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Advancing STEM Learning Opportunities for Students with Autism Spectrum Disorder Through an Informal Robotics and Coding Program: A Feasibility Study for an After-School Enrichment Program

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Abstract
Research has established that there have been limited opportunities for students with a diagnosis of autism spectrum disorder (ASD) to participate in science, technology, engineering, and mathematics (STEM) learning activities that are designed to meet their diverse needs, particularly activities that are intended to promote computer science literacy. Thus, the purpose of this study was to examine outcomes across time associated with a robotics program for children with ASD while accounting for a variety of relevant variables, including the degree of ASD symptoms, presence of ADHD symptoms, degree of challenging behaviors, quality of relationships, and sensory sensitivity. Participants included 12 elementary students with a diagnosis ASD who were enrolled in a community-based after-school program for students with ASD. Participants engaged in robotics and coding activities across 7 weeks through structured and unstructured exploration. Engagement and diagnostic markers were observed as students participated in robotics and coding tasks. Additionally, measures were obtained for indications of ASD, ADHD, quality of relationships, challenging behaviors, and sensory sensitivity. Data were used to evaluate the association of ASD diagnostic marker and engagement scores across time via the number of sessions. Results show a decrease in participants' diagnostic ASD markers and an increase in engagement as sessions progressed. Background variables such as presence of ADHD symptoms, challenging behaviors, and sensory sensitivities did not significantly influence outcomes, suggesting that the design of robotics and coding programs for students with ASD need not hinge upon on these factors.

Keywords Autism · ASD · STEM · Coding · After school programs · Informal learning · Computer science · Robotics

Research has established that there have been limited opportunities for students with a diagnosis of autism spectrum disorder (ASD) to participate in science, technology, engineering, and mathematics (STEM) learning activities that are designed to meet their diverse needs, particularly activities that are intended to promote computer science literacy. A recent review of literature reported that it is uncommon for STEM interventions that are implemented in schools to be designed in a way that supports the needs of students with a diagnosis of ASD (Ehsan et al., 2018). Yet, previous research points to the importance of STEM learning opportunities for increasing students' likelihood of future employment (Zollman, 2012), for helping students engage in daily problem-solving and decision making (Morrison, 2006), and for being prepared with common twenty-first century skills (Zviel-Girshin et al., 2020). Despite the perceived importance of STEM education, people with disabilities continue to be underrepresented in STEM education and STEM-related employment (Griffiths et al., 2021).

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The Emergence of Computer Science in the Elementary Grades

Recently, there has been increasing recognition of computer science (CS) education as an indispensable learning opportunity for all students. This is underscored by the

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implementation of computer science learning standards, which now commence as early as kindergarten in numerous states across the United States (Ericson et al., 2016). Proficiency in computer science is increasingly being touted as a fundamental skill, with scholars arguing that computer science education helps students acquire analytical and creative problem-solving abilities that are applicable across diverse fields (Grover & Pea, 2018; Wing, 2006). This heightened attention to computer science has spurred rapid growth in research within the field of CS education, leading to a variety of approaches for teaching computer science, while also highlighting the need for more inclusion in computing. While there have been notable efforts to close the gender gap in computing, there has been much less attention to the inclusion of students with disabilities in computer science education (Hutchison et al., 2023). Thus, the current study focuses on the inclusion of students with a diagnosis of ASD in computing.

Robotics as an Approach for Learning About Computing

One common approach for teaching computer science, especially to young children, has been through the use of programmable robots, which is often referred to as a form of physical computing (Navta, 2018). The use of robotics and physical computing are thought to be beneficial because they provide a physical representation of abstract ideas (Bers, 2010). Further, robotics education has been shown to improve children's computational thinking skills and other twenty-first century skills (Bers, 2010; Zviel-Girshin et al., 2020). Although there has been some research on the use of robots for delivering autism interventions (e.g., Begum et al., 2016), there is still a significant need for research about how students with a diagnosis of ASD can utilize robots to learn computer science skills (Prummer, 2022). There is a particular need to understand the role that factors such as challenging behaviors, severity of diagnostic behaviors, relevant comorbid behaviors, and sensory sensitivities may impact the participation of students with a diagnosis of ASD. For example, students may be unable to follow a series to structured steps that are necessary to control robots and make them run as expected. Alternately, students may dislike the sounds, colors, or motions made by robots, leading them to disengage or avoid robotics activities. We believe that an important first step in understanding ideal approaches for engaging students with ASD in robotics and computer science instruction is to observe these students in both unstructured and structured activities with a variety of robotics and computing tools.

