Developmental Psychology
2017, Vol. 53, No. 4, 642–651

0012-1649/17/$12.00 http://dx.doi.org/10.1037/dev0000278

Learning Higher-Order Generalizations Through Free Play: Evidence From 2- and 3-Year-Old Children

Zi L. Sim and Fei Xu
University of California, Berkeley

Constructivist views of cognitive development often converge on 2 key points: (a) the child's goal is to build large conceptual structures for understanding the world, and (b) the child plays an active role in developing these structures. While previous research has demonstrated that young children show a precocious capacity for concept and theory building when they are provided with helpful data within training settings, and that they explore their environment in ways that may promote learning, it remains an open question whether young children are able to build larger conceptual structures using self-generated evidence, a form of active learning. In the current study, we examined whether children can learn high-order generalizations (which form the basis for larger conceptual structures) through free play, and whether they can do so as effectively as when provided with relevant data. Results with 2- and 3-year-old children over 4 experiments indicate robust learning through free play, and generalization performance was comparable between free play and didactic conditions. Therefore, young children's self-directed learning supports the development of higher-order generalizations, laying the foundation for building larger conceptual structures and intuitive theories.

Keywords: free play, higher-order generalizations, self-directed learning

Proponents of constructivist views of cognitive development vary on many of their theoretical commitments (e.g., how to characterize the initial state, what is the nature of the learning mechanisms), but they all agree that (a) conceptual structures are built during the course of development, allowing the child to understand and explain the world, and (b) the child plays an active role in learning and the development of these conceptual structures (Bruner, 1961; Carey, 2009; Gopnik & Meltzoff, 1997; Piaget, 1954; Vygotsky, 1978; Xu & Kushnir, 2012, 2013).

One way to characterize children's construction of larger conceptual structures is through the development of intuitive theories (Carey, 1985, 2009; Gopnik & Meltzoff, 1997; Wellman & Gelman, 1992). One mechanism for building intuitive theories is by forming higher-order generalizations (also known as *overhypotheses*, Goodman, 1955). For example, children may begin by learning about specific animals (e.g., cows eat grass; frogs eat insects; goats milk their young; polar bears hibernate in the winter). Over time, they start to form second-order generalizations about animal kinds—that each kind has a typical diet, habitat, and method of reproduction. By forming these higher-order generalizations, children can go beyond the knowledge gained about specific exemplars and categories, and begin to differentiate mammals from nonmammals, insects from reptiles, and so forth The mechanism of forming higher-order generalizations, along with an understanding of the causal relationships among various biological phenomena, lay the foundation for developing an intuitive theory of biology (Carey, 1985; Kemp, Perfors, & Tenenbaum, 2007; Kemp & Tenenbaum, 2009; Perfors, Tenenbaum, Griffiths, & Xu, 2011; Shipley, 1993; Xu, Dewar, & Perfors, 2009). Similarly, in word learning, children may begin by learning about individual words (e.g., balls are round; spoons are spoon-shaped) then draw the second-order inference that names for object categories tend to refer to distinct shapes (e.g., Landau, Smith, & Jones, 1988). Several developmental studies have shown that the capacity for making higher-order generalizations is present in infants and young children across domains (e.g., Dewar & Xu, 2010; Macario, Shipley, & Billman, 1990; Samuelson, 2002; Smith, Jones, Landau, Gershkoff-Stowe, & Samuelson, 2002; Walker & Gopnik, 2014), allowing young learners to make inferences even when the specifics of new examples have almost nothing in common with previously seen examples. Many have also argued that these higher-order generalizations provide a larger framework that propels development forward, an idea that has been termed as the *blessing of abstraction* argument (Kemp et al., 2007; Perfors et al., 2011; Tenenbaum, Kemp, Griffiths, & Goodman, 2011). By extracting generalizations at multiple levels, the learner needs less specific evidence before building a general conceptual framework that guides future learning. For example, if a child has extracted the shape bias from the few object category labels she already knows, she will look for a distinct shape when encountering a new object category label. Similarly, if a child is fairly confident that each animal kind has a distinct diet given her current biological knowledge, she may ask "what does it eat?" when meeting a new kind of animal at the zoo.

A rich body of research has also documented a myriad of ways in which children are active learners. Starting from the second half of the first year, infants manipulate and play with objects in ways that may promote learning (Adolph, Eppler, & Gibson, 1993; Gibson, 1988; Needham, 2000; Stahl & Feigenson, 2015) and

Zi L. Sim and Fei Xu, Department of Psychology, University of California, Berkeley.

Correspondence concerning this article should be addressed to Zi L. Sim, Department of Psychology, University of California, Berkeley, 3210 Tolman Hall, Berkeley, CA 94720. E-mail: zi@berkeley.edu

allocate their attention systematically to more learnable parts of a cluttered environment that surrounds them (e.g., Gerken, Balcomb, & Minton, 2011; Kidd, Piantadosi, & Aslin, 2012). Preschoolers explore more when they encounter ambiguous evidence (e.g., Schulz & Bonawitz, 2007), and as they become more proficient in language, they begin to ask questions and seek explanations frequently and spontaneously (Chouinard, 2007; Frazier, Gelman, & Wellman, 2009; Legare, Mills, Souza, Plummer, & Yasskin, 2013). Other studies have also shown that young children can sometimes learn from self-generated evidence (e.g., Bonawitz, van Schijndel, Friel, & Schulz, 2012), and they may even learn better when given the opportunity for discovery first (Bruner, Jolly, & Sylva, 1976; Sobel & Sommerville, 2010; Sylva, Bruner, & Genova, 1974).

These previous studies have demonstrated in powerful ways that children actively engage their environment from early on. Yet one key aspect of constructivist views of cognitive development has yet to be explored: Are young children able to build larger conceptual structures through active learning? That is, can they form higher-order generalizations using self-generated evidence? If yes, can they do so as effectively as when they are provided with the relevant data? These are the main research questions we investigate in the current experiments.

