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Wiggleometer: Measuring Selective Sustained Attention in Children

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Abstract

Understanding the nuanced relationship between attention and learning in young children is difficult due to the lack of developmentally appropriate measures of attention. Young children are in a measurement gap - they are too old for measures typically employed with infants and toddlers and often too young to produce useful data from more traditional measures used with older children and adults. Due to the paucity of developmentally appropriate measures it is challenging to employ best practices and utilize converging measures of attention. Additionally, existing behavioral observation methods are time consuming and can suffer from poor reliability due to their subjective nature. The present study aims to address these limitations by leveraging affordable technology to create a novel measure of attention, the *Wiggleometer*. The *Wiggleometer* is a custom chair that covertly measures body movement as an index of attention. The preliminary results help establish the concurrent validity of the measure and suggest the *Wiggleometer* can be employed to better predict children's learning outcomes.

Keywords: attention; selective sustained attention; measurement; learning

Introduction

One student factor widely believed to be important for learning is selective sustained attention, or the ability to modulate attention and ignore extraneous information. Indeed, a commonly held assumption in education is that the more time children attend to something, the better they should learn the material (e.g., Carroll, 1963). Thus, inattention is presumed to reduce learning opportunities and is therefore hypothesized to be detrimental to learning. However, understanding the nuanced relationship between selective sustained attention and learning is difficult due to the lack of developmentally appropriate and ecologically valid measures of attention.

Measuring attention in young children is challenging – primarily because preschool and primary grade children are in a measurement gap - they are too old for selective sustained attention measures typically employed with infants and toddlers and often too young to produce useful data from more traditional attention measures used with older children and adults (Fisher & Kloos, 2016; Godwin, Lomas, Koedinger, & Fisher, 2015; Fisher, Thiessen, Godwin, Kloos, & Dickerson, 2013; Erickson, Thiessen, Godwin, Dickerson, & Fisher, 2015). For example, the Continuous performance task or CPT is a standard performance-based measure of attention in which participants are asked to respond to a target but withhold a response for non-targets. The long duration of the task and unfamiliar stimuli (e.g., letters and numbers) makes it developmentally inappropriate for use with young children. Child friendly versions have been created but have only met with limited success as its been estimated that 50% of children under 4.5 years of age fail to meet the minimum performance criteria (see Fisher & Kloos, 2016). Consequently, there is a lot of lost or unusable data.

In addition to performance-based measures of selective sustained attention, behavioral measures of attention are also quite common both inside and outside the laboratory. One of the most widely used behavioral measures is eye gaze. Eye gaze is a common and reasonable measure of selective sustained attention (for reviews see Henderson & Ferreira, 2004; Just & Carpenter, 1976); however, it is admittedly not a perfect measure. Observational data often suffers from poor reliability due to its subjective nature (e.g., Poppe, Van Der Zee, Heylen & Taylor, 2013; Scherer & Ekman, 1982). Despite employing extensive coding protocols, coding behavior is difficult because there are inevitably ambiguous cases where coders must use their own judgment. These situations pose a challenge for establishing good inter-rater reliability.

Because all measures are imperfect it is also important to utilize converging measures. However, for researchers interested in the development of attention, this is challenging due to the aforementioned shortage of developmentally appropriate measures. Consequently, we are interested in using technology to enhance measurement design in order to address some of the common issues that make behavioral data collection so challenging while also developing a converging measure of attention that could be utilized to better predict children's learning outcomes.

The present study aims to address these limitations by developing and testing the *Wiggleometer*, a novel measure of selective sustained attention. The *Wiggleometer* provides an automated and objective approach to measuring attention. The *Wiggleometer* is a custom chair that covertly measures children's extraneous body movements as an index of selective sustained attention. Justification for the use of movement as an indicator of attention and additional details regarding the *Wiggleometer* are provided below.

Extraneous Movement: Wiggleometer

Although eye gaze is a common and reasonable measure of selective sustained attention, it is admittedly not a perfect measure. Consequently, we sought to incorporate a physiological index of selective sustained attention that could be utilized as a converging measure of attention; thus helping to resolve the task impurity problem (Miyake, et al., 2000). Several physiological signatures of selective sustained attention have been noted in the prior literature including: specific facial expressions (e.g., pursed lips, furrowed brow), body position (e.g., leaning forward, encircling the object), and movement (see Choudhury & Gorman, 2000; Ruff & Capozzoli, 2003; Ruff & Rothbart, 1996; Tellinghuisen, Oakes, & Tjebkes, 1999).

