately generalizable to educators with different experience, this environment was designed to mitigate confounding influences and provide an optimal learning experience. Next each teachers' students were divided into 3 groups by class with at least one class in each group (See Table 1). All groups completed pre and post surveys (See Table 2). One group did no other activities. The other remaining groups completed the top suggested activity at the time by Code.org for the 7th grade, "Minecraft Hour of Code."

Finally, the last group also participated in a discussion about CS careers, further education, impact, etc following the guidelines provided by HoC. These conversations included discussion of a variety of different potential careers ranging from design to development to testing as well as discussion about the facilitator's specific work experiences. They also included answering students' questions about technologies they commonly interact with like the cloud and email as well as discussions about inequality in CS.

Table 1: **Group Treatments**

Group	Treatment
A	Discussion about CS following the suggestions provided in "Start your Hour of Code strong" and the HoC Digital Activity
B	HoC Digital Activity
C	No intervention (Control Group)

The surveys include questions about students' interest in CS, further CS learning, and perceived capacity. These questions were selected from those published by Mason & Rich (2020) and the National Center for Women & Information Technology (2017).

Table 2: **Selected Survey Questions**

Question	Answer Choices if applicable
What gender do you most identify with?	Male, Female, Other
What race do you most identify with?	Asian, Black or African American, Hispanic, Native American or Alaska Native, Native Hawaiian or Pacific Islander, White, Other
How much coding have you done?	None, Less than 10 hours, More than 10 hours
What type of coding have you done?	
Where did you code before?	In school, After school, In a club, At home, Other
I like math.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
I usually do well in math.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
I can learn to code.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
I can create new technology inventions.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
People like me can do well in technology jobs.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
I like coding, or I think I would like coding.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
Solving coding problems seems fun.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
Knowing how to code will help me solve problems.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
Coding is interesting.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
I would like to learn more about coding.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree
I would like to study coding in the future.	Strongly disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly agree

4 Results

Multiple statistical methods were employed in order to provide a well-rounded view of the impact of the interventions. The differences in student responses for each question from their pre- to post-surveys were calculated and processed using Single factor ANOVA statistical techniques. Then a McNemar Bowker test was used to view the shifts in greater detail.

4.1 Single Factor ANOVA

Each of the students' answers was recorded as number 1 to 5 (from strongly disagree to strongly agree). Then the difference between each students' answers was calculated. For example, a student who answered disagree (2) originally and then agree (4) on the post-test would have a score of two (4-2). Then each of these scores were used in an ANOVA comparison. Of these 11 questions asked on a

Likert scale, all 11 were found to have statistically significant differences between treatment groups (p-value < .02).

For all but two of the questions, Group A, the group that participated in a discussion and a digital activity, had the most positive change in responses, followed by Group C, the control group and then by Group B, the group that only participated in a digital activity. The remaining two questions, "I would like to learn more about coding" and "I usually do well in math", had the most positive change for Group C followed by Group A and then Group B. On average Group B students' responses shifted negatively from the pre-intervention survey to the post-intervention survey for all questions. Only the responses to the question "I would like to learn more about coding" shifted negatively for all Groups. All other questions showed a positive shift for either Group A or C. While it is not useful to include the results for each of the questions separately, several of the representative questions will be discussed.

Many of the questions followed a similar pattern to the responses to "I can learn to code" (See Figure 1). Students in Group A had a significant positive shift in their self-efficacy, while students in Groups B and C had a negative shift with the shift being larger for Group B.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
A	242	32	0.132231405	0.4554713487
B	217	-32	-0.1474654378	2.33926438
C	159	-12	-0.07547169811	0.3993312634

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9.622949637	2	4.811474818	4.36346386	0.01313080081	3.010372317
Within Groups	678.1440407	615	1.102673237			
Total	687.7669903	617				