The current study also bears on a lively debate in education and developmental psychology, namely the role of self-directed learning using self-generated evidence in development and learning in school settings. On the one hand, research in education has demonstrated that play promotes academic skills such as literacy, language and math (Bergen & Mauer, 2000; Bruner, 1961; Hirsh-Pasek, Golinkoff, Berk, & Singer, 2008; Roskos, Christie, Widman, & Holding, 2010; Sarama & Clements, 2009a; Seo & Ginsburg, 2004; Singer, Hirsh-Pasek, & Golinkoff, 2009), but children in most of these studies were not required to independently generate evidence during play to fulfill a learning goal. A recent study by Fisher, Hirsh-Pasek, Newcombe, and Golinkoff (2013) has made significant headway in mitigating this gap in the education literature, demonstrating that for geometric concepts (e.g., the definitional properties of a triangle), 4- and 5-year-old children may benefit from learning within a playful context with guidance from an experimenter, but not from free play alone (see further discussion in the General Discussion).

On the other hand, previous studies in cognitive development have largely focused on when children explore more (e.g., when encountering surprising or ambiguous evidence, Schulz & Bonawitz, 2007; Stahl & Feigenson, 2015), but most of these studies do not typically include outcome measures for learning. Therefore it remains an open question what children learn from the evidence that they generate by themselves (Cook, Goodman, & Schulz, 2011; Legare, 2012; Schulz & Bonawitz, 2007). Two exceptions are Bonawitz et al. (2012) and Schulz and Bonawitz (2007), both of which examined the relationship between exploration and eventual learning accuracy in 5- to 7-year-olds. Bonawitz et al. (2012) tested 6- and 7-year-old children who had incorrect beliefs about how objects balance. These children were considered "Center Theorists," as they believed that blocks would balance at the geometric center, rather than the center of mass. After these children were shown evidence conflicting with their prior belief, and were also given the opportunity to freely interact with the block, researchers found that the children revised their belief and made a correct prediction that a new block should balance at its center of mass. Schulz and Bonawitz (2007) examined whether 5-year-olds could, through the course of free play, generate interventions that would help them learn the causal structure of the system they were interacting with. The causal system was a machine consisting of two gears that spin simultaneously when a switch was flipped on. Several different causal structures were possible; for example, causal chain (the switch causes gear A to spin, and gear A causes gear B to spin), or common cause (the switch causes gears A and B to spin, independently of each other), and so forth. Their findings suggest that children could generate the requisite evidence when they played in dyads, but it was unclear that the children who played with the system singly actually performed better than chance when asked to identify the underlying causal structure of the machine.

Thus it remains an open question how early children can effectively learn from self-generated evidence, and whether self-generated evidence through play can support the development of larger conceptual structures.

Like Schulz and Bonawitz (2007) and Sobel and Sommerville (2010), we chose to examine these research questions in the causal domain. Causal learning is particularly important, as learning about our world is to learn the casual relations among the objects and events within it. It is the basis of all theory formation and change (Gopnik, 2012; Gopnik, Sobel, Schulz, & Glymour, 2001; Gopnik & Wellman, 2012). There is extensive evidence that children are good at causal learning: from an early age, they make causal predictions and give causal explanations (see Gopnik et al., 2004; Gopnik & Wellman, 2012; Griffiths & Tenenbaum, 2009 for reviews). More recently, studies have demonstrated that even infants and toddlers can engage in causal learning with just small amounts of training evidence (Gweon, Tenenbaum, & Schulz, 2010; Sobel & Kirkham, 2006; Walker & Gopnik, 2014). Furthermore, children's real-world environment is filled with many examples of causal systems, and they have numerous opportunities to interact with such systems; for example, they play with toys that have buttons and levers, they turn on light switches and remote controls, and so forth. Given the rich environmental input, there is reason to believe that even younger children may be able to successfully learn about simple causal systems based on self-generated evidence.

In the current study, we designed a causal learning task in which 2- to 3-year-old children were presented with three different categories of "blicket" machines (cf. Gopnik & Sobel, 2000) and three blocks of different shapes and colors. For half of the children, the machines were activated using a shape rule: a shape-match block had to be used to activate the machine, while for the other half, the machines were activated using a color rule: a color-match block had to be used to activate the machine. The causal system was intentionally designed to be more straightforward—each block activated one and only one category of machine—than the causal systems presented in Schulz and Bonawitz (2007) and Sobel and Sommerville (2010), where children had to learn more complex causal structures such as common cause or chain.

In Experiment 1, we tested children in a didactic learning condition. Like most other experiments, we gave children the data directly, and examined what they had learned from the training data. To do this, an experimenter demonstrated the activations of three categories of machines by using the appropriate block to activate each machine. We then asked the children to make both first-order generalizations, where they had to choose from a new set of blocks to activate a previously seen machine, and second-order generalizations, where they had to choose from a new set of blocks to activate a novel machine. We then tested children in two different versions of free play in Experiments 2 and 3, in order to compare children's performance with that in the didactic condition. Finally, in Experiment 4, we measured children's baseline performance in these generalization tests.

Experiment 1

Method

Participants. Thirty-two English-speaking 2- and 3-year-olds (12 boys and 20 girls) with a mean age of 35.8 months (range = 31.1 to 42.3 months) were tested. The sample size in this experiment, as well as in Experiments 2 and 3, was determined based on previous generalization studies (e.g., Smith et al., 2002; Walker & Gopnik, 2014) that had sample sizes of 16–38 children. All participants were recruited from Berkeley, California, and its surrounding communities. The sample was representative of the ethnic diversity in these communities: the participants were predominantly non-Hispanic White, with 9% Asian, 9% Hispanic, and 6% African American. An additional two children were tested but excluded due to refusal to make a choice at test ($N = 1$), or experimenter error ($N = 1$).