ASD is a lifelong disorder consisting of two core areas of impairment: social communication/interactions and restricted, repetitive behaviors, interests, or activities (APA, 2022). There is a well-established body of literature that has examined the clinical characteristics of ASD (e.g., Matson & Sturmey, 2022; Volkmar et al., 2014). The fifth edition of the Diagnostic and Statistical Manual ([DSM-5-TR]; APA, 2022) provides the most updated information as to the diagnostic criteria for ASD in the United States, which was the context for the current study. Attention deficit hyperactivity disorder (ADHD) consists of symptoms of inattention and hyperactivity and can be a commonly co-occurring disorder with ASD (Antshel & Russo, 2019; Stevens et al., 2016); thus, we will want to statistically account for symptoms of ADHD. Examining for the presence of symptoms of core impairment of ASD in situ does not negate the relative permanence or persistence of the diagnostic criteria, but rather provides insight into the level of interest and engagement of the student in a particular task for a particular period of time (i.e., less than 1 h for each after-school session in the current study). The distinction between state versus trait is well discussed in the literature (Steyer et al., 2015) such that individuals, for instance, may have anxiety for a certain period of time or in a certain circumstance as a state that they are in but do not have atypically high levels of trait of anxiety (Knowles & Olatunji, 2020). The determination of a trait requires the presentation across multiple contexts (APA, 2022). ASD is no different. Individuals can have autistic traits that may manifest to constitute a diagnosis but there are states or situational contexts that may heighten or lessen the presentation of symptoms as individuals interact with their environment.

Indeed, engagement with robotics or physical computing may well align with diagnostic characteristics of the disorder such as having restricted or repetitive interests (APA, 2022) for some individuals with ASD. Thus, being particularly focused on a specific mechanism of a robot would serve as an indication of engagement but may also be reflective of the disorder itself when engaging in a restricted interest (Gunn & Delafield-Butt, 2016; Richler et al., 2010). Engagement for a task such as working with robots may look very different than engagement with a task such as writing and delivering a speech regardless of disability. Thus, engagement in working with robots may be well suited to individuals with ASD who are interested in robotics. Additionally, students with ASD may consider the need to communicate more with an instructor more relevant or socially valid (Hong et al., 2018; Qualls & Corbett, 2017) to them in order to achieve their end goal of learning how to make the robot work for instance. Increased social communication in the session would be a likely outcome if a student with ASD is interested in robotics. Students with and without ASD would similarly make more verbalizations when interested in an activity versus when they are less interested. ASD is a spectrum not only across individuals but within them as they interact with their environments to co-construct their understanding in the learning process.

Accordingly, the purpose of the current study was to examine outcomes across time associated with a robotics program for children with ASD while accounting for a variety of relevant variables, including the presence of ADHD symptoms, degree of challenging behaviors, quality of relationships, and sensory sensitivity. The robotics program occurred in the informal learning context of an after-school program for students with ASD. The current study was not a training study such that the current study examined the outcomes associated with an after-school enrichment program but there was no explicit training related to ASD. The current study may be best characterized as the initial feasibility study (Jebrin, 2017), in which we examined the ability to implement informal learning while accounting for a variety of factors via an after-school enrichment program students with ASD. To achieve this purpose, the following research questions were examined:

(1) What was the association of ASD diagnostic marker scores across time via the number of sessions?
(2) What was the association of engagement scores across time via the number of sessions?

