Title

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Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 40(0)

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Publication Date

2018

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Abstract

In crowded and cluttered environments, infants can reduce visual clutter by using manual actions to bring objects closer to the eyes, what we refer to as hand-eye coordination. Hand-eye coordination is therefore hypothesized to be an important ability for controlling and distributing attention. Little is known about how the emerging ability to integrate both gaze and manual actions onto objects impacts how attention is distributed. Twenty-five infants participated in a naturalistic toy play session that included 24 toys. Overall, infants generated distributions of attention that were right-skewed, reflecting *coherence*: a composition of *selectivity* of a few highly-frequent toys and *exploration* of many less-frequent toys. We observed that individual differences in hand-eye coordination impacted distributions of attention, with infants displaying low hand-eye coordination having dramatically less coherent distributions of visual attention during bouts of hand-eye coordination. These results suggest that hand-eye coordination is a critical pathway for visual attention.

Keywords: Hand-Eye Coordination; Visual Attention; Eye-tracking; Infancy; Play

Introduction

In visual environments cluttered with many objects, infants have choices. These choices impact what they see and for how long, generating the visual data used for learning. Learning requires the exploration, selection and stabilization of attention to information in the environment. Attention is therefore hypothesized to be a sensory-motor process because it includes the integration of actions across the body like postural stability, head movements, and manual actions. (Yu & Smith, 2012). For example, when an infant holds and looks at an object, what we refer to as *hand-eye coordination,* they create a stable, centered visual field, effectively reducing the visual clutter of competing objects (Bambach, Crandall, & Yu, 2013; Yu & Smith, 2012), providing optimal moments for learning to occur (Pereira, Smith, & Yu, 2014). For toddlers, smoothly integrating gaze and manual actions is a coordination problem still being solved, and rapidly changing. Here we report new findings on how visual attention is impacted during this period of rapid change in hand-eye coordination.

Recent advances in head-camera technology have started to uncover important spatiotemporal patterns of early visual experiences (Clerkin et al., 2017; Jayaraman, Fausey, & Smith, 2015, 2017). One key observation is that in the first few years of life, the frequency distributions of faces (Jayaraman et al., 2015) and objects (Clerkin et al., 2017) are extremely right-skewed: only a few faces account for a high proportion (~80%) of all faces in view and only a few object categories account for all of the object categories in view. What is the consequence of these natural visual statistics? One hypothesis is that right-skewed distributions offer a balance between *consistency* of a few high-frequent events with *diversity* of low-frequent events (Clerkin et al., 2017; Smith & Slone, 2018; Montag, Jones, & Smith, 2017). This balance between consistency and diversity, what we will call *coherence*, has been shown to offer computational benefits for visual object recognition (Salakhutdinov, Torralba, & Tenenbaum, 2011).

In our study, because we are investigating visual attention, instead of observing a balance between consistency and diversity, we predict to observe a balance between *selectivity* and *exploration*. Consistent with recent findings showing right-skewed distributions in natural scenes, Figure 1 depicts what we should expect in a ranked order distribution of toy look proportions for 24 toys: a large proportion of looks to only a few toys (*selectivity*; green rectangle) and a small proportion of looks to the rest of toy set (*exploration*; blue rectangle).

Our main hypothesis is that, during the second year, a developmental a period with rapid cognitive and motor development, visual attention is intimately linked to current sensory-motor abilities. The overarching idea is this: Because hand-eye coordination supports and organizes visual attention, this coordination is central to a coherent distribution of attention – many repeated looks to a select set

