Social Influences on Executive Functioning in Autism: Design of a Mobile Gaming Platform

Beibin Li[1,2], Adham Atyabi[1,3], Minah Kim[1], Erin Barney[1], Amy Yeojin Ahn[1,3], Yawen Luo[1], Madeline Aubertine[1], Sarah Corrigan[1], Tanya St. John[4], Quan Wang[5], Marilena Mademtzi[5], Mary Best[5], Frederick Shic[1,2,3]

[1] Innovative Technologies Lab
Seattle Children's
Seattle, WA, USA
beibin.li@seattlechildrens.org

[2] School of Computer Science and Engineering
University of Washington
Seattle, WA, USA

[3] Department of Pediatrics
University of Washington
Seattle, WA, USA

[4] Autism Center
University of Washington
Seattle, WA, USA

[5] Yale Child Study Center
Yale University School of Medicine
New Haven, CT, USA

ABSTRACT

Most studies of executive function (EF) in Autism Spectrum Disorder (ASD) focus on cognitive information processing, emphasizing less the social interaction deficits core to ASD. We designed a mobile game that uses social and nonsocial stimuli to assess children's EF skills. The game comprised three components involving different EF skills: cognitive flexibility (shifting/inference), inhibitory control, and short-term memory. By recruiting 65 children with and without ASD to play the mobile game, we investigated the potential of such platforms for capturing important phenotypic characteristics of individuals with autism. Results highlighted between-diagnostic-group differences in playing patterns with children with ASD showing broad patterns of EF deficits, but with relative strengths in nonsocial short-term memory, and preserved response to emotional inhibition cues. We showed the system could predict IQ, an important target for clinical treatment, towards the goal of developing platforms to act as long-term, efficient, and effective behavioral biomarkers for ASD.

Author Keywords

Autism; mobile application; game; executive functioning; working memory; shifting; inhibitory control.

ACM Classification Keywords

• Human-centered computing~Ubiquitous and mobile computing design and evaluation methods • Human-centered computing~Empirical studies in HCI • Applied computing~Health informatics

INTRODUCTION

The development of new treatments and personalized medicine approaches for neuropsychiatric conditions, such as autism spectrum disorder (ASD), has been hindered by a lack of robust, sensitive measures and biomarkers for tracking and predicting the effects of treatment. Because psychiatric conditions are primarily defined behaviorally, video games, which can tap into behavioral biases at an elementary level, have been long forwarded as a potential complementary method for therapy [16, 25]. Although video games have not often been used for tracking change, recent advances highlight their potential to target specific psychiatrically-relevant constructs [16, 25].

In this study, with the ultimate goal of augmenting the design process of technologies geared towards improving learning in children with developmental issues, we designed a game to quantitatively assess children's executive functioning (EF) skills, an area of known vulnerability for children with ASD and understudied in Human-Computer Interaction (HCI). This paper presents the preliminary game design, which considers theoretical and practical facets of ASD and EF, and an analysis of pilot data collected in a laboratory setting. We designed systems specifically to accommodate dichotomous social and nonsocial EF performance in ASD. This work has implications for the development of accessible, practical, desirable, and clinically-relevant tools designed for specific developmental conditions, en route to the ultimate goal of pairing next-generation quantitative measures with therapeutic systems capable of effecting positive behavioral change.

BACKGROUND

Autism and Executive Functioning

Individuals with ASD demonstrate impaired social communication and restricted and repetitive behaviors [2]. In addition to these core features of autism, many children with ASD also exhibit deficits in EF skills, i.e. skills used for planning, focusing attention, remembering instructions, and juggling multiple tasks simultaneously [13]. Researchers have argued that cognitive theories of autism based on social (e.g. theory of mind) or generalization (e.g. weak central coherence) deficits [18] can be complemented by executive dysfunction perspectives, especially given the relationship of EF deficits to repetitive behaviors and restricted thinking [13].

Previous studies have compared EF skills in children with and without autism in three core domains: *set shifting*, *inhibitory control*, and *short-term memory*. For set shifting or mental flexibility tasks, such as the Wisconsin Card Sorting Task (WCST), individuals with autism have been shown to be have more impairments compared to their typically developing (TD) peers [7]. Findings in inhibitory control are more mixed [10], particularly with go/no-go tasks. Previous work has found that individuals suffering from attention-deficit/hyperactivity disorder (ADHD) experience more difficulties with go/no-go tasks [17]. This is notable because a significant portion of the community with ASD suffers from comorbid ADHD. In DSM-IV, ASD was an exclusionary criterion for ADHD. DSM-V allows for dual ASD-ADHD diagnoses, and therefore work in this area is still evolving [48]. There are also mixed findings related to memory and ASD [27]. For instance, Williams and her colleagues found impairments in spatial but not verbal working memory for those with high-functioning autism [12]. Given the importance of these skills for navigating everyday life (e.g. for planning, redirecting focus, impulse control, and problem-solving), EF deficits lead to additional challenges for the child with ASD.