Materials. Four categories of toy machines were used in this experiment, with two identical machines in each category. The categories differed in shape and color, that is, machines in Category 1 were blue and rectangular; machines in Category 2 were red and triangular; machines in Category 3 were green and circular; and machines in Category 4 were orange and L-shaped (each approximately 30 cm × 10 cm × 5 cm). Each set of machines produced a unique sound when activated (see Figure 1). This effect was achieved by hiding a doorbell in each machine that was activated by an experimenter with a remote-control device.

A variety of small blocks (approximate 4 cm × 2 cm × 1 cm) with different shapes and colors were used to activate these machines. Some of these blocks matched the toy machines in shape but not color (shape-match blocks), some matched the machines in color but not shape (color-match blocks), and others did not match the machines in shape or color (distracter blocks). Three white trays with separators were also used to easily present the activator blocks during the learning phase and the test phase.

Procedure. Children were tested individually in the laboratory. The parents were also present in the testing room, but sat about 80 cm behind the children throughout the experiment, in order to not influence their actions and choices. Children were introduced to the machines and blocks under the pretext of the experimenter showing them her toys.

The experiment consisted of two phases: a learning phase and a test phase. To begin the learning phase, the experimenter presented a white tray containing three blocks differing in shape and color. The child was free to play with these blocks for about 20 seconds. After this exploration, the blocks were returned onto the tray and pulled close to the experimenter, but remained visible to the child.

The experimenter then presented the first toy machine (e.g., blue rectangular machine), and activated the machine with one of the

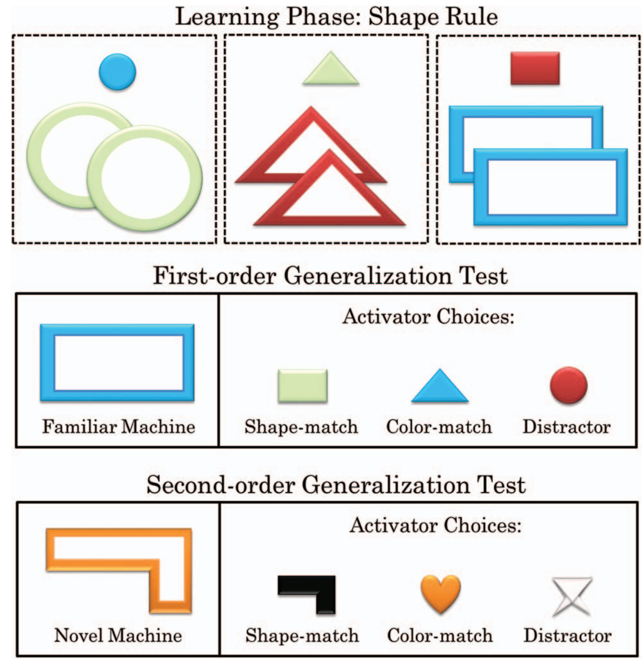

Figure 1. Schematic diagram of materials and procedure for children presented with the machines, which were activated according to a shape-match rule. See the online article for the color version of this figure.

three blocks by placing it on top of the machine (e.g., red rectangular block, if the machines were being activated by a shape rule; blue triangular block, if the machines were being activated by a color rule). Upon the machine's activation, the experimenter drew attention to the event by saying, "Look! The block made the machine go; it made it go!" The experimenter next showed the child another machine that was identical to the first one, and activated it using the same block. This first set of two machines was then cleared from the table. The experimenter repeated this procedure with two other sets of training machines, activating them with their respective shape-match or color-match blocks.

A total of six machines were presented during the learning phase, and each child saw each machine being activated only once. The three categories of machines chosen as the training set were randomized, leaving the fourth category of machines for the test phase (i.e., each category could be used in the training or the test phase). The order of presentation for the categories of training machines was also counterbalanced. The duration of this phase was about 4 min.

A test phase immediately followed the learning phase. The test phase consisted of a first-order generalization test and a second-order generalization test (see Figure 1). In the first-order test, each child was presented with a *familiar machine*, which is a machine that was previously presented in the learning phase. Then, the child was provided with three novel choice blocks in a white tray: a shape-match block, which is similar to the target machine in shape but not color; a color-match block, which is similar to the target machine in color but not shape; and a distracter block, which differed from the target in both color and shape. The experimenter requested the child to hand her a block that made the target machine go, "Can you give me the block that makes this machine go?"

In the second-order test, each child was presented with a *novel machine*, which is a machine that was not previously presented in the learning phase. The child was again asked to activate the machine by choosing among three novel choice blocks: a shape-match block, a color-match block, and a distracter block. The presentation order of the three choice blocks were counterbalanced for both test trials. The duration of the test phase was about 1 min.

Coding. The children's responses in the test trials were scored for accuracy. For the children exposed to the shape rule during the learning phase, choosing a shape-match block was scored as 1 point. Correspondingly, for children exposed to the color rule, choosing a color-match block was scored as 1 point. The maximum score for each child was 2 points, as there were 2 test trials in total. The children's scores were then converted into percentage of accuracy. A second coder recoded all of the children's responses offline, and the level of agreement between the coders was 100%.

Results

An alpha level of 0.05 was used in all statistical analyses. As Figure 2 shows, children performed accurately on the test trials, frequently selecting the correct block to activate the machines. We found that 69% of the children chose the correct activator block in the first-order generalization test, exact binomial p (two-tailed) = .05. Seventy-five percent of the children chose the correct activator block in the second-order generalization test, exact binomial p (two-tailed) = .007. Note that we used a conservative criterion of .5 for the binomial test even though children were offered three activator choices in each test trial, as the children chose the shape-match (52%) or the color-match block (34%) more often than the distractor block (14%).

Using children's responses on the two test trials, we also performed a repeated measures logistic regression. Our results indicate that there were no effects of gender, age, trial order (first test trial vs. second test trial), presentation order of the training machines (e.g., whether machines from the different categories were presented first, second, or third during the training phase), and rule type (shape rule vs. color rule) on children's accuracy on the test trials. Critically, there was no difference between children's performance on the first-order and second-order generalization trials, Wald Chi-Square = .49, p = .48.