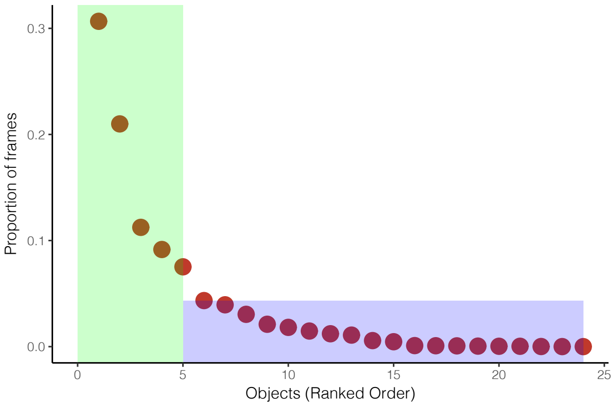

Figure 1: Example right-skewed distribution for 24 objects. The x-axis is rank ordered by proportion of frames. The top five objects (green) account for 80% of the total proportion. The remaining 19 objects (blue) account for 20% of the total proportion.

of objects and less frequent looks to other available toys. But this may be an emergent skill. Accordingly, we examined the relation between coordinated hand-eye actions directed to a single object during a period of development in which – because sensory-motor skills are changing – we should see considerable individual (and typical) variation. We expect to observe overall distributions of visual attention to be right-skewed, that is, a coherence between selectivity and exploration. In other words, when visual attention is not disrupted by difficulties in integrating actions by eyes and hands, we should expect to observe coherent distributions of visual attention. For infants with low hand-eye coordination, we expect to observe disrupted visual attention in the form of less selectivity and exploration during moments when they are in bouts of hand-eye coordination.

Method

Participants

25 infant-parent dyads with infants (12 female) ranging from 15.2 to 25.3 months (*M*=19.52, *SD*=2.42) were included in the final sample.

Stimuli and Experimental Setup

24 toys were used. The toys were pilot-tested to be interesting and engaging to infants (see Figure 2A). The toys were randomly spread out across the playroom floor at the beginning of each play session. Parents and infants both sat on a carpeted floor in a playroom environment. Parents were told to sit in any orientation with their child but were instructed to try to keep their child sitting on the ground as much as possible during the play session (see Figure 2B).

Eye-tracker and Calibration

Parents and infants wore head-mounted eye trackers (Positive Science LLC). The eye-tracker was designed for specific use with infants. The tracking system has been successfully used in both infant and adult experiments (Franchak & Adolph, 2010; Yu & Smith, 2017). The eye-tracking system includes an infrared camera mounted on the head and pointed to the right eye of the participant that records eye images and a scene camera that captures and records images from the participant's perspective. The visual field of the scene camera is 108°. Each tracking system – the infants' and parents' – recorded egocentric video and the x- and y-position of the right eye in the captured scene at a sampling rate of 30 Hz (see Figure 2B).

For eye-tracker setup, one experimenter engaged with the infant with an enticing toy while the second experimenter affixed the eye-tracker on the parent. After the parent's eye-tracker was secure and the scene and eye cameras were properly adjusted and oriented, both experimenters and the parent worked together to place the headgear and eye-tracker on the infant. The parent and one of the experimenters played with the infant while the other experimenter placed the infant's headgear (a small hat with Velcro stickers on the forehead) on the infant. The eye-tracker was then affixed to the headgear and the scene and eye cameras were adjusted and oriented appropriately.

Once the parent's and infant's eye-trackers were securely affixed and the cameras were adjusted and oriented appropriately, a ~3-minute calibration phase was completed. For eye-tracking calibration, a large calibration board with colored lights and sounds was placed approximately 30cm away from the infant. One of the experimenters controlled the calibration board with a remote and displayed one of the lights on the board for ~10s or until a saccade and look were elicited by both the infant and parent before displaying another light. This procedure was repeated approximately 15 times in various locations on the tabletop. The same procedure was used to calibrate the parent's eye-tracker. We have used similar procedures in multiple previous head-camera and head-mounted eye-tracking experiments (Pereira et al., 2014; Smith, Yu, & Pereira, 2011; Smith et al., 2015; Yu & Smith, 2017).