Method

Approach

Over the course of 7 weeks, 12 participants were introduced to seven different robotics and coding activities at an after-school program for 2 days per week. Over the 7-week period, instructional activities averaged 40 min each and moved from less structured in week 1 to more structured, with week 7 being the most structured. Researchers observed each session for evidence of engagement and to identify diagnostic markers. Robotics and coding programs used during this study included the following physical robots: Sphero Bolt (see https://sphero.com/products/sphero-bolt), Ozobot (see www.ozobot.com), Lego Spike (see https://spike.legoeducation.com/), and Finch Robot (see https://www.birdbraintechnologies.com/products/finch-robot-2-0/). These physical robots all have connected programming applications that enable the user to program and control the robots from a tablet or computer. Each robot has slightly different features, but all of them have simple interfaces that are easy to navigate. Students were also introduced to Makey Makey (see https://makeymakey.com/), which is a kit with a circuit board and alligator clips that allows users to turn everyday objects into computers. Finally, students were introduced to programming apps that do not have any related physical objects, including Scratch/Scratch Jr. (see www.scratch.mit.edu) and OctoStudio (see https://octostudio.org/en/). Specifically, in weeks 1 and 2, students were provided with the opportunity to tinker with app-controlled robots (Sphero Bolt and Ozobot) in any manner they chose. Researchers provided input or ideas when requested, but students were allowed to engage with the robots in any way they chose. In weeks 3 through 5, activities were slightly more structured, with (1) researchers pre-programming Makey Makey circuits and allowing students to engage with them and learn about the code, (2) students following app-based instructions to build programmable projects with Lego Spike, and (3) students being instructing to program a sequence of commands to navigate a Finch robot through a maze designed by the researchers. In the final 2 weeks of the program, activities were more abstract, with researchers introducing app-based coding programs (Scratch and OctoStudio) that did not have an associated robot. Students were first allowed to explore without a specific task and were then asked to program a specific sequence of events that they chose based on their individual interests. The researchers observed how the participants responded to more and less structured activities and used observations of student engagement and diagnostic markers to plan each subsequent session.

Sample

Participants included 12 elementary-aged students in grades 1–5 (ages 6–11) with a diagnosis of ASD who participated in an after-school program specifically designed for children with ASD and located in the southeastern United States. With respect to gender, 42% ($n = 5$) of the participants were female and 58% ($n = 7$) were male. As for race, 25% ($n = 3$) of participants were identified as African American and 75% ($n = 9$) were identified as White by the parents.

Measures

Several measures were utilized in conducting the current study. The average number of sessions was 3.64 ($SD = 1.85$) across individuals as not all students attended the after-school program every day or were picked up earlier. Diagnostic ASD markers present in each session were coded according to diagnostic criteria for autism spectrum disorder according to the DSM-5-TR (APA, 2022) across 24 categories that included stereotyped behavior, restricted interests, and social communication and interactions. Engagement was coded for each session according to the engagement and diagnostic markers present in the sessions were coded by two individuals associated with the study and revealed strong inter-observer agreement at 0.90 and 0.94 respectively. Beyond two time points of pre- and post participation in the after-school enrichment program, we measured engagement and diagnostic markers at each session. We did not obtain information regarding the full diagnosis of ASD as this is not typical information collected for participation in an after-school enrichment program. With regard to comorbid diagnoses, please note that this information was not collected as it would not be part of the inclusion or exclusion criteria for study participation. ASD screening scores were obtained via the Child Autism Spectrum Quotient that consisted of 50 items as reported by parents (Auyeung et al., 2008), in which all students but one student met the measure's cutoff criteria for ASD; however, all students were participants in an after-school program for students with ASD. We implemented this measure to provide a sense of the level of severity of ASD symptoms as higher scores indicate a higher likelihood of an ASD diagnosis but there is no indication of severity by the measure. ADHD scores (18 items) and performance scores (5 items) were obtained via the Vanderbilt Assessment Scales of the National Institute for Children's Health Quality (NICHQ) as rated by parents (Anderson et al., 2022). The ADHD screening scores indicate that five out of the 12 participants met the screening criteria for some form of ADHD and there is no indication of severity provided by the measure but higher scores indicate a higher likelihood of ADHD. For the purposes of the current study as well as to reduce respondent fatigue in responding to surveys (thereby potentially increasing accuracy by reducing respondent fatigue), thus, we used the items outlined above as related to ADHD (Anderson et al., 2022). We did not have information regarding IQ as this information would not be requested to participate in an after-school program such as this. Challenging behavior was measured using the short form of the Behavior Problems Inventory (BPI-S), which consists of 30 items of frequency and severity across three subscales of aggressive/destructive behavior, stereotyped behavior, and self-injurious behavior (Rojahn et al., 2012). Sensory sensitivity scores were derived from the Glasgow Sensory Questionnaire that was comprised of 42 items across six subscales (or modalities) of visual; auditory; gustatory, tactile; olfactory; proprioception; and vestibular (Robertson & Simmons, 2013). Table 1 provides the descriptive statistics for each measure.