Utilizing physiological measures to infer cognitive states is a common practice. For example, prior research has documented that changes in posture can reflect changes in levels of engagement. For instance, when adults completed a task on a computer tutor, leaning back (marked by increased pressure on the back of a chair and more rapid changes in pressure) was associated with boredom, while leaning forward (marked by increased pressure on the seat of a chair) was associated with engagement (D'Mello, Chipman, & Grasser, 2007; D'Mello & Grasser, 2010). Similar work has also been pursued with children (Mota & Picard, 2003; Dragon, Arroyo, Park Woolf, & Burleson, 2008).

In the present work, extraneous movement was selected as a converging physiological measure of attention as prior research has documented that extraneous movements decrease during episodes of selective sustained attention (see Ruff & Rothbart, 1996; Ruff & Lawson, 1990; Lawson & Ruff, 2004). For instance, Milich (1984) assessed 6 to 12 year-old boys' attention and activity level during a structured play activity (i.e., the children were told they could play with specified toys at a table). Milich found that on-task behavior increased with age, while extraneous gross motor movements (i.e., getting out of one's seat, entering other areas of the play room, etc.) and fine motor movements (i.e., fidgeting) declined with age - presumably due to age related improvements in executive function.

Recent studies with adults have also found an inverse relationship between extraneous movement and attention. For example, Seli et al. (2014) gave adults an arbitrary behavioral response task in which participants were asked to press a button in synchrony with a metronome. Seli et al. found that extraneous movements (i.e., fidgeting) decreased when participants reported being on-task compared to periods when participants reported being off-task (or what the authors refer to as mind wandering). However, questions regarding social desirability effects and in turn reporting accuracy should be noted as a potential cause for concern due to the use of self-report. Nevertheless, these studies highlight the relationship between motor activity and attention, and point to movement as another behavioral measure that can be collected as an index of selective sustained attention.

The *Wiggleometer* provides an automated approach to behavioral data collection which has several important advantages compared to traditional behavioral observational methods. As mentioned previously, observational data often suffers from poor reliability due to its subjective nature (e.g., Poppe, Van Der Zee, Heylen & Taylor, 2013; Scherer & Ekman, 1982). The *Wiggleometer* reduces subjectivity by utilizing modern and affordable technology to automate behavioral data collection. Second, traditional behavioral observational methods can be cumbersome and time consuming. Increasing advancements and ease of access to technology allow one to automatize the data collection process, which makes it feasible to collect larger quantities of data from more subjects with more precision. Therefore, if successful, the *Wiggleometer* will help to resolve both of these issues while providing a converging measure of selective sustained attention. The present study begins to test the feasibility and concurrent validity of the *Wiggleometer,* a novel converging measure of attention, by (1) examining whether extraneous body movements indexed by the *Wiggleometer* are correlated with an existing measure of attention (time spent off-task) and (2) determining whether statistical models incorporating the *Wiggleometer* successfully predict children's learning outcomes over and above models using time off-task alone.

Method

Participants

The sample consisted of 23 kindergarten children (*Mage* = 5.00 years, *SD* = 0.24 years, Range: 4.72 years to 5.63 years, 18 females, 5 males). All participants attended a laboratory school at a private university in Pennsylvania. Children were tested individually in a quiet room adjacent to their classroom by the first author of this paper and by trained research assistants.

Design

In the present study children completed paired associates learning tasks. The amount of time children spent off-task was calculated as a measure of children's selective sustained attention. Additionally, the *Wiggleometer*, which measured children's extraneous body movements, was employed as a converging measure of children's selective sustained attention. The dependent variable was children's accuracy on the learning task (i.e., proportion of correct responses).

Procedure

Children participated in five sessions. In session 1, children completed the pre-test. In sessions 2-5, children completed the paired associates learning tasks (comprised of a learning phase and a post-test). Extraneous movement (indexed by the *Wiggleometer*) and time off-task (based on eye gaze) were utilized as measures of selective sustained attention. Additional details for each measure are provided below.