Figure 1: **ANOVA results for "I can learn to code"**

The next common pattern was for Groups A and C to improve with A having the larger shift while Group B had a negative shift. The responses to "I can create new technology inventions" followed this pattern (See Figure 2). The responses to "People like me can do well in technology jobs", "I like coding or think I would like coding", and "I would like to study coding in the future" all follow the same pattern.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
A	242	61	0.2520661157	0.7038338877
B	217	-13	-0.0599078341	1.963987029
C	159	14	0.08805031447	0.4858689595

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	11.16747458	2	5.583737289	5.120689868	0.006229116021	3.010372317
Within Groups	670.6124607	615	1.090426765			
Total	681.7799353	617				

Figure 2: **ANOVA results for "I can create new technology inventions"**

In only one case did all student responses, on average, negatively shift in response to the question "I would like to learn more about coding" (See Figure 3).

SUMMARY

Groups	Count	Sum	Average	Variance
A	242	-15	-0.06198347107	0.6973869209
B	217	-89	-0.4101382488	1.743044888
C	159	-10	-0.06289308176	0.350449805

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	17.03186082	2	8.515930409	8.729716001	0.000182621095	3.010372317
Within Groups	599.939013	615	0.9755105902			
Total	616.9708738	617				

Figure 3: **ANOVA results for "I would like to learn more about coding"**

4.2 McNemar Bowker

The McNemar Bowker test is used to test for paired-table symmetry. In the ANOVA analysis the data was analyzed by assigning numbers and calculating the difference, meaning that a shift from strongly disagree to neutral is viewed the same as a shift from neutral to strongly agree. In the McNemar Bowker each possible pairing of pre- and post-responses are placed in a table and the frequencies of each combination are recorded. Again, the numbers 1 to 5 represent the responses strongly disagree to strongly agree. One example of such a table is given in Table 2.

Table 2: **Frequency Table for "**Knowing how to code will help me solve problems."

	1	2	3	4	5
1	12	11	0	0	0
2	1	15	7	1	0
3	2	12	49	28	4
4	1	2	15	52	16
5	0	0	0	10	16

After the table is constructed the numbers symmetrically across the major axis are paired. For example, the number of students who initially disagreed and then agreed is paired with those who agreed and then disagreed, which in the example in Table 2 would be a one paired with a two. The number of students who made a positive shift in this case is one and those who made a negative shift is two. Once all these pairs are collected (See Table 3) a total number of students who positively and negatively shifted can be calculated and a chi-squared test can be run to see if there was a significant shift. In this example 67 students answered more positively in the post-test than the pre-test and only 43 students answered more negatively in the post-test than the pre-test. A chi-squared test resulted in the significant p-value of 0.01 meaning that there was a significant shift in student responses.

Table 3: **Paired responses for "**Knowing how to code will help me solve problems."

Response A	Response B	Number shifted from A to B	Number shifted from B to A
1	2	11	1
1	3	0	2
1	4	0	1
1	5	0	0
2	3	7	12
2	4	1	2
2	5	0	0
3	4	28	15
3	5	4	0
4	5	16	10
	Total:	67	43

Further analysis is possible given this data. For example, one can see that the most common shift for students is to move from undecided if they believe code is helpful to agreeing that knowledge of code is helpful. This added detail can provide additional information in understanding the true impact.

While each of the individual tables like Table 3 are interesting, there is insufficient space to include them all so the total positive shifts, negative shifts and p-values are listed in Table 4. The control group had no significant shifts which suggests that this statistical analysis may be slightly more informative than the ANOVA. Both group A and group B shifted significantly in response to the questions "I can create new technology inventions" and "People like me can do well in technology jobs." Group A shifted in response to "I like coding or think I would like coding", "Knowing how to code will help me solve problems" and "Coding is interesting." Group B shifted in response to "Solving coding problems seems fun", and "I would like to study coding in the future." Even though the ANOVA showed multiple negative shifts, all the statistically significant shifts seen through the lens of the McNemar Bowker are positive with more students shifting positively than negatively. As the ANOVA weights a larger shift more and the McNemar Bowker does not, this suggests that even though less students have negative shifts, those shifts are often larger than the students who positively shift.