Table 1 Descriptive statistics

Measures	*M*	*SD*	Range
Engagement	17.95	6.45	0 to 28
Diagnostic markers	7.10	5.01	0 to 24
ADHD screening score	17.25	12.9	0 to 54
Autism screening score	80.58	37.96	0 to 150
Quality of relationships	30.92	18.59	0 to 40
Challenging behaviors	27.17	12.55	0 to 90
Sensory sensitivity	47.67	23.616	0 to 168

Analysis

In the current study, engagement and diagnostic markers data points across time have been nested within sessions within the individuals in the current study, suitable for multilevel analyses (Hoffman & Walters, 2022). M*plus* was utilized to perform multilevel analyses with a Bayesian estimator via M*plus* (*v*. 8.0; Muthén et al., 2017). The default in M*plus* is two independent Markov chain Monte Carlo chains across 2000 iterations for each Markov chain. After estimating the degree of autocorrelation for the dependent variables of interests as lagged, we examined the covariates of the number of sessions at the within level and then ASD screening score, ADHD screening score, quality of relationships, degree of challenging behaviors, and sensory sensitivity at the between or individual level. Thus, we examined the intra-individual state-level behaviors during the sessions as contrasted with the trait level at the individual level via the ASD screening measure scores. In examining model fit, we first tested the unconditional or intercepts-only model value and then evaluated this model against the conditional model with all the planned covariates. We then employed chi-square (χ^2) difference testing comparing the Deviance Information Criterion (DIC) values and the number of estimated parameters for the unconditional versus the conditional model. Similar to Bayesian Information Criterion and Akaike Information Criterion value interpretation, lower values for DIC indicate better model fit (McNeish & Hamaker, 2020). Upon determining model fit, the standardized individual parameter estimates were evaluated with those being statistically significant at the 0.05 level or less being considered worthy of further discussion. We also simulated the parameter estimates to determine the degree of statistical power or parameter recovery for those results that were statistically non-significant in particular.

Results

Table 2 provides the DIC values and the number of free parameters for the unconditional and conditional models. In comparing DIC values of models, the conditional model fit significantly better than the unconditional value, $\Delta\chi^2(6) = 462.81$, $p < 0.001$. Table 2 provides the individual

Table 2 Unconditional versus conditional models

	Unconditional model	Conditional model
Estimated number of parameters	36.83	30.89
Deviance information criteria	1075.37	612.56

parameter estimates for the conditional model along with 95% confidence interval values. The estimated degree of autocorrelation was $\beta = 0.375$ for diagnostic ASD markers across individuals, which was moderate and statistically significant, $p = 0.02$. For engagement, the estimated degree of autocorrelation was $\beta = 0.347$, which was also moderate and statistically significant, $p = 0.02$. As the number of the sessions increased, the diagnostic markers subsequently decreased, $\beta = -0.293$, $p = 0.005$. As the number of sessions increased, engagement increased as well, $\beta = 0.199$, $p = 0.025$. Additionally, diagnostic markers and engagement were inversely associated across time as well, $\beta = -0.461$, $p = 0.005$. As indicated on Table 3, none of the covariates at the between or individual level was statistically significant. Simulating those parameter estimates across 1000 iterations indicated stability of those estimates remaining statistically non-significant as well as little difference between the model and simulated estimates. Table 4 provides the summary of these results indicating little difference in the model versus simulated estimates for the covariates. These results indicate the stability of these estimates for these covariates with minimal difference.