Current methods for understanding clinically-relevant profiles of individuals with autism involve intensive and sometimes tedious psycho-behavioral assessments. Although these methods can generate invaluable information regarding ASD, the tests themselves can be very time consuming, tiring for participants, and often can only be obtained under strict supervision, usually in laboratory settings by highly trained individuals with relevant clinical, psychological and/or scientific backgrounds. A lack of resources and trained personnel can result in late diagnosis of disorders like ASD, and lead to delays in obtaining clinical data needed for treatment planning. For this reason, it is imperative to develop newer, more efficient, and more accessible tools to complement and improve the traditional phenotypic characterization of affected individuals in clinics, laboratories, and at home. Unlike many psychological and experimental research methods, gaming platforms and mobile applications are widely available and impose few restrictions to access. The present study aims to design and test an executive functioning mobile game through which clinically-meaningful information can be extracted via participants' gaming habits and strategies.

Mobile Applications

Mobile application research in ASD benefits from the popularity of smartphones and applications. In 2016, 68% of adults reported owning smartphones in countries with advanced economies, such as the US, Canada, major Western European nations, developed Pacific nations, and Israel [21]. In the United States, the percentage of adult smartphone owners is higher, reaching up to 87%. The large number of people with access to smartphones (including many individuals with ASD) means that mobile applications have enormous potential for advancing data collection in homes, mitigating the need for complex and extensive infrastructure often used in autism research.

As the use of mobile devices grows rapidly, many scientists have utilized mobile applications to assess skills and developmental ability in children with ASD. For example, Escobedo et al. studied a mobile assistive tool to help children with ASD learn social interaction skills, and emphasized the emergent practice of using mobile technologies [26]. Mintz et al. studied mobile applications in the classroom to improve children's social and life skills. In another study, Leijdekkers et al. used a mobile app to improve emotion learning for children with ASD [39]. Atyabi et al. analyzed usage patterns of an Augmented Assistive Communication (ACC) tool, designed to help children with ASD communicate with the outside world, to predict the diagnostic classification of users [1].

Similarly, the National Institutes of Health (NIH) published a digital mobile-enabled toolbox for the assessment of neurological and behavioral function with the goal that it could be used as "common currency" for researchers to compare cognitive measures across studies and populations [40, 42]. Zelazo et al. found that the NIH Toolbox Cognition Battery had excellent sensitivity, reliability, and convergent validity for assessment of EF skills in children [40, 42]. However, the NIH toolbox was designed as a task-based assessment, and thus lacked the focus on "fun" as would be emphasized in a digital game, potentially creating a barrier for long-term repeated use. Furthermore, the instructions for the NIH toolbox could be confusing for young children with ASD or developmental delays (DD) because it is not designed to be a user-only app or to be self-explanatory. (e.g. the Flanker Inhibitory Task tells the user to push a button that matches the direction a fish is pointing) [35]. In addition, though the NIH Toolbox could be a "common currency" for researchers, it is not able to be used directly by nor free for private use by families. The NIH Toolbox digitizes standard clinical EF assessments, but it is not tailored to the ASD population.

Social and Nonsocial Comparison

Prior work has found that individuals with ASD perform better on nonsocial/nonverbal IQ tests (e.g. matrix puzzles) than social/language-mediated tests [33]. However, most existing HCI work targets social ability in children with ASD. For instance: Abirached et al. interviewed parents and found that they recognized the importance of tools to help children with ASD learn socially-important recognition skills [8]; Boucenna et al. reviewed HCI literature for children with ASD and concluded that many existing information communication technologies for children with ASD (most focused on social interactions) have limited capabilities and have not been validated beyond proof-of-concept studies [44]; Indumathi et al. proposed a paradigm that act as a portable VR-based facial expression recognition system to enhance emotional expression recognition for individuals with ASD [29]; Rehg et al. created machine-learning models to recognize children's social behaviors from video and audio data [22]; Tanaka et al. created a mobile application aimed at improving children's social skills by providing them more nuanced metrics on facial expressions [20]; Voss et al. presented a wearable aid for recognizing emotions and social cues with Google Glass [9].

Relatively less emphasis in HCI has been placed on the substantial cognitive difficulties often observed in ASD. As noted by Grynszpan and colleagues, a more complete clinical profile of individuals with ASD considers not only social deficits and cognitive deficits, but also their interaction [37]. In this study, we assess EF skills and, by including social and non-social components, we hone in on specific difficulties faced by individuals with autism, such as diminished attention towards social stimuli [31]. Our current work uniquely considers the interplay between executive function skills and their social content, exemplifying the need to consider the specific characteristics of a disorder (i.e. the fundamental deficit in social interaction in ASD) when designing HCI tools to investigate classically-studied areas of deficit, such as executive function. Differences in game performance with social and nonsocial stimuli could provide additional information about children's behavior patterns, social cognition, and autism-specific phenotypic features, potentially leading to refinement as behavioral biomarkers in the future.

Application of Gyroscope and Accelerometer

Although many mobile applications with a focus on autism exist, very little attention is given to usability, desirability, social/nonsocial comparison of EF skills, sensor information, and users' usage patterns.

In addition to gaming strategies, patterns of behavior and habits can be valuable sources of information for analyzing EF skills in autistic individuals. Certain interactional patterns, such as how the mobile device is held and moved throughout the game, can complement other sources of information to help us better understand the differences between autistic and non-autistic individuals with respect to their EF skill limitations. This information can be obtained from accelerometer and gyroscope sensors.