Table 4: **McNemar Bowker Results**

	A- Activity & Conversation			B- Activity			C- Control		
	Positive	Negative	p-value	Positive	Negative	p-value	Positive	Negative	p-value
I like math.	18	14	0.074	13	17	0.064	10	13	0.741
I usually do well in math.	14	22	0.332	9	25	0.406	10	4	0.706
I can learn to code.	55	27	0.075	47	29	0.749	19	27	0.688
I can create new technology inventions.	77	27	0.001	61	26	0.034	30	14	0.112
People like me can do well in technology jobs.	64	35	0.041	49	28	0.042	23	17	0.098
I like coding, or I think I would like coding.	71	32	0.014	57	31	0.074	28	20	0.287
Solving coding problems seems fun.	67	47	0.057	51	26	0.003	26	29	0.380
Knowing how to code will help me solve problems.	67	43	0.014	44	31	0.077	33	28	0.741
Coding is interesting.	63	34	0.040	54	33	0.275	18	37	0.196
I would like to learn more about coding.	50	62	0.495	31	50	0.353	18	30	0.591
I would like to study coding in the future.	65	34	0.139	49	24	0.017	24	22	0.798

5 Contribution

With all the resources being used for HoC, the authors assumed that HoC activities would lead to purely positive shifts in student attitudes and interest. As such both interventions included those activities. While the expectation was that exposure initiatives like the HoC digital activities, while not the most effective method, would have a positive impact on students' interest, self-efficacy, and intention to pursue CS. While both the ANOVA and the McNemar Bowker showed positive shifts for students who engaged in both the HoC activity and the conversation, these statistical methods gave conflicting results about the impact of only interacting with the HoC activity. The apparently negative ANOVA results and the positive McNemar Bowker suggest that while some students become strongly uninterested in CS a larger group of students become slightly more interested in CS. If one acknowledges that CS is not a field that everyone will enjoy, then this may be the best-case response. Some students are benefitted from learning early that this is not a field they wish to pursue while many other students are incentivized to continue exploring the field. Additional qualitative data from students as well as continued analysis of the distributions in the McNemar Bowker paired tables may provide more insight into this consideration.

As Group A consistently shifted in a more positive manner than Group B, it appears that participating in a discussion about CS has a positive impact on students. However, as we did not have a group of students who only engaged in the discussion, additional research would be necessary to find how the impact of the discussion interacts with the impact of the digital activity. It may be the discussion and the activity combine to be more effective than either of them separately. Further research would be useful in determining the effectiveness of discussions led by guest speakers without the education background that the authors possess, but this data suggests that guest speakers may be an effective way to expose students to CS.

Overall, further evaluation of HoC programs is both possible and useful, to ensure that resources are being used efficiently. The results of this research done with near ideal circumstances differed from expectation and demand consideration. Some interpretations of this data suggest a reasonable outcome where HoC helps all students to make decisions about their interest in coding, either positively or negatively. However, it is important that the CS education community better define their goals in regards to increasing students' exposure to CS.

REFERENCES

[1] Ashcraft, C., Eger, E. L., & Friend, M. (2012). *Girls in IT: the facts*. NCWIT. https://www.ncwit.org/sites/default/files/resources/girlsinit_report2012_final.pdf.

[2] Bailey, D., Duncan, G. J., Odgers, C. L., & Yu, W. (2016). Persistence and Fadeout in the Impacts of Child and Adolescent Interventions. *Journal of Research on Educational Effectiveness*, *10*(1), 7–39. https://doi.org/10.1080/19345747.2016.1232459

[3] Basawapatna, A., Repenning, A., Savignano, M., Manera, J., Escherle, N., & Repenning, L. (2018). Is drawing video game characters in an hour of code activity a waste of time? *Proceedings of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education.* https://doi.org/10.1145/3197091.3197136