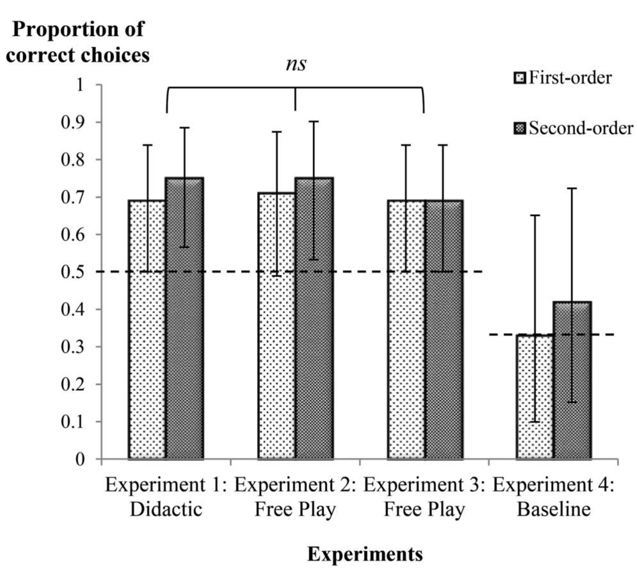

Figure 2. Proportion of children choosing the correct activator block at test. Dashed line indicates chance performance. Error bars represent 95% confidence intervals.

Discussion

These results converge with and extend the results found in many previous training studies examining learning and generalization in young children. With a short training session and a small amount of instructive evidence, 2- and 3-year-old children in Experiment 1 learned first-order and second-order generalizations about the causal structure of the machines, picking out the correct activator blocks according to the rule that they were exposed to within a didactic learning context.

Experiment 2

In Experiment 2, we investigated whether children would successfully acquire first-order and second-order generalizations based on evidence generated by themselves during the course of free play.

Method

Participants. Twenty-four English-speaking 2- to 3-year-olds (10 boys and 14 girls) with a mean age of 36.1 month (range = 30.3 to 42.3 months) were tested. All participants in Experiment 2 were recruited from Berkeley, California, and its surrounding communities. The sample was representative of the ethnic diversity in these communities: the participants were predominantly non-Hispanic White, with 17% Asian, 13% Hispanic, and 4% African American. An additional three children were tested but excluded due to refusal to make a choice at test (N = 1), no attempts to make any activations (N = 1), or experimenter error (N = 1).

Materials and procedure. The procedure for Experiment 2 consisted of three phases: a familiarization phase, a learning phase, and a test phase. To begin the familiarization phase, the experimenter presented the child with a cross-shaped yellow machine, together with its activator block. This block matched the machine both in shape and color. The familiarization phase served to introduce the child to the sound-making function of these novel machines. This phase was not necessary in Experiment 1, since the machines' function would be introduced in the learning phase. The experimenter then activated the machine, drawing attention to the event by saying, "Look! The block made the machine go. It made it go!" The child was then given the activator block, and was allowed to activate the machine freely. The experimenter ensured that each child saw at least two activations of this familiarization machine.

The learning phase followed, and it began by the experimenter exclaiming, "Oh no! I just remembered that I have some work to do. While I'm doing my work, you can play with some of my toys!" The experimenter then laid out three plastic bins, each consisting of two identical machines together with their corresponding activator block (e.g., if the machines were being activated by a color rule, then the blue activator block was placed in the same plastic bin as the blue machines). The experimenter subsequently moved to a table and pretended to work, telling the child, "You can go ahead and play!" All three activator blocks and the three categories of machines were simultaneously available to the child, who was then given 5 min to play freely with the machines and blocks. After 5 min, the experimenter announced that she was done with her work and that it was time to put the toys away. The test phase that immediately followed was identical to that in Experiment 1.

Coding. The coding scheme used in Experiment 2 was identical to that of Experiment 1.

Results

Due to the free-play nature of Experiment 2, individual children's behaviors varied in the following dimensions: the number of activations for each category of machines ($M = 5.07$, $SD = 5.12$; recall that children in Experiment 1 each saw two activations per category of machines), and the number of times that negative evidence was generated, as defined by the number of times the child placed an activator block on a machine from a different bin ($M = 3.7$, $SD = 5.11$). We also found that 79% of the children activated every category of machines that was presented during the free-play phase (i.e., the set of activations presented in Experiment 1), and 42% of the children generated more evidence than what was presented to children in Experiment 1.

Children performed accurately under free play in Experiment 2, often selecting the correct block to activate the machines. Our results showed that 71% of the children chose the correct activator block in the first-order generalization test, exact binomial p (two-tailed) = .06, and 75% of the children chose the correct activator block in the second-order generalization test, exact binomial p (two-tailed) = .02. Note once again that we used a conservative criterion of .5 for the binomial test even though children were offered three activator choices in each test trial, as the children chose the shape-match (37%) or the color-match block (50%) more often than the distractor block (13%).

Using children's responses on the two test trials in Experiment 2, we performed a repeated measures logistic regression. Our results indicate that there were no effects of gender, age, trial order (first test trial vs. second test trial), presentation order of the training machines (e.g., whether machines from the different categories were presented first, second, or third during the training phase), and rule type (shape rule vs. color rule) on children's accuracy on the test trials. Critically, there was no difference between children's performance on the first-order and second-order generalization trials ($M = .75$, $SD = .44$), Wald Chi-Square = .13, $p = .71$.

Discussion

The results of Experiment 2 demonstrate that children can successfully acquire higher-order generalizations in the causal domain during the course of free play. However, the way to generate useful evidence in this experiment was quite transparent to the children—all they had to do was to place each block on top of the machines that were placed in the very same bin. Would children also learn successfully when the evidence generation process is more obscure?