Abowd et al. collected accelerometer data from wearable devices on children's bodies and used these data to identify children with ASD by using the Hidden Markov Model [19]. Albinali et al. collected sensor data from six school-aged children in classroom and lab settings to measure repetitive movements and predict which children had ASD diagnoses [15]. Similarly, Chuah and Diblasio used accelerometer and acoustic signals to identify stereotypical behaviors in children with ASD [34]. Aiming to create an intervention system, Boyd et al. used accelerometers to detect and correct self-stimulatory behavior in adults with ASD during face-to-face communication sessions [28]. However, all these methods require children to wear electric devices on their bodies, which is a hard task for young children with ASD. Moreover, these studies involved relatively small participant samples.

Accelerometers and gyroscopes are also widely used in mobile phones and tablets, but few scientists have used them in mobile application research for autism. Anzulewicz is one of the few scientists who has used these sensors in tablet-based games and discovered unique motor patterns for children with autism [3]. The only drawback to Anzulewicz's study is that children were using the tablet in a restricted environment, where the tablet was left on the table in a fixed position. Collecting accelerometer and gyroscope data from unconstrained environments has the potential to provide additional ecological validity, since in natural settings children hold tablets in different ways -- with the tablet sometimes in their hands, at a table, or in their laps. This data will allow us to examine between-group differences in physical interactions with the mobile device which is an area that is largely unexplored.

Video Games

Video games have been studied in psychological and cognitive research, and gamification has already been used in many other cognitive batteries [4]. E.g. Weng and colleagues utilized the Microsoft Kinect to study emotion orientation and social capacities, and argued that Kinect gameplay may relate to psychological and psychiatric phenomena [30]. Joaquin and colleagues showed a custom-designed video game can be used to assess aging effects on cognitive abilities in adults [24].

In regards to video game studies in the ASD population, Mazurek et al. found boys with ASD spent much more time playing video games and may be at higher risk for problematic game play than other children [32]. Their findings inspired us to design video game strategies that could engage children with ASD, but for only short periods of time, so as to provide benefit rather than harm. However, because children with ASD may play video games more intensely, they potentially have more to gain from eHealth video games than TD children.

The need for a convenient EF assessment system, the prevalence of EF deficiencies in children with ASD, and the widespread availability of mobile applications inspired us to design an easily understandable, short, and entertaining mobile game for children with autism. The purpose of our game is to assess EF skills and ultimately develop systems for improving those skills.

METHODS

Participants

Sixty-five children aged 2 to 17 were recruited in the study as shown in Table 1. All participants had normal or corrected vision and normal hearing.

Children in the ASD group were recruited through participation pools from the University of Washington and Seattle Children's Autism Center. To confirm diagnostic classification, research-reliable staff (i.e. staff trained to a standard of administration even more stringent than those required for clinical service) performed an Autism Diagnostic Observation Schedule Second Edition (ADOS-2; the gold standard direct behavioral assessment supporting autism diagnosis) on 28 of the 33 ASD participants. For two of the participants, ADOS-2 Scores were obtained from previous autism studies that occurred within the last eight months. Three participants could not complete an ADOS-2 but had their diagnoses confirmed by their primary care providers. The 32 participants without ASD (non-ASD) were associated with a wide range of phenotypic characteristics, including 2 children with DD, 6 siblings of children with ASD, and 24 TD children.

	ASD		Non-ASD	
Sex	*n*	Age *M* (*SD*)	*n*	Age *M* (*SD*)
Female	5	96.69 (43.28)	13	94.42 (48.47)
Male	28	102.90 (45.17)	19	90.03 (59.56)

Table 1. Diagnosis, Gender, and Age (in months) of Participants

A combination of assessments was used to obtain nonverbal and verbal IQ measures. The abbreviated battery of the Stanford-Binet (SB) Intelligent Scales was administered to 26 of the 33 ASD participants. The remaining seven in the ASD group did not complete an IQ test due to time constraints. Ten out of 24 in the TD group completed the Differential Ability Scales-II (DAS-II) and the rest completed the Stanford-Binet. In the Non-ASD group, all participants except one received the Stanford-Binet; one participant received the Mullen Scales of Early Learning (because the child was not old enough to complete the DAS-II). Differences in IQ measures reflect a change in protocol that occurred mid-way through the experiment to decrease the experimental battery time and burden on participating families. To ensure comparability across scores, only SB scores were used for correlation analyses. Across all groups, 69% of the participants had a valid SB score.

Game Design

We followed gamifiable EF task literature [11, 40, 42] with iterative feedback from psychology trained staff and clinical neuropsychologists in our game design. To fine tune our design, we conducted pilots and elicited feedback from 15 TD adults and 3 children (1 ASD, 2 TD) aiming to assess usability of our EF game. Social-nonsocial analogues were designed to be similar in complexity and perceptual attraction. Starting with Pokemons and nonsocial emojis as stimuli in earlier designs we converged to human face and fractals as stimulus in addition to incorporating audio feedback (human voice of "Yes" or "No") as reinforcement. Our EF game design pilots indicated that participants were more engaged into the game with those feedbacks. In addition, our design pilots indicated attractiveness of color stimuli in comparison to grayscale styles. In the final version of the game, we reduced complexity by removing more aversive feedback from the memory game so that participants could have an infinite number of guesses until they picked all correct answers. We also began recording accelerometer and gyroscope data in the final version.