Learning Measures

Pre-test A pre-test was administered to ensure the test items were in fact novel to young children. The pre-test was presented on a laptop computer. Children were asked to identify the object labeled by the experimenter from 3 pictorial response options. The pre-test included 72 trials: 54 novel test items and 18 familiar items, which served as fillers. The test items were derived from 6 natural kind domains: *Fish, Plants and Flowers*, *Fruit*, *Butterflies*, *Land Animals*, and *Exotic Mammals*. Two presentation orders of the pre-test were created. In Order 1 the test items were randomized with the constraint that the pre-test began and ended with a familiar item. For Order 2, the presentation order was simply reversed. The inclusion of familiar items and the order constraint were employed to prevent children from becoming discouraged on the pre-test since we were anticipating that the test trials would be novel to most children of this age group.

Based on the pre-test results, 4 natural kind domains were selected for inclusion in the experiment: *Fish*, *Plants and Flowers*, *Butterflies*, and *Land Animals*. Accuracy for these domains (novel items only) ranged from 24% to 28% indicating that the content was novel to the children. Indeed children's pre-test performance was either not significantly different from chance (i.e., 33%; *Plants & Flowers*: single sample $t = 1.94$, $p = 0.07$) or significantly below chance (all other domains: single sample $ts \geq 2.11$, $ps \leq 0.05$).

Learning Task In each testing session, children completed a computerized Paired Associates Learning (PAL) task. In the PAL task children are presented with pictures of nine novel natural kinds and taught the corresponding label for each object. The PAL task consisted of 27 trials. Two presentation orders were created. For Order 1 the items were blocked and randomized within each block. Blocking was employed to create a relatively even presentation distribution: each item was presented once within each block. For Order 2 the presentation order utilized in Order 1 was simply reversed.

The learning phase of the PAL task was designed to approximate 'seat-work,' an independent learning activity common in elementary schools. Consequently, the experimenter stood in the hallway behind a one-way mirror while the child completed the learning phase independently. Thus, if the child engaged in off-task behavior, the experimenter did not redirect the child.

Post Test The post-test included 18 items and was composed of recognition and recall test items (9 questions each); see Figure 1. The post-test was administered on a laptop computer. For recognition items, children were asked to point to the item labeled by the experimenter from 3 pictorial response options. For recall items, children were shown a picture of an item and asked to recall the item name. Two presentation orders were created. For Order 1 question type was blocked (Block 1: recognition questions, Block 2: recall questions) and the items were randomized within each block. For Order 2, the blocking sequence was held constant (Block 1: recognition questions, Block 2: recall questions) and the presentation order of items within each block was reversed.

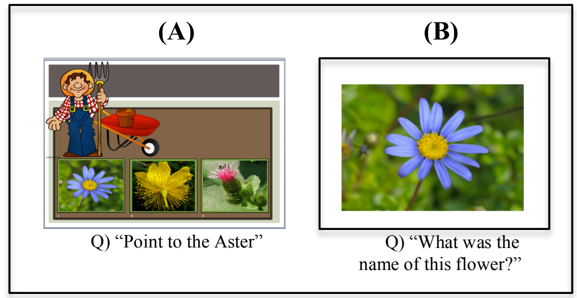

Figure 1. Sample assessment items from the *Plants and Flowers* PAL task. Panel A provides a recognition test item and Panel B provides a recall test item.

Measures of Attention

Time Off Task PAL sessions were videotaped for coding purposes. For each trial, children's behavior was coded at the second-by-second level in order to calculate the proportion of time children spent off-task. Coders were taught to classify the child's behavior as on- or off-task. On-task behavior was operationalized as engagement with the learning materials (i.e., the computer). Engagement was determined by the direction of children's gaze. For each instance of off-task behavior, the coders marked the timing of its onset and cessation.

All coders were trained by the first author of this paper. Training consisted of extensive practice coding videotapes. A subset of the data (25%) was re-coded to ensure good inter-rater reliability (Cohen's (1960) Kappa = 0.78). All coders were hypothesis-blind.

Wiggleometer Extraneous body movements were quantified using a *Wiggleometer*. The *Wiggleometer* is a custom chair that was designed to measure changes in force. The hardware components of the chair include an Arduino Uno – R3 (primary microcontroller) and 4 interlink Electronics Force Sensing Resistors (Part # 406), which are sensitive to a range of 100g to 10kg. The Arduino analog to digital converter has a 10bit resolution from 0 volts to 5 volts. The voltage is linearly converted on a scale from 0 to 1023 where 0 indicates a minimal force detected by the sensor (i.e., less than 100g). Data is pulled from the sensors approximately 5 to 6 times per 100 milliseconds. The data is sent over serial to the computer where the Python software records the values in a csv file. The data from the *Wiggleometer* is then used to determine the size of movements children made.