Discussion

After statistically controlling for the degree of autocorrelation, the results of the current study indicate that engagement and diagnostic ASD markers present in sessions may be predicted as a function of the number of sessions. However,

Table 3 Parameter estimates along with confidence intervals

	Std. estimate	Posterior *SD*	One-tailed *p*-value	Lower 2.5%	Upper 2.5%
Within level					
Diagnostic markers lagged	**0.375**	**0.165**	**0.02**	**0.051**	**0.674**
Diagnostic markers on session	**−0.293**	**0.12**	**0.005**	**−0.519**	**−0.047**
Engagement lagged	**0.347**	**0.153**	**0.02**	**0.011**	**0.613**
Engagement on session	**0.199**	**0.105**	**0.025**	**−0.011**	**0.401**
Engagement with diagnostic markers	**−0.461**	**0.134**	**0.005**	**−0.723**	**−0.136**
Between level					
Diagnostic markers on autism score	0.33	0.982	0.36	−1.657	2.121
Diagnostic markers on ADHD score	0.018	0.666	0.49	−1.342	1.159
Diagnostic markers on relationships	−0.002	0.765	0.495	−1.527	1.349
Diagnostic markers on challenging behaviors	−0.01	0.843	0.495	−1.658	1.518
Diagnostic markers on sensory sensitivity	0.171	0.644	0.36	−1.132	1.321
Engagement on autism score	0.11	1.006	0.465	−1.684	2.008
Engagement on ADHD score	0.114	0.696	0.435	−1.252	1.225
Engagement on relationships	−0.277	0.825	0.385	−1.631	1.327
Engagement on challenging behaviors	0.404	0.853	0.335	−1.253	1.926
Engagement on sensory sensitivity	0.088	0.657	0.455	−1.168	1.244

Statistically significant results in bold

Table 4 Model versus simulated estimates

Path	Model	Simulated	*d*
Diagnostic markers on ASD total	0.33	0.33	0.009
Diagnostic markers on ADHD total	0.018	0.012	0.031
Diagnostic markers on relationships	−0.002	−0.005	0.021
Diagnostic markers on challenging behavior	−0.01	−0.0104	0.002
Diagnostic markers on sensory sensitivity	0.08	0.087	−0.043
Engagement on ASD total	0.11	0.106	0.023
Engagement on ADHD total	0.114	0.111	0.015
Engagement on relationships	−0.277	−0.278	0.005
Engagement on challenging behavior	0.404	0.4065	−0.014
Engagement on sensory sensitivity	−0.118	−0.1275	0.052

we will note that it may be difficult to continuously engage students in activities such as those offered in this study due to the nature of school programs, which may have irregular attendance. Even so, in the current study, as the number of sessions increased, engagement increased and diagnostic ASD markers decreased. This decrease in ASD diagnostic markers in session does not indicate a permanent change in symptoms rather a temporary change in symptoms as reflective of state or in situ manifestation of symptoms. Indeed, the trend in ASD diagnostic markers across sessions was not significantly related to an individual's autistic traits as reported by the screening instrument indicating a distinction between state (in session) versus trait (screening total) variables among students with ASD. This phenomenon was further revealed in simulating the results of the current study as well (see Table 4). In developing programming for students with ASD, state or in situ presentation of symptoms should be evaluated more than an ASD screening score. Thus, the potential of students should not be limited due to a high ASD screening score as an indicative of trait over state. Trait characteristics of ASD should not be considered determinative of the participation or predictive of performance in any enrichment program. Engagement and ASD diagnostic markers were also inversely related such that as engagement increased, then ASD diagnostic markers present in the session decreased as well. Stated alternatively, approximately 21% of the variance in engagement in sessions may be accounted for by the ASD diagnostic markers indicating some degree of displacement (i.e., $0.461^2 = 0.212$). This result provides further evidence of the role that interest-based STEM activities may have on increasing engagement and minimizing ASD symptoms in situ.