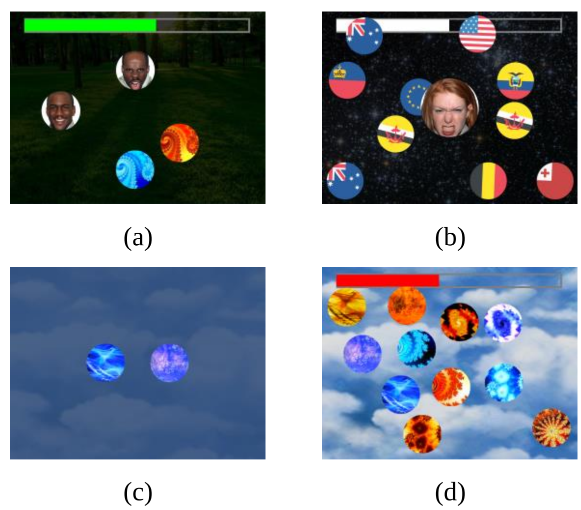

Figure 1. Screenshots of the Video Game: (a) Shifting Game: players have to guess the rule associated with the correct answer as the rule changes over time; (b) Inhibitory Control game: players are required to stop touching flags when an angry face or a stop sign appears; Short-Term memory game: c) targets player needs to select, and d) the playfield where targets must be selected.

The mobile game was designed for use with an iPad 2 using Unity and C#. The touch screen of an iPad 2 is 9.5 by 7.31 inches in dimension, and children were instructed to interact with the iPad in their preferred manner (e.g. in their hands, on the desk, or in their lap). The game was always displayed in landscape mode, as shown in Figure 2. The upper left corner is the origin (0, 0) coordinate of the screen. After each session of gameplay, users' game logs were exported and uploaded to our data server.

Unlike existing arcade games and similar digital clinical tools, such as the NIH toolbox, the designed platform contained two sets of stimuli, social and nonsocial, in order to disentangle relevant social/nonsocial advantages or disadvantages inherent to ASD. The designed social stimuli comprised three main emotions: neutral, happy and angry. The faces, adapted from the NimStim Face Stimulus Set, included females and males from three races (African American, Asian, and Caucasian) [35]. The nonsocial stimuli were red and blue fractal images and videos, often used in cognitive experiments for children with ASD [43, 41, 6]. The number of unique nonsocial stimuli matched the number of unique social stimuli. All stimuli were cropped to a circle so that they could "physically" bounce around on the screen, imitating how a ball might act in a 2-D cartoon world. Both the social and nonsocial stimuli were always oriented upright to avoid the inverted face effects [23]. The diameter of all circles was set to 3 centimeters. The stimuli in this game were intentionally designed to be bigger than stimuli in other commercial mobile games so that younger children without mature fine motor skills could still accurately touch the targets on screen.

The gameplay was designed to be similar to commonly available commercial mobile games, where both correct and incorrect targets are presented on the screen simultaneously and users have to touch the correct targets to gain points. The platform was designed to accept and record both finger touches and swiping motions (including information regarding target hits). Correct and incorrect target touches triggered unique sound effects for reinforcement. Upon being touched, the target disappeared from the screen and a visual particle effect was displayed in the target's place.

The designed game platform contained three tasks involving rule shifting, short-term memory, and inhibitory control. The choice to use three unique smaller games was made to assess different areas of executive functioning skills. Each task contained four trials, and each participant played 12 trials of game for the experiment.

An instruction screen is presented at the beginning of the games and before each block of the short-term memory and inhibitory control games. This instruction screen is accompanied by auditory instruction to guide the participant.

Participant's touches and target locations are recorded for post-hoc analysis. The tri-axis accelerometer and gyroscope sensors in the iPad are used to record movement signals at a 60 Hz frame rate during the videogame. Game accuracy and score are calculated in real-time, but this information is not presented to the players during the session.

Shifting Game: Shifting skills are crucial for children to flexibly adapt to the changes in everyday life. The shifting game is similar to the WCST [11], where four images appear on the screen in each trial and users are instructed to guess which image fits an unspoken rule. The underlying rule (happy face, angry face, red fractal, or blue fractal) changes every ten trials. Four blocks are presented, where each block contains ten trials with the same underlying rule. Participants are not given any clues about the hidden rules, nor are they informed of the block changes. The main difference between the designed shifting game and the WCST version is that, in the original WCST, a trial ends if the player makes a wrong guess about the hidden rule. In our design, the game continues by removing the falsely guessed item from screen. Players can pick another item from the remaining objects on the screen until the correct answer is found. This decision was made to accommodate the younger players and developmentally delayed children. The shifting task ends after all trials are completed or 2 minutes have elapsed (whichever comes first). This ensures that our young players do not become stuck in this game if they have difficulty understanding the hidden rules.

Short-Term Memory game: Short-term memory is a subcomponent of working memory that involves retaining and accessing information in one's mind over a short period of time. The game was designed to be accessible to special populations and short-term memory was targeted for simplicity. In this game, one to four memory targets are presented for 10 seconds along the middle horizontal line of the iPad screen for participants to memorize. After the memory targets disappear, 10 objects are presented on the screen. The participant must select the target(s) from the previous screen in order to proceed to the next, more difficult level. If the memory targets are not identified correctly within the first 45 seconds, the game proceeds to an easier level. Similar to the shifting game, touching the wrong object results in the elimination of that object from screen and the player is allowed to try again.