Results

Learning Measures

Recall that the PAL content was purposely selected to be novel to young children. As discussed above, children's pre-test scores were either at chance or significantly below chance confirming that the content was novel to participants. Despite the novelty of the items and minimal exposure to the items (27 trials per domain) children did show evidence of learning: Children's mean total learning score was .39 (SD = .11). Children's recognition performance was significantly above chance (single sample $t(22) = 9.58$, $p<.0001$). Children exhibited stronger recognition performance (M = .61, SD = .14) than recall performance (M = .17, SD = .10).

Selective Sustained Attention

Off-Task Behavior In line with prior research examining on and off-task behavior, in the present study children were largely on task (e.g., Godwin et al. 2016): Across the PAL tasks, children spent 21% (SD = 15%) of their time off-task (TOT).[1]

Extraneous Movement From the *Wiggleometer* an index of the size of children's movements was calculated[2]. The mean size of children's movements was determined by calculating the absolute difference in force at each sensor reading. This process was repeated for each sensor and the mean was calculated. Larger difference scores signify greater changes in force, indicating bigger movements, whereas smaller values reflect small changes in force or minimal movement. Children's mean movement size was 1.72 (SD = 0.83).

The *Wiggleometer* was calibrated by running 10 test trials in which data was collected without a child in the chair to determine how much noise is present in the data. The mean movement size was 0.21 (SD = 0.01). The calibration data was then compared to the data obtained in the experiment. The movement size obtained in the experiment was significantly greater than the mean obtained in the calibration (single sample $t(22)=8.72$, $p \leq 0.0001$) suggesting that the *Wiggleometer* is detecting more than noise. Furthermore, the low variability across individual calibration trials is taken to suggest that although some level of noise is present in the data, the instrument is reliable.

[1] For 3 children, the mean proportion of TOT is based on 3 (out of 4) PAL sessions. The missing data is due to experimenter error, technical difficulties, or failure to comply with the experimenter's instructions.

[2] Due to experimenter error, for 1 child, data from 1 PAL session could not be obtained. Their mean score is based on 3 (out of 4) testing sessions. Due to technical difficulties for 36% of the sessions (33 out of 91 sessions) there is a small portion of missing data. On average the missing data accounts for less than 1% of the data within a session.

Converging Measure of Attention

Recall that the *Wiggleometer* was included in the present experiment to provide a converging measure of selective sustained attention that could be employed to better predict children's learning outcomes. The goal of generating a converging measure of attention is based on the limitations of the primary measure of attention – eye gaze – which although it is a reasonable measure of attention, it is neither perfect nor free from subjectivity. Thus, the *Wiggleometer* was designed to provide a more sensitive and unbiased measure of children's selective sustained attention.

To this end, a correlation analysis was conducted to ascertain whether the total proportion of time spent off-task (based on eye gaze) was positively related to children's movement size (indexed by the *Wiggleometer*). Children's movement size was found to be significantly correlated with time off-task (r = 0.44, p = 0.037); See Figure 2. Thus, children who spent more time off-task tended to engage in larger extraneous movements.

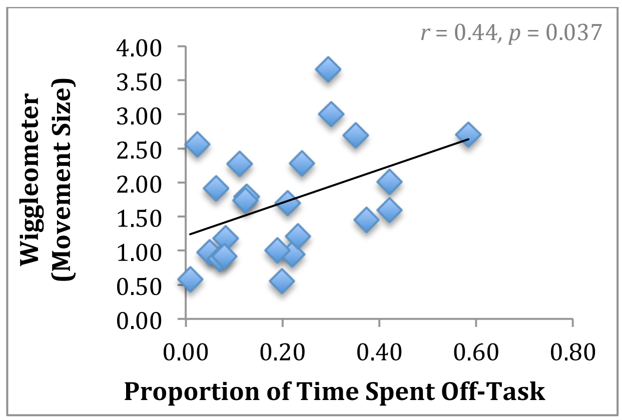

Figure 2. Association between movement size (indexed by the *Wiggleometer*) and the proportion of time spent off-task.

Predicting Learning

The variables total proportion of time spent off-task and children's movement size were converted into Z-scores and averaged together to create an attention composite. Two linear regressions were performed in which the attention composite was entered as the sole predictor of children's learning scores (recognition and recall scores) on the PAL post-test; see Table 1.