[4] Benitti, F. B. V. (2012). Exploring the educational potential of robotics in schools: A systematic review. *Computers & Education*, 58(3), 978-988. doi: 10.1016/j.compedu.2011.10.006

[5] Braga, C. & Mochetti, K. (2018). Programming teaching tools and the gender gap in the Information Technology field. *Anais Do XXIV Workshop De Informática Na Escola* (WIE 2018). https://doi.org/10.5753/cbie.wie.2018.70

[6] Cheryan, S., Drury, B. J., & Vichayapai, M. (2012). Enduring influence of stereotypical computer science role models on women's academic aspirations. *Psychology of Women Quarterly*, *37*(1), 72–79. https://doi.org/10.1177/0361684312459328

[7] Clarke-Midura, J., Allan, V., & Close, K. (2016). Investigating the role of being a mentor as a way of increasing interest in Cs. *Proceedings of the 47th ACM Technical Symposium on Computing Science Education*. https://doi.org/10.1145/2839509.2844581

[8] Clarke-Midura, J., Poole, F., Pantic, K., & Allan, V. (2017). Playing mentor: A new strategy for recruiting young women into computer science. *Journal of Women and Minorities in Science and Engineering*, *23*(3), 193–210. https://doi.org/10.1615/jwomenminorscieneng.2017019307

[9] Code.org. (n.d.). About us. Retrieved April 19, 2023, from https://code.org/about

[10] *Code.org 2018 Annual Report*. Code.org. (2019, February 12). https://code.org/about/2018.

[11] Dickinson, D. K., & Caswell, L. (2007). Building support for language and early literacy in preschool classrooms through in-service professional development: Effects of the Literacy Environment Enrichment Program (LEEP). *Early Childhood Research Quarterly*, *22*(2), 243–260. https://doi.org/10.1016/j.ecresq.2007.03.001

[12] Du, J., Wimmer, H., & Rada, R. (2018). "Hour of Code": A Case Study. *Information Systems Education Journal*, 16(1).

[13] Du, J., Wimmer, H., & Rada, R. (2016). "Hour of Code": Can It Change Students' Attitudes toward Programming? *Journal of Information Technology Education: Innovations in Practice*, 15, 053–073. https://doi.org/10.28945/3421

[14]Du, J., & Wimmer, H. (2019). Hour of Code: A Study of Gender Differences in Computing. *Information Systems Education Journal*, 17(4), 91–100.

[15] Du, J & Wimmer, H. (2015). Impact of Hour of Code: A Five-Year Study. *AMCIS*.

[16] Fisher, L. M. (2016). A decade of ACM efforts contribute to computer science for all. *Communications of the ACM*, 59(4), 25–27. https://doi.org/10.1145/2892740

[17] GhasemAghaei, R., Arya, A., & Biddle, R. (2017). Affective Walkthroughs and Heuristics: Evaluating Minecraft Hour of Code. *Learning and Collaboration Technologies 4th International Conference*, 22–40. https://doi.org/10.1007/978-3-319-58515-4_3

[18] Kelleher, C., & Pausch, R. (2005). Lowering the barriers to programming: A taxonomy of programming environments and languages for novice programmers. *ACM Computing Surveys*, 37(2), 83-137. doi: 10.1145/1089733.1089734

[19] Labouliere, J. J., Pelloth, A., Lu, C.-L., & Ng, J. (2015). An exploration of the attitudes of young girls toward the field of computer science. *2015 IEEE Frontiers in Education Conference (FIE)*. https://doi.org/10.1109/fie.2015.7344265

[20] Lin, J., & Liu, S.-F. (2012). An Investigation into Parent-Child Collaboration in Learning Computer Programming. *Educational Technology & Society*, *15*(1), 162–173.