Experiment 3

In Experiment 3, we increased the difficulty of the free-play task by handing the activator blocks directly to the child, such that the blocks were no longer presented together with their associated machines.

Method

Participants. Thirty-two English-speaking 2- to 3-year-olds (17 boys and 15 girls) with a mean age of 36.4 months (range = 30.3 to 44.4 months) were tested. All were recruited from Berkeley, California, and its surrounding communities. The sample was representative of the ethnic diversity in these communities: the participants were predominantly non-Hispanic White, with 16% Asian, 9% Hispanic, and 3% African American. An additional three children were tested but excluded due to parental intervention ($N = 1$), no attempts to make any activations ($N = 1$), or experimenter error ($N = 1$).

Materials and procedure. The materials and procedure used in Experiment 3 were identical to those of Experiment 2, except that after laying out the machines in three separate bins in the free-play phase, the experimenter handed the three activator blocks directly to the child.

Coding. Children's responses in the test trials of Experiment 3 were scored in the same way as that of Experiments 1 and 2.

Results

Just as in Experiment 2, individual children's behaviors varied in the following dimensions: the number of activations for each category of machines ($M = 18.81$, $SD = 16.08$), and the number of times that negative evidence was generated, as defined by the number of times the child placed an activator block on a machine that leads to a nonactivation ($M = 13.06$, $SD = 15.51$). Sixty-eight percent of the children activated every category of machines that was presented during the free play phase (i.e., the set of activations presented in Experiment 1); this group of children also all generated more evidence than the data presented to children in Experiment 1. Regression analyses found that the above variables were not significant predictors of children's overall accuracy at test: (a) the number of successful activations, $\beta = .043$, $t(28) = 1.28$, $p = .21$, (b) the number of negative evidence children generated, $\beta = -.05$, $t(28) = -1.31$, $p = .20$, and (c) the number of categories activated, $\beta = -.052$, $t(28) = -1.04$, $p = .31$.

Children also performed accurately under free play in Experiment 3, selecting the correct block to activate the machines. We found that 69% of the children chose the correct activator block in the first-order generalization test, exact binomial p (two-tailed) = .05, and 69% of the children chose the correct activator block in the second-order generalization test, exact binomial p (two-tailed) = .05. Note once again that we used a conservative criterion of .5 for the binomial test, even though children were offered three activator choices in each test trial, as the children chose the shape-match (42%) or the color-match block (45%) more often than the distractor block (13%).

A repeated measures logistic regression indicated that there were no effects of gender, age, trial order (first test trial vs. second test trial), presentation order of the training machines (e.g., whether machines from the different categories were presented first, second or third during the training phase), and rule type (shape rule vs. color rule) on children's accuracy on the test trials. Critically, there was no difference between children's performance on the first-order and second-order generalization trials, Wald Chi-Square = .0, p = 1.

An overall comparison also revealed that children's performance on the test trials did not differ across the three experiments. A repeated measures logistic regression with Experiment (1 vs. 2 vs. 3) as a between-subjects variable did not indicate Experiment to be a significant predictor of children's accuracy on the two test trials, Wald Chi-Square = .14, p = .71.

Discussion

The results of Experiment 3 replicated those of Experiment 2. Two- to 3-year-old children, in the course of free play, can generate the necessary data for their own learning; they were able to use the self-generated evidence to acquire higher-order generalizations, even when the data generation process was less transparent. The accuracy of their learning did not differ whether they were trained by an experimenter (Experiment 1), or allowed to play with the toys freely by themselves (Experiments 2 and 3).

Experiment 4

In Experiment 4, we tested another group of children in a baseline condition to address the possibility that children would be similarly successful at the generalization tests without any prior training or free play.

Method

Participants. Twelve English-speaking 2- to 3-year-olds (7 boys and 5 girls) with a mean age of 39.2 months (range = 30.0 to 44.6 months) were tested.[1] All participants were recruited from Berkeley, California, and its surrounding communities. The sample was representative of the ethnic diversity in these communities: the participants were predominantly non-Hispanic White, with 17% Asian, 17% Hispanic, and 8% African American. An additional two children were tested but excluded due to parental interference (N = 1) or experimenter error (N = 1).

Materials and procedure. The procedure of Experiment 4 consisted only of the test phase of Experiments 1–3. The test phase consisted of two test trials. For each test trial, the experimenter presented the child with one machine and said, "This machine makes a sound." She then provided the child with three choice blocks: a shape-match block, a color-match block, and a distractor, and asked, "Which block makes this machine go?"

Coding. Children's responses in the test trials of Experiment 4 were scored in the same way as that of Experiments 1–3.

Results

We used a criterion of .33 for the binomial tests. As Figure 2 shows, 33% of the children chose the correct activator block in the first-order generalization test, exact binomial p (two-tailed) = 1, and 42% of the children chose the correct activator block in the second-order generalization test, exact binomial p (two-tailed) = .55.

A repeated measures logistic regression indicated that there were no effects of gender, age, trial order (first test trial vs. second test trial), presentation order of the training machines (e.g., whether machines from the different categories were presented first, second, or third during the training phase), and rule type (shape rule vs. color rule) on children's accuracy on the test trials. Critically, there was no difference between children's performance on the first-order and second-order generalization trials, Wald Chi-Square = .21, p = .65.

An overall comparison across the four experiments with Experiment (1 vs. 2 vs. 3 vs. 4) as a between-subjects variable indicated Experiment to now be a significant predictor of children's accuracy on the two test trials, Wald Chi-Square = 4.22, p = .04.

Discussion

Children's accuracy in Experiment 4 differed from those in Experiments 1–3. This finding demonstrated that without any prior training or free play, children were not successful at the generalization tests.