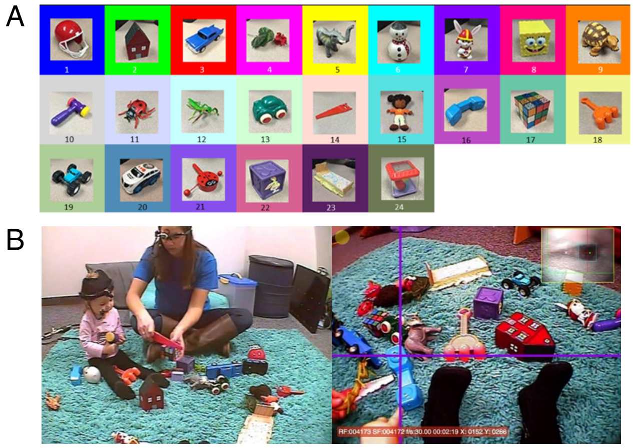

Figure 2: (A) Stimuli set. (B) Experimental setup (left) and infant ego-centric view from eye-tracker. Cross-hair indicates direction of gaze.

Instructions and Procedure

After the calibration phase, one of the experimenters distributed the set of toys on the floor and left the parent and infant to play. The experimenters watched the interaction in an adjoining room and monitored the parent's and infant's eye and scene cameras for large movements from external sources like if the infant touched a camera or bumped a camera with a toy. If movements like this occurred, the experimenters went into the room, readjusted the cameras, completed a new calibration phase, and left the room so the parent and infant could complete the rest of the toy play session. Parents were asked to engage with their infants and toys as naturally as possible for ten minutes.

Data Processing

Video and head-mounted eye-tracking were used to collect manual actions and eye gaze, respectively. Manual actions on and gaze to objects by infants were recorded and coded. Hand-eye coordination was derived by measuring the frames that included the infant holding on to and gazing towards the same toy. Eye-tracking software yielded scene camera footage with crosshairs superimposed where the eye was spatially located on the scene. This footage was then sampled at a rate of 30 frames per second. Using an in-house coding program, regions of interest (ROIs) were coded manually by coders who watched the first-person view video. Coders annotated when the cross hair overlapped on any portion of an object or face, and if so, which ROI. With this coding procedure, two gaze data streams containing ROIs were provided for each parent-infant dyad, although in the current paper, we only report look properties from the infant. There were 24 ROIs: one ROI for each of the 24 toy objects (see Figure 3).

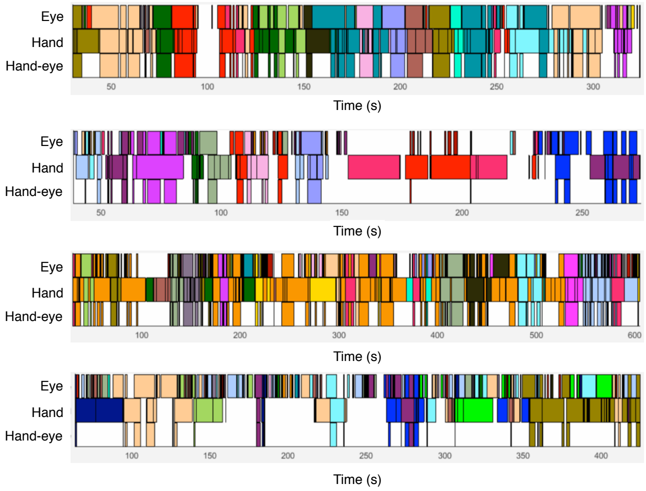

Figure 3: Visual streams of eye, hand, and hand-eye regions of interest (ROIs) from four infants. Color corresponds to a specific toy in the stimuli set.

Results

This section is organized into two parts. In the first part, we report on descriptive statistics of looking and holding behavior based on individual differences inside and outside of bouts of hand-eye coordination. In the second part, we investigate the distributions of visual attention using growth curve modeling.

Looking and Holding Behaviors

A median split was conducted on the proportion of time in hand-eye coordination to partition infants into either the ‘low’ hand-eye coordination group or the ‘high’ hand-eye coordination group. There was no difference in age between the two groups (*t*[23]=.067, *p*=.51), and the high group (*Min*=0.27, *Max*=0.53, *M*=0.38, *SD*=.07) had a higher proportion of time in hand-eye coordination relative to the low group (*Min*=0.14, *Max*=0.26, *M*=0.20, *SD*=0.04, *t*(23)=7.18, *p*<.001.