[21] Majherová, J. (2017). Innovative Teaching of Programming in Secondary Education. *Information and Communication Technologies in Education.*

[22] Mallios, N., & Vassilakopoulos, M. (2015). Evaluating Students' Programming Skill Behaviour and Personalizing their Computer Learning Environment Using "The Hour of Code" Paradigm. *International Conference e-Learning.*

[23]L. & Rich, P. J. (2020). Development and analysis of the Elementary Student Coding Attitudes Survey. *Computers & Education*. https://doi.org/10.1016/j.compedu.2020.103898.

[24] Majumdar, A. (2018). The Hour of Code: An initiative to break the barriers of coding. *XRDS: Crossroads, The ACM Magazine for Students*, 24(3), 12–13. https://doi.org/10.1145/3186711

[25] Miller, A., & Kay, J. (2002). A mentor program in CS1. *ACM SIGCSE Bulletin*, *34*(3), 9–13. https://doi.org/10.1145/637610.544420

[26] National Center for Women & Information Technology. (April 2017). NCWIT Grade 4-12 Computing Program Participant Pre-Survey. Retrieved from https://www.ncwit.org/sites/default/files/file_type/grade_4-12_computing_program_participant_presurvey.doc

[27] Natsuaki, M. N. (2015). Intervention effect fades over time: when, how, and for whom? *The Lancet Psychiatry*, *2*(7), 573–574. https://doi.org/10.1016/s2215-0366(15)00158-3

[28] *New Data: AP Computer Science Principles Course Bringing More Diverse Set of Students Into Computer Science Pipeline*. (2020, December 9). Newsroom; College Board. https://newsroom.collegeboard.org/new-data-ap-csp-course-bringing-more-diverse-set-students-computer-science-pipeline

[29] Nikou, S. A., & Economides, A. A. (2014). Measuring Student Motivation during "The Hour of CodeTM" Activities. *IEEE 14th International Conference on Advanced Learning Technologies.* https://doi.org/10.1109/icalt.2014.218

[30] Partovi, H. (2014). Transforming US education with computer science. *Proceedings of the 45th ACM Technical Symposium on Computer Science Education - SIGCSE '14.* https://doi.org/10.1145/2538862.2554793

[31] Phillips, R. S., & Brooks, B. P. C. (2017, January). The Hour of Code: Impact on Attitudes Towards and Self-Efficacy with Computer Science. Code.org. https://code.org/files/HourOfCodeImpactStudy_Jan2017.pdf.

[32] Papastergiou, M. (2009). Digital game-based learning in high school computer science education: Impact on educational effectiveness and student motivation. *Computers & Education*, 52(1), 1-12. doi: 10.1016/j.compedu.2008.06.004

[33] Sim, T. Y. (2015). Exploration on the impact of online supported methods for novice programmers. *2015 IEEE Conference on e-Learning, e-Management and e-Services (IC3e).* https://doi.org/10.1109/ic3e.2015.7403505

[34] Sparks, S. D. (2020, December 1). *Studies Explore Reasons for 'Fade-Out' Effect*. Education Week. https://www.edweek.org/teaching-learning/studies-explore-reasons-for-fade-out-effect/2016/01.

[35] Voogt, J., Fisser, P., Good, J., Mishra, P., & Yadav, A. (2017). Computational thinking in compulsory education: Towards an agenda for research and practice. *Education and Information Technologies*, 22(2), 1-14. doi: 10.1007/s10639-015-9412-6

[36] Xion, T., & Lye, L. (2019). Block-Based Programming: The Way to Introduce Computer Programming. *International University Carnival on e-Learning.*
[37] Yauney, J., Bartholomew, S. R., & Rich, P. (2021). A systematic review of "Hour of Code" Research. *Computer Science Education*, 1–33. https://doi.org/10.1080/08993408.2021.2022362
[38] Yauney, J. M. (2022). K-12 CS Teacher Licensing in the US. In *SIGCSE 2022: The 53rd ACM Technical Symposium on Computer Science Education*. Providence, Rhode Island; Association for Computing Machinery. Retrieved April 28, 2022, from https://doi-org.erl.lib.byu.edu/10.1145/3478432.3499202.