General Discussion

The present study examined whether 2- and 3-year-old children can form higher-order generalizations in the causal domain based on self-generated evidence during the course of free play, or experimenter-generated evidence within a didactic learning context. The results demonstrate that children can do so: In Experiments 1–3, children as young as 2½ rapidly made first-order and second-order generalizations about how the machines and the activator blocks interacted with one another, and they extended these generalizations appropriately to novel toy machines. Furthermore, the accuracy of children's generalizations was comparable across the first three experiments, indicating that young children are equally effective in learning from both types of evidence. Experiment 4 provided a baseline measure, demonstrating that without prior training or free play, children would perform at chance levels on the generalization tests.

These results make several important contributions to the literature. First, previous research has documented that children, even infants, explore in a nonrandom manner, and they can learn from self-generated evidence under some circumstances. Here we show that even when children were not shown a confounded or surprising event (as in Bonawitz et al., 2012; Schulz & Bonawitz, 2007), and in the absence of explicit instructions, they can, in the course of free play, generate the relevant evidence in order to form appropriate higher-order generalizations.[2] This learning condition is much closer to what children encounter in the real world, where preschoolers are often allowed to play freely, and engage with whatever aspects of the environment they find interesting and appealing. Although the setup in Experiments 2 and 3 is more constrained than the free play one may observe in children's homes, we believe that it nonetheless captures the most important characteristic of free play, namely that no parent, teacher, or

[1] The sample size in this experiment was smaller as we had strong intuitions that children would not be successful at the generalization tests without any prior training or free play.

[2] We thank Elizabeth Bonawitz for this suggestion.

experimenter guides the play and learning process. Therefore, our results constitute new evidence that children's spontaneous exploratory play may indeed be motivated by their desire to understand what rules govern the behavior of the objects around them, in the service of developing larger conceptual structures that generate predictions and explanations.

Second, children's success in these experiments constitutes the first demonstration that data from children's free play supports the formation of higher-order generalizations. Our finding that children performed comparably in the first-order and second-order generalization tests is consistent with previous computational work with hierarchical Bayesian models demonstrating that abstract knowledge can be acquired very quickly with sparse data. At times, higher-order learning may even proceed faster than the learning of lower-level details (Simons & Keil, 1995), in what is known as the *blessing of abstraction*, because while specific data points provide evidence for lower-level generalizations, the entire set of data points provides evidence for higher-order generalizations (Kemp et al., 2007; Perfors et al., 2011; Tenenbaum et al., 2011). These findings therefore lend further empirical support to the *learning to learn* view (e.g., Griffiths & Tenenbaum, 2009; Kemp et al., 2007; Tenenbaum, Griffiths, & Niyogi, 2007), which argues that early input provides the basis for developing inductive constraints and biases, and that subsequent learning is guided by these learned constraints.

Third, and most importantly, this series of experiments investigates a key question in developing a constructivist theory of cognitive development: Given that conceptual structures and intuitive theories are built in the course of development, and given how actively engaged children are in their own learning from early on, are children capable of generating evidence themselves in support of building larger conceptual structures? The answer is clearly "yes", and even toddlers can do so as effectively as when they are provided with highly instructive evidence by an experimenter. Previous studies investigating how children acquire higher-order generalizations, which is one important mechanism by which children develop larger conceptual structures and intuitive theories, often take the form of providing children with the relevant data in the laboratory, and test to see if they have formed generalizations at multiple levels. In the real world, especially during the early years, children are rarely provided with such informative evidence by parents or caregivers. Instead, the child is largely on her own—playing and tinkering with toys and gadgets, pointing at objects they may want to learn more about, and asking questions that interest them. It is not obvious how these spontaneous activities facilitate learning, even though most of us have strong intuitions that they are likely to play an important role in development. The results of the current study demonstrate clearly that when children engage in free play (admittedly in an environment that is more controlled than a typical American middle-class family room), they spontaneously generate evidence that may be critical for conceptual development. This type of empirical evidence lends strong support to a constructivist view of cognitive development, and helps all students of cognitive development understand what it means for a child to be an *active*, *constructivist* learner.

Several aspects of our results merit further discussion, especially in the context of understanding the nature of active learning in early development and potential implications for education. Our findings also raise many questions for future research.

First, how do children generate data on their own? Our work leaves open the issue of why children performed just as well under free play as compared to a didactic learning context. Our analyses of children's choice of actions during the free play period in Experiment 3 did not reveal any relationship between children's generalization accuracy and (a) the number of successful activations, (b) the number of unsuccessful activations (i.e., negative evidence: observing that a block does not make the machine go), and (c) the number of categories of machines successfully activated. We speculate that one important reason for children's success under free play in Experiments 2 and 3 is that they successfully generated a superset of the evidence observed by children in Experiment 1, possibly through a trial-and-error approach. Given that the set of evidence presented in Experiment 1 was instructive in forming the appropriate higher-order generalizations, it is perhaps unsurprising that children in Experiments 2 and 3—who generated more relevant data themselves—were likewise able to perform well at test. Future work will more closely examine the systematicity of children's actions during the free-play period of Experiments 2 and 3, with one promising direction being information gain analyses. Information gain is a formal measure that quantifies how much uncertainty is reduced, with respect to the true hypothesis (e.g., in our studies, the shape or color rule that governs how the machines work), when a particular action is taken (Nelson, 2005). To engage effectively in hypothesis testing, learners should systematically choose actions that lead to the highest expected information gain. Such analyses may shed light on the underlying processes that drive children's actions during free play, and give insight about how engaging in free play may lead to learning and generalization, as demonstrated in the present study. At the same time, we note that such an analysis would be neither straightforward nor comprehensive. It is not clear that every action that children take during free play is about hypothesis testing. For example, 2- and 3-year-old children in our study often repeated their actions during free play, especially after successfully activating a machine. Repetitions provide no new information when it comes to learning about a deterministic system, but they do generate a lot of joy and excitement. When it comes to free play, the learner may have at least two competing goals: (a) to learn about the system that one is interacting with, and (b) to enjoy that very interaction. Given these different goals, it remains to be seen how children's actions during free play can be properly analyzed (see Coenen, Rehder, & Gureckis, 2015 for discussion of similar issues in adults).