Overall, including looking behaviors both inside and outside of hand-eye coordination, the high group (*Min*=0.60, *Max*=0.94, *M*=0.76, *SD*=0.29) had a higher proportion of toy looks relative to the low group (*Min*=0.32, *Max*=0.82, *M*=0.60, *SD*=0.18), *t*(23)=2.94, *p*<.001. In addition, the high group (*Min*=0.59, *Max*=1.0, *M*=0.78, *SD*=0.11) had a higher proportion of toy holding relative to the low group (*Min*=0.44, *Max*=0.83, *M*=0.68, *SD*=0.12), *t*(23)=2.12, *p*=.04. Overall, the high group had a higher proportion of toy looking, toy holding, and by definition joint toy holding and toy looking.

The high group (*Min*=13.23, *Max*=30.41, *M*=21.79, *SD*=5.57) and the low group (*Min*=9.71, *Max*=33.12, *M*=21.71, *SD*=7.61) did not differ in the frequency (per minute) of toy looking, *t*(23)=0.03, *p*=.97. The high group (*Min*=0.25, *Max*=6.50, *M*=12.80, *SD*=6.38) and the low group (*Min*=0.26, *Max*=10.94, *M*=10.54, *SD*=3.90) did not differ in the frequency (per minute) of toy holding, *t*(23)=1.06, *p*=.30. The high group (*Min*=1.14, *Max*=2.89, *M*=1.92, *SD*=0.60) and the low group (*Min*=1.16, *Max*=3.45, *M*=1.71, *SD*=0.60) did not differ in the duration (seconds) of toy looking, *t*(23)=0.89, *p*=.38. The high group (*Min*=7.15, *Max*=241.03, *M*=8.35, *SD*=8.95) and the low group (*Min*=4.24, *Max*=174.23, *M*=6.32, *SD*=6.32) did not differ in the frequency (per minute) of toy holding, *t*(23)=0.77, *p*=.45.

To determine whether looking behavior was impacted by the overall increase in behaviors inside of hand-eye coordination – the main source of our group differences – we computed the relative proportion of toy looking (1) inside and (2) outside of hand-eye coordination. For the high group, there was no difference in the relative proportion of toy looks inside (*Min*=0.36, *Max*=0.70, *M*=0.50, *SD*=0.10) or outside (*Min*=0.30, *Max*=0.64, *M*=0.50, *SD*=0.10) of hand-eye coordination, *t*(23)=-0.16, *p*=.99. For the low group, the relative proportion of toy looks outside (*Min*=0.47, *Max*=0.82, *M*=0.64, *SD*=0.10) of hand-eye coordination was higher compared to inside (*Min*=0.18, *Max*=0.53, *M*=0.36, *SD*=0.10) of hand-eye coordination, *t*(23)=3.82, *p*<.001. Infants with low hand-eye coordination had *a higher proportion of their total toy looking behavior outside of bouts of hand-eye coordination.* This is a pattern that seems opposite to the studies (Bambach, Crandall, & Yu, 2013) showing holding increases and stabilizes looks to toys and suggests that for children still working on coordinating hands and eyes, doing so actually may disrupt rather than support visual attention to objects. Does this affect the distribution of toys sampled? Do both groups of infants show the same degree of selectivity – over time and in the play session – repeatedly looking and holding the same few toys?

Figure 4 shows ranked order histograms of toy look proportions inside and outside of hand-eye coordination for the high and low hand-eye coordination groups. The histograms are distinctly right-skewed which is indicative of visual selectivity of toys in the set. Overall, 8 toys (*Min*=1, *Max*=14, *M*=7.60, *SD*=3.24) account for over 80% of the total proportion of toy looking time. As discussed in the Introduction, right-skewed distributions likely reflect a balance between stability and exploration.