Inhibitory Control game: Inhibitory control is the ability to resist impulsive actions. The inhibitory control game is similar to go/no-go tasks in psychology research. Participants must click as many targets as possible onscreen and must stop touching the screen whenever a stop sign or an angry face is presented. Unlike the shifting and short-term memory games, only angry faces are employed as a social stimulus (no neutral or happy faces). During the "go" phase of the game, circular flag targets are shown, along with a score meter on the top of the screen. The flag targets were selected for their colorfulness, in hopes of attracting the attention of the children. Flags disappear from the screen when touched and are replaced by new flags in random locations to maintain the same number of flag targets throughout the game. Each time the participants pressed a flag target during the "go" phase, the score meter fills up and provides live visual feedback of their progress. Each of the four blocks of the inhibitory control game only contains one type of stop signal (either a stop sign or an angry face). The stop signal is 1-6 seconds long and appears five times in each block. The start time and duration of the stop signal is pseudo-randomized and appears at 20% or 50% of the total trial length (30 seconds).

Experiment Design

Participants played four blocks of each game, two blocks with social stimuli and two with non-social stimuli. The order of the games was counterbalanced to reduce effects of task ordering. Therefore, three different orders were created. The sequence of the three orders are listed below in Table 2. The entire game takes 6-15 minutes to complete. To avoid children exiting out of the game of their own accord, the iPad home button was disabled during play. Few of the participants attempted to exit out of the game and most continued the game with verbal prompting.

Order	Game 1	Game 2	Game 3
A	Shifting (S, N, S, N)	Inhibitory (S, N, S, N)	Memory (S, N, S, N)
B	Inhibitory (N, S, N, S)	Memory (N, S, N, S)	Shifting (N, S, N, S)
C	Memory (S, N, S, N)	Shifting (S, N, S, N)	Inhibitory (S, N, S, N)

Table 2. Orders of the Experiment with Social (S) and Nonsocial (N) Stimuli

Participants played the game while seated at a table in a closed-off experimental room while an experimenter was present. The iPad was placed in front of the child and they were allowed to engage with the iPad in any way they preferred (e.g. holding it up against their lap, laying it on the table, etc.) so that we could examine the holding preferences of children with and without ASD, which is not well studied in previous HCI literature. They were told that the instructions would be read out loud, and they were also encouraged to ask any clarifying questions about the instructions before clicking the "next" button to start the game. The only part of the game that the experimenter could not give specific instructions on was the Shifting Game because it was based on association and inference. The volume level of the iPad was set to mid-range unless the participant requested otherwise. Once the game started, the experimenter did not intervene unless the participant needed verbal encouragement or prompting. For the younger participants, often the caregiver accompanied the child into the room but was asked only to observe and not intervene. Cases of experimenter and parent interference were documented in run logs and that data was excluded as needed.

RESULTS

Analysis of Variance (ANOVA): variable ~ group was used as statistical model in the analysis. Three participants failed to complete the whole experiment, and were excluded from the analyses. Within the remaining 62 participants, there was no age difference between the ASD group and non-ASD group $F(1,60) = .106$, $p = .746$, nor between males and females; $F(1,60) = .096$, $p = .758$.

Feedback from Children

During the game session, the experimenter observed participants' behavior and guided them along if they could not understand the rules. Experimenter and parent interference was documented in run logs. After the experiment, experimenters would briefly interview selected participants about the game. Participant comments about the game were recorded (e.g. "want more sound", "too easy", "enjoyed it!", etc.).

Figure 2. Participant Playing the Game in Lab Setting with the Experimenter

Notes from the run log and interview indicated that most young children could understand the game well, and only 4 ASD and 5 non-ASD out of the 65 participants failed to understand some parts of the game, where experimenters guided them and explained the rules to them before each trial.

Some children thought the visual and audio feedback was not only attractive but also very helpful for them to understand the rules. One child complained that the audio feedback was too boring because only "Yes", "Good Job", "No", "Nope", etc. are used in the audio feedback. This comment indicates that more varied feedback is necessary to increase engagement of the game.

Non-ASD Children and Children with ASD Play Differently

Mental Set Shifting Game

Learning latency, the number of trials a participant needs to learn the hidden rule, is the main measure for the WCST. However, we did not find any significant differences of learning latency (social stimulus $F(1, 60) = 2.14$, $p = .15$, nonsocial stimulus $F(1, 60) = 2.58$, $p = .11$) between children with and without ASD. Because the rules in the original WCST are different from the rules in our shifting game, where participants can make multiple guesses until they get the correct answer in a trial, we compared the number of wrong guesses participants made during the game, and significant differences were found between children with and without ASD (social stimulus $F(1, 60) = 6.23$, $p = .02$, nonsocial stimulus $F(1, 60) = 5.61$, $p = .02$). This result demonstrates the importance of well-selected metrics balanced against game rules. Our findings show that participants with ASD make more mistakes than participants without ASD, which agrees with and supplements traditional ASD vs. non-ASD findings on the WCST.