For recognition scores the model was statistically significant ($F(1, 21) = 14.54$, $p = 0.001$). The attention composite (standardized $\beta = -0.64$) accounted for 41% of the variance in children's recognition scores (adjusted $R^2 = 0.38$). For recall scores, the model was also statistically significant ($F(1, 21) = 8.39$, $p = 0.009$). The attention composite (standardized $\beta = -0.534$) accounted for 29% of the variance in children's recall scores (adjusted $R^2 = 0.25$).

Is the attention composite a better predictor than TOT? The same linear regression models were run with time off-task as the sole predictor of children's learning scores (recognition and recall scores) on the PAL post-test; see Table 1. Time off-task (standardized β =-0.53) was a significant predictor of children's recognition scores; $F(1, 21) = 8.19$, $p = 0.01$. Time off-task (standardized β =-0.437) was also a significant predictor of children's recall scores $F(1, 21) = 4.95$, $p = 0.04$. However, time off-task accounted for a numerically smaller proportion of the variability in children's learning outcomes compared to the attention composite (R^2: 41% vs. 28% and 29% vs. 19% for recognition and recall respectively).

Table 1: Variability (R^2) Accounted for by the attention composite and Time off-Task (TOT)

	Attention Composite (*Wiggleometer* +TOT)	**TOT**
Recognition	41%	28%
Recall	29%	19%

For both recognition and recall performance the more optimal models, based on the Bayesian Information Criterion (BIC), were the models in which the attention composite variable was used as the predictor rather than time off-task; see Table 2. Taken together, the results of the analyses suggest that the attention composite variable (total proportion of time spent off-task *and* children's movement size) served as a better predictor of children's learning outcomes than total time off-task alone. Thus, the *Wiggleometer* successfully provided an index of children's selective sustained attention that could be employed as a converging measure of children's attention to better predict their learning outcomes.

Table 2: Comparison of Models (BIC)

Predictor	**Outcome**	
	Recognition	Recall
Attention Composite (*Wiggleometer* + TOT)	-29.33	-39.65
TOT	-24.80	-36.79

Discussion

The results from the *Wiggleometer* are promising. First, this work shows that it is possible to create an automated measure of selective sustained attention. This is a significant contribution as the *Wiggleometer* allows for data collection that is automated and thereby reduces the subjectivity of traditional observational approaches. Second, the significant correlation between children's movement and time off-task support the use of this measure of attention and serves as a first step in establishing the concurrent validity of the measure. Lastly, by combining the data from the *Wiggleometer* with the proportion of time children spend off-task we were able to create a composite variable of attention that proved to be a better predictor of children's learning outcomes than time off-task alone. Thus, the *Wiggleometer* helps attenuate the task impurity problem (Miyake, et al., 2000) as it provides a converging measure of selective sustained attention. This is a particularly valuable contribution to the field due to the paucity of developmental appropriate measures available for use with young children (Fisher & Kloos, 2016).

This research is ongoing and we are currently working to make a number of modifications to the *Wiggleometer* to improve its validity and utility for research. Specifically, the *Wiggleometer* requires further refinement in order to: (1) increase the age range with which the measure can be utilized, (2) increase the accuracy of the digital signals thereby reducing measurement error, and (3) increase the features of the *Wiggleometer* and its compatibility with other data collection tools. To this end, we are currently developing a new prototype of the *Wiggleometer* that will have the following features: (1) increased weight capacity so the *Wiggleometer* can be utilized with older children; (2) improved accuracy of digital signals by incorporating signal processing approaches and improving sensor hardware to reduce noise and focus on recording only those extraneous movements that are hypothesized to be relevant to selective sustained attention; and (3) synchronization of *Wiggleometer* data to video frames. Connecting children's movements to the video data will have great utility so that researchers are able to directly link periods of greater movement (i.e., inattention) to specific learning episodes.

In conclusion, the initial results from the *Wiggleometer* provide an interesting test case where affordable technology is leveraged to increase the precision of behavioral data collection. The tool also makes it possible to collect larger quantities of data and to obtain a continuous measure of attention leading to a very rich data set that is not possible with some of the current behavioral measures. With more refinement of the prototype, the *Wiggleometer* will ultimately add to future researchers' toolbox as an additional measure of attention that can be used to triangulate and thereby better predict children's learning outcomes. The *Wiggleometer* provides a promising new converging measure of selective sustained attention that can be used in the lab but may also be scaled up for measuring attention in genuine learning settings (e.g., classrooms, museums, and home settings).

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