To determine the selectivity of looking behavior across individual differences in hand-eye coordination and inside and outside of bouts of hand-eye coordination, we computed

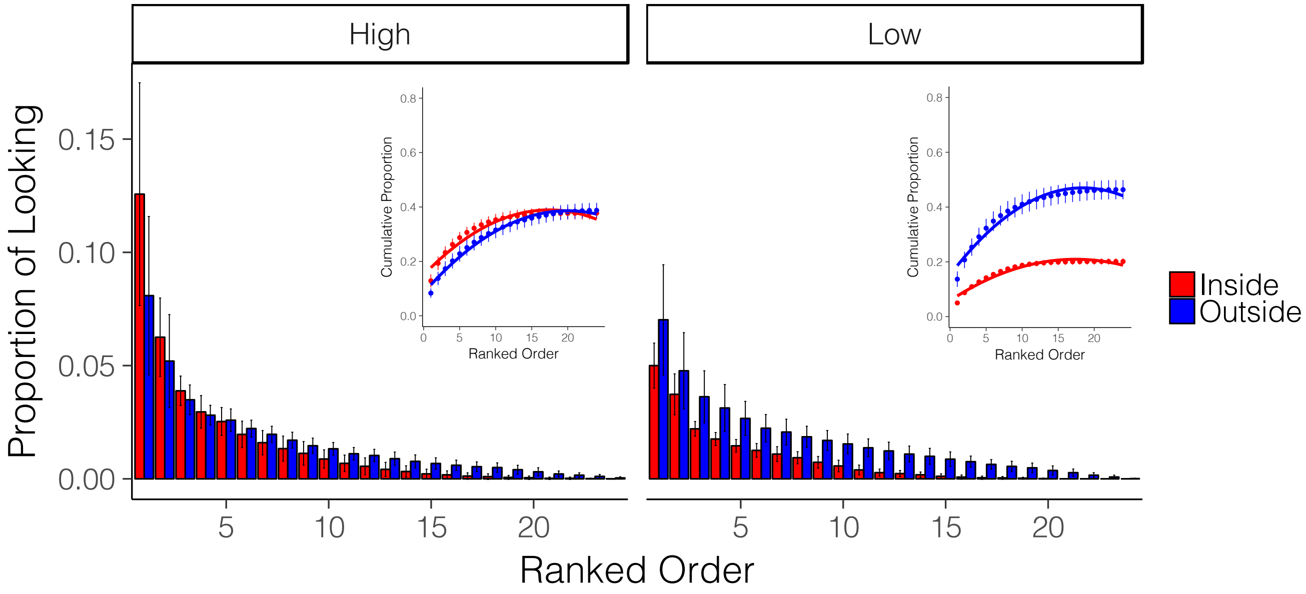

Figure 4: Ranked order histograms of toy look proportions inside (red) and outside (blue) of hand-eye coordination for the High (left) and Low (right) hand-eye coordination groups. Error bars indicate 95% confidence intervals. Inset. Growth curve models of ranked order toy look cumulative proportions. Solid lines represent quadratic fit estimates. Error bars indicate 95% confidence intervals.

the relative proportion of toy looks for the top five most attended to toys for each infant. Higher relative proportion would indicate higher selectivity. For the high group, there was higher selectivity inside (*Min*=0.26, *Max*=0.57, *M*=0.38, *SD*=0.08) of hand-eye coordination relative to outside (*Min*=0.15, *Max*=0.54, *M*=0.29, *SD*=0.11) of hand-eye coordination, *t*(23)=2.05, *p*=.05. In contrast, for the low group, there was higher selectivity outside (*Min*=0.26, *Max*=0.56, *M*=0.34, *SD*=0.08) of hand-eye coordination relative to inside (*Min*=0.17, *Max*=0.39, *M*=0.25, *SD*=0.08) of hand-eye coordination, *t*(23)=-2.72, *p*=.01. The visual attention of infants with high hand-eye coordination was more selective inside of hand-eye coordination. The visual attention of infants with low hand-eye coordination was less selective inside of hand-eye coordination, showing more selectivity in their visual attention when they were not in bouts of hand-eye coordination. These results suggest that for infants with still immature hand-eye coordination, joint looking and holding *disrupts* the natural distribution of looks to objects. While more fully developed hand-eye coordination may support visual attention – and balanced exploration and selectivity – this may be a hard-won skill. In the following section, we use growth curve modeling to test for differences in the distributions of visual attention across groups and inside and outside of hand-eye coordination.