Inhibitory Control Game

The number of targets children touched during the "stop" or "angry face" phase of the inhibitory game (i.e. the period of time when players were not supposed to touch any targets) was compared for children with and without ASD. A significant difference was found in nonsocial trials ($F(1, 60) = 5.66$, $p = .02$) but not in social trials ($F(1, 60) = 0.67$, $p = .41$). As shown in Table 3, children with autism touched more targets during the "stop" phase than "angry face" phase ($F(1, 60) = 5.46$, $p = .02$), and they touched more wrong targets than children without ASD in general ($F(1, 60) = 7.05$, $p = .01$). This result shows that children with autism have less inhibitory control when the nonsocial "stop" sign appears, which could mirror rigidities, restricted interest, or perseveration traits associated with autism. Interestingly, performance in response to social stimulus cues was better in both groups, suggesting that the angry face may have been too salient, leading to floor effects. Regardless, this suggests that inhibitory action is preserved in response to salient emotional cues in ASD.

Short-Term Memory Game

No significant difference was found between children with and without ASD in either the social ($F(1, 60) = 0.16$, $p = .69$) or nonsocial ($F(1, 60) = 0.15$, $p = .70$) conditions by using one-way ANOVA to examine accuracy and correctness in the memory game. However, when the effects of IQ and age were controlled for, significant differences emerged (social: $F(1, 38) = 5.50$, $p = .02$, nonsocial: $F(1, 38) = 7.70$, $p = .01$), suggesting that children with ASD had lower accuracy in both conditions of the memory game.

Diagnosis	Nonsocial Stimulus (Stop Sign)	Social Stimulus (Angry Face)
ASD	14.06 (12.25)	5.06 (3.40)
Non-ASD	7.97 (6.77)	4.38 (3.03)

Table 3. *M* (*SD*) Targets Touched During "Stop" or "Angry Face" Status.

Within the ASD population, significant differences ($F(1, 64) = 12.770$, $p < .001$) were observed for the number of correct answers children touched between the social and nonsocial conditions, in which they memorized and chose more correct nonsocial targets than social targets. Such effect was not found in the group of children without ASD ($F(1, 56) = 0.73$, $p = .40$).

Touches

In contrast to a prior study by Anzulewicz and colleagues [3], no significant differences on number of touches, touch duration, or swipe distance were found between the ASD and non-ASD groups. This is possibly because, unlike Anzulewicz's game, our game does not require long swipes or drawing lines [3].

Finger touch coordinates were also analyzed and compared between the two groups. The average vertical coordinate of finger touches from children with ASD (M = 737.63, SD = 49.23) was lower than touches from non-ASD children (M = 707.42, SD = 47.92; $F(2, 55) = 5.16$, $p = 0.03$). On the other hand, the average horizontal coordinate of finger touches from children with ASD (M = 1046.099, SD = 71.162) was not significantly different than touches from non-ASD children (M = 1037.37, SD = 70.93; $F(2, 55) = 0.20$, $p = 0.65$). Additional experiments should be conducted to study ASD versus non-ASD motor preferences.

Accelerometer and Gyroscopic Signals

During the game session, the iPad recorded accelerometer and gyroscope signals at 60 Hz. Each sensor had three channels (x, y, and z), where x is the horizontal axis, y is the vertical axis, and z is the depth axis of the device. The sensors' data were analyzed post-hoc over the course of the whole experiment in order to understand iPad manipulation patterns during game play. The mean and standard deviation of the six channels were calculated for each participant.

Significant differences between ASD and non-ASD groups were found in the standard deviations of both the accelerometer's y-axis ($F(1, 51) = 5.76$, $p = .02$) and the gyroscope's y-axis ($F(1, 51) = 5.81$, $p = .02$) signals, with children with ASD having higher standard deviations in both sensors' y-axis signals. This result suggests that children with ASD interacted with the iPad more by manipulating the iPad's vertical position during the game.

We also compared the means of all six channels of accelerometer and gyroscope sensors across groups controlling for both age and IQ using an Analysis of Covariance (ANCOVA). In this model, group was not a significant predictor of sensor mean readings. However, the mean signal of both the accelerometer's z-axis ($F(1, 41) = 4.90$, $p = .03$) and the gyroscope's z-axis ($F(1, 41) = 4.95$, $p = .03$) was significantly related to age, with older children demonstrating greater accelerometer and gyroscope mean values. This could be related to younger children having more difficulty holding and lifting the iPad as compared to older children.

Interestingly, we found marginal differences on the frequency domain energy of the gyroscope's z-axis between the ASD (M = .024, SD = .042) and non-ASD (M = .015, SD = .028) group; ($F(1,41) = .89$, $p = .05$). This difference was not found on the gyroscope's x-axis ($F(1,41)$

= .07, p = .80) or y-axis ($F(1,41)$ = .32, p = .57), suggesting children with ASD might manipulate the system more repetitively in the up-down direction.

Using Game Performance to Predict IQ

As shown in Table 4, accuracy in the inhibitory game correlated with IQ. Moreover, accuracy scores of all three games have significant relationships with age. This result suggests that this mobile game might be useful in predicting clinically-relevant information about its players. In autism research, IQ is frequently an outcome measure of behavioral interventions [38]. Moreover, one of the primary goals of this mobile game was to quantitatively predict clinical characterization information (such as EF skills and IQ scores) in children. In practice, diagnosis would not be available a priori to predict IQ, therefore we did not include diagnosis as a predictor variable in the regression. Only age and game performance were included as predictor variables, with the SB standard score (IQ) as the dependent variable in the regression model. If diagnosis is included as predictor variable, the IQ regression including diagnosis would always perform better than the results in Table 4.