Second, are there any developmental changes in the capacity to learn through self-generated evidence in the causal domain? Preliminary results with 19-month-olds suggest "yes" (Sim & Xu, 2015). When 19-month-old infants were tested in procedures similar to Experiments 1 and 2, we found a different picture: these toddlers produced chance performance whether they were directly provided with instructive evidence or given a free-play opportunity. When their play was facilitated by an experimenter or a parent, we found instead that these toddlers were able to acquire the appropriate higher-order generalizations like the 2- and 3-year-olds in the present study. It is noteworthy that these preliminary results align very well with Fisher et al. (2013). In their study, when 4- to 5-year-olds were allowed to engage in free play, they failed to extract the definitional properties of geometric shapes (e.g., all triangles have three sides and three angles) despite being provided with enriched materials. In contrast, children who engaged in guided play, where an adult experimenter was present to scaffold their learning (e.g., guiding children to "discover" the definitional properties of triangles as having three sides and three angles), showed a robust improvement in their shape knowledge with relatively little decline over a 1-week period.

At the same time, the striking difference we found between the 19-month-old infants and the 2- and 3-year-old toddlers begs the question of what would explain the developmental change. Was the task too open-ended for the 19-month-old infants, who presumably have less well-formed prior beliefs to constrain the hypothesis space, as compared to the toddlers?[3] Or do they not understand what constitutes evidence and how to generate it through their own actions? As Weisberg, Hirsh-Pasek, Golinkoff, and McCandliss (2014) explain, guided play is an example of an adult-structured *mise en place* (i.e., an environment that prepares and nudges children toward engaging in particular types of actions), and having such a *mise* may be especially important for younger children who have poorer proactive control mechanisms as compared to their older counterparts. More research is necessary to better understand how this capacity may develop and interact with contextual factors over early childhood.

Lastly, how do our findings bear on the debate on discovery learning in education? The findings of the present study may appear inconsistent with previous work in the field of education suggesting that free play (also known as "pure discovery" or "unassisted discovery"), as an instructional method, leaves little to be desired (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011; Chien et al., 2010; Kirschner, Sweller, & Clark, 2006; Mayer, 2004; Weisberg, Hirsh-Pasek, & Golinkoff, 2013). However, it should be noted that many of these education studies focus on academic content—domains such as literacy, mathematics, and science. While these domains are appropriate for investigating the effectiveness of different instructional methods in preschool and school settings, they may not be the best candidates for revealing a natural capacity for young children to learn from evidence that they independently generate through free play. Reasoning about causal relations, on the other hand, is fundamental and central to building intuitive theories without formal instruction, and consequently, causal knowledge may thus be a domain in which young children can effectively learn about through free play. In contrast, it is highly unlikely that young children can discover mathematical concepts when they play with math-related objects by themselves (Fisher et al., 2013; Sarama & Clements, 2009b). In addition, pure discovery or unassisted discovery tasks within education are likely to be more complex and open-ended, resulting in a much larger set of possible hypotheses that children would have to sift through, as compared to our free play task in Experiments 2 and 3, where the hypothesis space is relatively constrained and children were somewhat limited in their choice of actions. We suggest that a child's capacity to learn from self-generated evidence is likely to be strongly influenced by both the domain and the complexity of the learning task. Future work is needed to more closely examine the cognitive and task factors that influence children's success in these different learning contexts.

In summary, the present study provides strong evidence that young children are motivated to understand the world, and their exploratory behavior supports learning that goes beyond figuring out properties of individual objects ("Does pushing this button make the toy play music?"). Children are able to generate the relevant evidence on their own that supports the learning of higher-order generalizations ("What kinds of buttons would make what kinds of toys play music?"), which lays the foundation for building larger conceptual structures and intuitive theories. Future research will investigate the optimality of the active learning that children partake in, as well as its limits, to shed light on how early learning occurs in the real world.

[3] We thank the anonymous reviewers for this suggestion.

References

Adolph, K. E., Eppler, M. A., & Gibson, E. J. (1993). Development of perception of affordances. *Advances in Infancy Research, 8,* 51–98.

Alfieri, L., Brooks, P., Aldrich, N. J., & Tenenbaum, H. R. (2012). Does discovery-based instruction enhance learning? A meta-analysis. *Journal of Educational Psychology, 103,* 1–18.

Bergen, D., & Mauer, D. (2000). Symbolic play, phonological awareness, and literacy skills at three age levels. In K. A. Roskos & J. F. Christie (Eds.), *Play and literacy in early childhood: Research from multiple perspectives* (pp. 45–62). Mahwah, NJ: Lawrence Erlbaum.

Bonawitz, E. B., van Schijndel, T. J. P., Friel, D., & Schulz, L. (2012). Children balance theories and evidence in exploration, explanation, and learning. *Cognitive Psychology, 64,* 215–234. http://dx.doi.org/10.1016/j.cogpsych.2011.12.002

Bruner, J. (1961). The act of discovery. *Harvard Educational Review, 31,* 21–32.

Bruner, J., Jolly, A., & Sylva, K. (1976). *Play: Its role in development and evolution*. New York, NY: Wiley.

Carey, S. (1985). *Conceptual change in childhood*. Cambridge, MA: MIT Press.

Carey, S. (2009). *The origin of concepts*. New York, NY: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780195367638.001.0001

Chien, N. C., Howes, C., Burchinal, M., Pianta, R. C., Ritchie, S., Bryant, D. M., . . . Barbarin, O. A. (2010). Children's classroom engagement and school readiness gains in prekindergarten. *Child Development, 81,* 1534–1549. http://dx.doi.org/10.1111/j.1467-8624.2010.01490.x

Chouinard, M. M. (2007). Children's questions: A mechanism for cognitive development. *Monographs of the Society for Research in Child Development, 72,* vii–ix, 1–112.