Growth Curve Analysis

To test for differences in the distributions of toy looks inside and outside of bouts of hand-eye coordination across the two hand-eye coordination groups, we used the approach to mixed-effects models and growth curve analyses described in Mirman (2014). In growth curve analysis, the predictor variables are considered in terms of change over time (or ‘growth’). We use growth curve analysis to analyze the ranked order cumulative proportion profiles transformed from the ranked order histograms.

In the model, cumulative proportion is the outcome variable and the linear and quadratic terms are used to predict cumulative proportion. Given that the outcome variable is cumulative proportion, the linear term will be positive and the quadratic term will be negative. The linear term quantifies the overall cumulative proportion increment from the first ranked order proportion value and the last ranked order proportion value. The quadratic term quantifies the extent to which the cumulative proportion function asymptotes. For example, consider if ranked order histogram A’s asymptote was at 12 toys, ranked order histogram B’s asymptote was at 8 toys, and ranked order histogram A had twice as much proportion for each toy compared to ranked order histogram B. Once converted into ranked order cumulative proportion, the coefficient for the quadratic term for histogram A would be more negative compared to the coefficient for histogram B. A higher negative coefficient for the quadratic term indicates a distribution of looking patterns that includes looks to more toys before an asymptote, suggesting (1) more *selectivity* but also (2) more *exploration* of toys. Because our primary interest is in investigating differences in the shapes of the visual attention distributions, testing for differences in the quadratic term is the most relevant polynomial term in this analysis.

As suggested by Mirman et al. (2014), polynomial terms were generated orthogonally to allow for independent contributions of the linear and quadratic terms. Therefore, our models are second-order polynomial regression models. The goal of this analysis was to test for differences in look distributions inside and outside of hand-eye coordination bouts for the high and low hand-eye coordination groups. We used the **lme4** library (Bates, Maechler, Bolker, & Walker, 2016) in R to construct linear mixed effects regression models. The models were maximally specified as long as the models converged. We used random intercepts (subject ID) and nested the ranked order terms (linear and quadratic). The predictor variable was Look Type (*outside* or *inside* a bout of hand-eye coordination). A significant interaction between the Look Type variable and the linear and/or quadratic terms would suggest differences in look distributions inside and outside of hand-eye coordination. See inset of Figure 4.

Our first model was constructed for the high hand-eye coordination group. A significant interaction between the Look Type variable and linear term suggested that there was a larger relative increase in look proportion from the 1st-ranked toy to the toy at asymptote outside of hand-eye bouts compared to inside hand-eye bouts, b=.12, p<.001. The Look Type X quadratic term was not significant, suggesting that the selectivity and exploration of toys did not differ inside or outside of hand-eye bouts, b=.007, p=.38.

Our second model was constructed for the low hand-eye coordination group. A significant interaction between the Look Type variable and linear term suggested that there was a larger relative increase in look proportion from the 1st-ranked toy to the toy at asymptote outside of hand-eye bouts compared to inside hand-eye bouts, b=.21, p<.001. A significant interaction between Look Type and the quadratic term suggested that visual selectivity and exploration was highly constrained inside of hand-eye bouts relative to outside of hand-eye bouts, b=-0.09, p=.01.

Overall this pattern of results suggests that as children develop hand-eye coordination skills, joint manual and visual attention to an object may initially disrupt the coherent pattern of consistent and exploratory attention to objects. This is potentially important as both the selectivity of visual experiences and sensory-motor development have been linked to visual object name learning (Yu & Smith, 2012; Pereira, Smith, & Yu, 2014).