We used two sets of variables to represent game performance in the regression model. One set contained four variables: participant age, and accuracy in each of the three games (inhibitory, shifting, and short-term memory, regardless of stimuli types [social or nonsocial]). The other set contained seven variables: participant age, and accuracy in the shifting, inhibitory control, or memory game with social stimuli or with non-social stimuli (3 x 2 = 6 variables). In order to avoid inflation of R-squared due to the increase in predictors, both R-squared and adjusted R-squared were used to evaluate the regression models. R, correlation coefficient of actual and predicted IQ, is also included in the table for reference.

		IQ		Age	
Game	Condition	*r*	*p*	*r*	*p*
Shifting Accuracy	Social	.27	.08	.42	<.01
	Nonsocial	.30	.05	.36	<.01
Inhibitory Accuracy	Social	.35	.03	.51	<.01
	Nonsocial	.46	<.01	.58	<.01
Memory Accuracy	Social	.17	.27	.70	<.01
	Nonsocial	.15	.34	.62	<.01

Table 4. Pearson's Correlation (*r*) and Significance (*p*) for Game Performance, IQ, and Age (*df* = 40)

Two types of regression were analyzed in this study: a standard statistical model approach without cross validation and machine learning models with Leave One Out Cross Validation (LOOCV). In standard psychological research, statistical models are used without separating training and testing datasets. However, separating datasets and using cross validation can additionally ensure the robustness of regression models. In this study, LOOCV was selected as the main cross validation method.

Linear regression, Support Vector Regression (SVR) with linear kernel, SVR with radial kernel, and Neural Network (NN) regression were used for the regression analyses. The regression results are included in Table 5, but the neural network regression results were not included because they performed the worst among all models. This may be expected given that neural networks often work better for larger data samples.

Linear regression provided the most stable results, with the R value typically greater than 0.6 even with LOOCV, suggesting that game performance in the three subgames was linear with participant IQ. When the model was built without LOOCV, SVR with Radial kernel outperformed all other models, but showed poor performance with LOOCV due to overfitting. Similarly, SVR with linear kernel failed because of overfitting when 7 features were used for prediction.

DISCUSSION

This work expands the state-of-the-art in computer-human interaction in multiple areas related to child mental health. From the results of our EF game, we identified different playing patterns for children with and without autism. For instance, children with ASD made more wrong guesses in both social and nonsocial conditions of the shifting game than non-ASD children. This result suggests that mental flexibility or mental set shifting may be a general deficit in ASD, spanning across both social and non-social domains. Similar results were found for short-term memory tasks, with general (social and non-social) deficits observed in ASD, but with a side note that performance in ASD was better for non-social targets as compared to social-targets – an effect not observed in the non-ASD group. This last point could suggest a relative advantage for non-social information encoding, or, alternatively, a relative deficit in social information encoding -- an effect also noted by Williams [12].

In the inhibitory control game, children with ASD showed worse performance than non-ASD children only during the non-social “stop” sign phase, as compared to the social inhibitory signal delivered via an angry face. Several not-necessarily mutually exclusive explanations could account for this finding. Floor effects could exist in the angry face condition with the saliency of the angry face making it too easy for children from both groups to inhibit their response. As a corollary, such an implication would suggest that (potentially reflexive) emotional recognition of the behavioral primitive of anger is largely intact in children, contrary to some reports (e.g. [14]). It could also be the case that children with ASD have difficulty understanding the abstract meaning of the word "stop" or a stop sign (and associated explanations related to deficits in verbal ability), given known difficulties in pragmatic language comprehension in ASD. However, it is important to note that the majority of children with ASD in our study were well above the verbal ability level needed to understand similarly developmentally-early concepts such as "stop". Lastly, it may be that our results can be interpreted at face value, suggesting that while inhibitory issues may exist in ASD more broadly, social signals involving salient emotional expression may yet provide an effective method for the external regulation of behavior in children with ASD.

		SVR with Radial Kernel			SVR with Linear Kernel			Linear Regression		
		R	R^2	Adj. R^2	R	R^2	Adj. R^2	R	R^2	Adj. R^2
Stats Model Without CV	3 acc + age	.804	.598	.555	.677	.457	.398	.681	.464	.406
	6 acc + age	.841	.610	.529	.674	.441	.326	.693	.481	.374
ML With LOOCV	3 acc + age	.455	.095	.013	.611	.368	.298	.562	.295	.217
	6 acc + age	.311	.046	-.157	.438	.042	-.161	.693	.481	.371

Table 5. Regression Result for IQ, where accuracies (acc) of game and age are used as predictors

These aforementioned results demonstrate the potential for understanding specific cognitive domains of relative strength and weakness in ASD, as well as the interaction of these cognitive domains with core social deficit symptoms. However, our results also suggest that these video game approaches may have practical utility as well. For instance, we found that game performance was strongly correlated to age (which can provide information regarding developmental norms) and IQ (which is an important target for behavioral intervention in ASD).