The issue of selection bias would appear to be the primary limitation of the current study. All participants expressed an interest in learning more about robots and physical computing and thus self-selected, with parental consent, to participate in the current study. Given the voluntary nature of research studies, the issue of self-selection bias in particular is not atypical for research studies. Future research should consider identifying individuals without an initial level of interest in robotics and develop ways to foster an interest in robotics and physical computing. Another limitation of the current study is the relatively small size of the sample. However, Bayesian estimation techniques permit the examination of smaller sample sizes with an appropriate number of iterations even with uninformed prior estimates (Hoffman & Walters, 2022; McNeish & Hamaker, 2020). Additionally, the smaller sample included repeated samples across sessions, which increases the number of observations to be analyzed as well. In conducting post hoc simulation analyses, the degree of bias was minimal despite the smaller sample size. Another limitation of the current study is that we did not request information regarding the medications prescribed for the participants. As an after-school enrichment program, medication status was not a criterion for inclusion or exclusion and it would be atypical to request this information for an after-school enrichment program. Future researchers studying this topic should consider requesting this information, but it should not be used in determining the development and participation in an after-school enrichment program.

A final limitation of this study is its nature as a feasibility study, which inherently focuses on assessing the practicality, viability, and potential challenges of implementing a project rather than providing comprehensive evaluative data or outcomes. Consequently, this study prioritized exploratory objectives. As such, while valuable for identifying potential barriers and informing future research directions, the insights gained should be interpreted with caution and considered as foundational groundwork for subsequent, more extensive investigation. We also note here that because our participant sample consisted of a mix of children with ASD, with or without ADHD, we cannot determine how our findings might apply to participants with ASD alone as compared to ASD with comorbidities. Future research should focus specifically on either ASD alone or ASD with comorbidities to provide deeper insights into the variability of engagement according to each participant's individual abilities and interest levels in informal robotics and coding programs.

Most interestingly, the relevant background variables such as presence of ADHD symptoms, degree of challenging behaviors, and degree of sensory sensitivities were also not significantly associated with outcomes of engagement and ASD diagnostic markers across sessions. This result indicates that programming does not need to hinge upon estimates of these background variables in developing and planning programming in the areas of robotics and coding as an interest of students. Interest-based programming can play a pivotal role in producing learning contexts that are engaging for students with ASD as well as provide much needed growth in an area of STEM. Even when simulating these model results, these statistically non-significant parameter estimates did not change across time (see Table 4).

In conclusion, the results of the current study indicate that, as the sessions progressed, the presence of diagnostic ASD markers decreased during the sessions while the engagement increased. The current study highlights the potential importance of informal learning contexts, such as after-school programs, given their greater flexibility outside of the traditional schooling context. Hagiwara et al. (2017) provide a review of extant research that discusses a self-determined model of learning as the mode of instruction for students with ASD, which would be useful to employ subsequent to our current study indicating evidence of feasibility. These informal learning contexts can provide an opportunity to field test possible learning opportunities for students with ASD that would be engaging and limited interruption due to symptoms presenting in situ.

Author Contribution All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Dr. Amy Hutchison, Dr. Lucy Barnard-Brak, and Ms. Caitlin Renda. The first draft of the manuscript was written by Dr. Lucy Barnard-Brak and Dr. Amy Hutchison, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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Data Availability Data will be available from the corresponding author upon reasonable request.

Declarations

Ethics Approval This study was approved by the University of Alabama Review Board (application # 23–05-6652). All participants provided informed assent as well as parental consent prior to enrollment in the study.

Consent to Participate Written informed consent was obtained from participants' parents and assent was obtained from participants.

Competing Interests The authors declare no competing interests.

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