Discussion

A large literature links sensory motor development to individual differences in perceptual, cognitive and motor development (see for review, Leonard & Hill, 2014). One hypothesis is that these effects emerge in part because the infants and young children's sensory-motor behaviors create and select the data for learning and more advanced sensory-motor abilities create new and better opportunities for learning. The new contribution of this work is the demonstration that early (or poorly coordinated) attempts at joint holding and looking may actually disrupt visual attention leading to less optimal visual data for learning. The major finding that supports this conclusion is this: infants with low hand-eye coordination show similar looking behaviors outside of the context of holding as infants with high hand-eye coordination; however, during bouts of jointly holding and looking, these infants show disrupted patterns of selectivity and exploration in their toy play.

Past research on joint looking and holding by toddlers has consistently suggested that joint looking and holding supports learning because it generates optimal data sets for learning. But this may not be the case early in development or for all children. For adults, successfully acting in the world with many changing frames of reference – from driving a car (Johnson, Rothkopf, Ballard, Hayhoe, 2013), walking across difficult terrain (Matthis, Barton, & Fajen, 2017), and making a peanut butter and jelly sandwich (Rothkopf & Pelz, 2004) – is, although fallible, usually a seamless process. But all this coordination is a developmental product (Jung, Kahrs, & Lockman, 2017) and the rate of that development is likely to determine the rate of development in other domains (Piek & Dyck, 2004).

There are a number of additional observations. First, there is high variability in hand-eye coordination during this developmental period. Not surprising, these individual differences led to markedly less overall gaze and holding behavior for infants with low hand-eye coordination. Nonetheless, infants with low hand-eye coordination looked more to objects outside of bouts of hand-eye coordination. Looking behavior for infants with high hand-eye coordination did not vary inside or outside bouts of hand-eye coordination.

Second, overall distributions of toy looks were right-skewed. We know that images from infant head cameras during mealtime events generate right-skewed frequency distributions of object categories suggesting that these statistics are perhaps the natural statistics generated from the interactions between the infant and their environment (Clerkin et al., 2017). Crucially, training sets of data that are generated by right-skewed distributions have been shown to have important computational benefits for visual object recognition (Salakhutdinov, Torralba, & Tenenbaum, 2011). The hypothesized benefit of right-skewed distributions for learning is motivated by the property of coherence, that is, beneficial learning data includes both consistency of highly-frequent objects and diversity of less-frequent objects (Montag, Jones, & Smith, 2017). Overall, infants in our study generated coherent visual data sets in a visual environment that included a large set of toys competing for their attention.

Third, and the main result, despite that overall distributions of infant toy looks were right-skewed, there were marked differences in the distributions depending on hand-eye coordination ability. Infants with high hand-eye coordination generated coherent toy look distributions inside and outside of hand-eye bouts. For these infants, integrating actions from eyes and hands did not interfere with the coherence of visual input. For infants with low hand-eye coordination, the distributions of toy looks during hand-eye bouts were less coherent compared to outside of hand-eye bouts, which approximated the canonical overall right-skewed distribution. For these infants, the integration of eye and hand actions dramatically affected their visual attention leading to less selectivity and exploration.

In the moment, infants are more likely to learn the referent of an object when they bring the object close to their face – creating an uncluttered visual field – while their caregiver provides a verbal utterance that includes the object referent (Pereira, Smith, & Yu, 2014; Yu & Smith, 2012). At longer timescales, effective learning likely includes a combination of consistency of frequent events and diversity of rarer events: learning the rarer events includes integrating information about the more frequent events (Montag, Jones, & Smith, 2017; Salakhutdinov, Torralba, & Tenenbaum, 2011). We argue that this is also true for how infants generate visual data for learning: infants select a few objects to attend to for a long period of time, but still thoroughly explore their environment. By extension, infants still developing the skill of integrating actions of the eyes and hands are missing out on important opportunities for learning in the moment and this leads to less coherent distributions of visual attention. Future work should focus on learning outcomes from visual experiences that are generated by distributions of visual attention with varying degrees of coherence.

Acknowledgments

This research was supported in part by NSF grant BCS-1523982, NICHD T32HD007475-22 and F32HD093280, and by Indiana University through the Emerging Area of Research Initiative – Learning: Brains, Machines, and Children.

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