Predicting IQ from performance was a proof-of-concept validation. Because EF skills are related to IQ, our work shows that games of the form presented in this work could be clinically useful in the future. The regression model, with age and game performances as predictors to predict IQ, achieved good performance (with r values in the "moderate" to "large" correlation range). When LOOCV was used while training the model, the regression model has R squared of about 0.5. With LOOCV, the math model we created was less stable than linear regression models but was more robust than SVR models. Other predictors, such as shifting game latency, touch speed, touch strategies, can be used to predict IQ in the future, but using more predictors requires more data for training the model, which can be advanced in the planned large-scale follow-ups of this research. The pairing of our current game with direct assessment (e.g. the SB IQ test) is a barrier to future large-scale, general deployment. Future work should consider complementary remote phenotyping techniques to assess convergent validity while addressing the inclusion of domains needed to obtain a more comprehensive clinical view of participants (e.g. characterization of motor deficits, known as an area of vulnerability in ASD [47]). In addition, consideration of individuals with an ADHD diagnosis, with and without ASD, should also be examined in order to clarify differences in social-nonsocial patterns of EF deficiencies [17]. Changes and modifications will be made in future work and the next version of this mobile game to improve its effectiveness and the convenience of predicting IQ in the future.

Children with ASD handled the iPad differently from the children without ASD, as demonstrated by the standard deviation of y-axis movement varying more in children with ASD. While the ultimate cause of this increased variability remains to be deciphered through more controlled experimental manipulations (currently, the open-ended nature of our tablet holding instructions likely leads to increased signal variation), it is possible that executive function difficulties and deficits, specifically focus, may contribute in a relatively direct fashion to higher movement variances in ASD. From a different perspective, the observed differences in the way autistic and non-autistic children handled the iPad also suggests that children with ASD may seek atypical angles of view and interaction for themselves which could possibly help them to activate different pathways in the neural brain structure. Complementary, simultaneous recording of neural brain activity during gameplay experimentations (beyond the scope of this study) in combination with analysis of neural functional connectivity may better reveal the underlying causes of this observed phenomena. Such analysis could also help us better understand the possible impact of excitation on observed behaviors.

In the future, we can redesign the memory game to unveil more differences between children with and without ASD. For instance, we can increase the difficulty, change the stimulus, add a spatial component, or change it to a “flip over and pair up” style game. Similar modifications could be applied to other EF tasks, with the goal of most efficiently sampling the space of clinically-relevant EF-related constructs.

In order to improve the accessibility of our mobile game, we have already begun to support multi-language deployment, have created a secure data hosting server, and are preparing to publish this mobile game to the iOS App Store and Google Play Store. After more users download and play this mobile game, deep learning and big data analyses could be applied to created better IQ regression models and ASD/non-ASD classification models. Once we acquire enough data and have built a model to predict IQ and EF skills in this second stage of research, the mobile game could support the automatic reporting of predicted IQ scores and areas of strength and weakness at the end of gameplay.

While this work has relevance to the design of systems for capturing phenotypic characteristics of special populations, it also embodies the changing theoretical landscape conceptualizing neuropsychiatric conditions. Research Domain Criteria (RDoC), in contrast to DSM-V, is a new research framework to understand mental disorders by bringing together perspectives from multiple modern areas of research spanning genetics, neuroscience, and behavior [45, 46]. Fundamental to the RDoC approach are continuum-based perspectives, i.e. thinking of mental health across disorders, across domains, and across the breadth of the phenotypic variation in the general population. This mobile game represents such an effort to create general tools applicable not only to autism, but also to understanding variation in general. It is our hope that it can be adapted as a behavior assessment tool to quantitatively assess children’s executive functioning skills in the future, which can provide robust, efficient, and effective methods to help address issues in mental health research, paving the way for new treatment opportunities for individuals in need.

CONCLUSION

We developed a mobile video game designed to explore and quantify executive functioning skills in children with ASD, separately considering social and nonsocial performance so as to disentangle broader patterns of cognitive deficit from the social deficits specific to the disorder. We found that there were specific diagnosis by performance class interactions, such as stronger non-social short-term memory in ASD as compared to their social short-term memory, but also preserved areas of ability in children with ASD, such as inhibitory response to angry faces. These results may be informative at a theoretical level regarding areas of strengths and weakness at a group level for children with ASD.

At the same time, with an interest in creating a prototype for longer-term monitoring of clinically-relevant change, we designed the system to be engaging for participants in a narrow time window (e.g. one time a day), so as to balance the increased enthusiasm children with ASD may have for digital platforms against the potential for problematic game play. We showed, using both standard psychological approaches as well as machine learning methods, that patterns of performance on our delivered tasks were associated with both developmental level and IQ, moving us towards the goal of developing video game behavioral biomarkers for clinically relevant targets for ASD. Physical patterns of play, derived via accelerometer and gyroscope readings provided an extra layer of interpretation which may be exploited in the future to further improve phenotypic prediction accuracy.

As a proof-of-concept, this work highlights social and nonsocial EF performance asymmetries in ASD, suggesting that digital systems modeling clinically-relevant features may need to consider pathology interactions. While a great deal of future work needs to be done to better assess the social and nonsocial asymmetry, this study represents a step towards targeting mobile video game development to specific characteristics of mental health conditions, with the end goal of developing more usable daily monitoring systems for children with ASD.

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