Coenen, A., Rehder, B., & Gureckis, T. M. (2015). Strategies to intervene on causal systems are adaptively selected. *Cognitive Psychology, 79,* 102–133. http://dx.doi.org/10.1016/j.cogpsych.2015.02.004

Cook, C., Goodman, N. D., & Schulz, L. E. (2011). Where science starts: Spontaneous experiments in preschoolers' exploratory play. *Cognition, 120,* 341–349. http://dx.doi.org/10.1016/j.cognition.2011.03.003

Dewar, K. M., & Xu, F. (2010). Induction, overhypothesis, and the origin of abstract knowledge. Evidence from 9-month-old infants. *Psychological Science, 21,* 1871–1877. http://dx.doi.org/10.1177/0956797610388810

Fisher, K. R., Hirsh-Pasek, K., Newcombe, N., & Golinkoff, R. M. (2013). Taking shape: Supporting preschoolers' acquisition of geometric knowledge through guided play. *Child Development, 84,* 1872–1878. http://dx.doi.org/10.1111/cdev.12091

Frazier, B. N., Gelman, S. A., & Wellman, H. M. (2009). Preschoolers' search for explanatory information within adult–child conversation. *Child Development, 80,* 1592–1611. http://dx.doi.org/10.1111/j.1467-8624.2009.01356.x

Gerken, L., Balcomb, F. K. F., & Minton, J. L. J. (2011). Infants avoid 'labouring in vain' by attending more to learnable than unlearnable linguistic patterns. *Developmental Science, 14,* 972–979. http://dx.doi.org/10.1111/j.1467-7687.2011.01046.x

Gibson, E. (1988). Exploratory behavior in the development of perceiving, acting, and the acquiring of knowledge. *Annual Review of Psychology, 39,* 1–42. http://dx.doi.org/10.1146/annurev.ps.39.020188.000245

Goodman, N. (1955). The new riddle of induction. In N. Goodman, *Fact, fiction and forecast* (pp. 59–83). Cambridge, MA: Harvard University Press.

Gopnik, A. (2012). Scientific thinking in young children: Theoretical advances, empirical research, and policy implications. *Science, 337,* 1623–1627. http://dx.doi.org/10.1126/science.1223416

Gopnik, A., Glymour, C., Sobel, D. M., Schulz, L. E., Kushnir, T., & Danks, D. (2004). A theory of causal learning in children: Causal maps and Bayes nets. *Psychological Review, 111,* 3–32. http://dx.doi.org/10.1037/0033-295X.111.1.3

Gopnik, A., & Meltzoff, A. N. (1997). *Words, thoughts, and theories*. Cambridge, MA: MIT Press.

Gopnik, A., & Sobel, D. M. (2000). Detecting blickets: How young children use information about novel causal powers in categorization and induction. *Child Development, 71,* 1205–1222. http://dx.doi.org/10.1111/1467-8624.00224

Gopnik, A., Sobel, D. M., Schulz, L. E., & Glymour, C. (2001). Causal learning mechanisms in very young children: Two-, three-, and four-year-olds infer causal relations from patterns of variation and covariation. *Developmental Psychology, 37,* 620–629. http://dx.doi.org/10.1037/0012-1649.37.5.620

Gopnik, A., & Wellman, H. M. (2012). Reconstructing constructivism: Causal models, Bayesian learning mechanisms, and the theory theory. *Psychological Bulletin, 138,* 1085–1108. http://dx.doi.org/10.1037/a0028044

Griffiths, T. L., & Tenenbaum, J. B. (2009). Theory-based causal induction. *Psychological Review, 116,* 661–716. http://dx.doi.org/10.1037/a0017201

Gweon, H., Tenenbaum, J. B., & Schulz, L. E. (2010). Infants consider both the sample and the sampling process in inductive generalization. *Proceedings of the National Academy of Sciences of the United States of America, 107,* 9066–9071. http://dx.doi.org/10.1073/pnas.1003095107

Hirsh-Pasek, K., Golinkoff, R. M., Berk, L. E., & Singer, D. (2008). *A mandate for playful learning in preschool: Applying the scientific evidence*. New York, NY: Oxford Press. http://dx.doi.org/10.1093/acprof:oso/9780195382716.001.0001

Kemp, C., Perfors, A., & Tenenbaum, J. B. (2007). Learning overhypotheses with hierarchical Bayesian models. *Developmental Science, 10,* 307–321. http://dx.doi.org/10.1111/j.1467-7687.2007.00585.x

Kemp, C., & Tenenbaum, J. B. (2009). Structured statistical models of inductive reasoning. *Psychological Review, 116,* 20–58. http://dx.doi.org/10.1037/a0014282

Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2012). The Goldilocks effect: Human infants allocate attention to visual sequences that are neither too simple nor too complex. *PLoS One, 7*(5), e36399. http://dx.doi.org/10.1371/journal.pone.0036399

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist, 41,* 75–86. http://dx.doi.org/10.1207/s15326985ep4102_1

Landau, B., Smith, L., & Jones, S. (1988). The importance of shape in early lexical learning. *Cognitive Development, 3,* 299–321. http://dx.doi.org/10.1016/0885-2014(88)90014-7

Legare, C. H. (2012). Exploring explanation: Explaining inconsistent evidence informs exploratory, hypothesis-testing behavior in young children. *Child Development, 83,* 173–185. http://dx.doi.org/10.1111/j.1467-8624.2011.01691.x

Legare, C. H., Mills, C. M., Souza, A. L., Plummer, L. E., & Yasskin, R. (2013). The use of questions as problem-solving strategies during early childhood. *Journal of Experimental Child Psychology, 114,* 63–76. http://dx.doi.org/10.1016/j.jecp.2012.07.002

Macario, J. F., Shipley, E. F., & Billman, D. O. (1990). Induction from a single instance: Formation of a novel category. *Journal of Experimental Child Psychology, 50,* 179–199. http://dx.doi.org/10.1016/0022-0965(90)90038-A

Mayer, R. E. (2004). Should there be a three-strikes rule against pure discovery learning? The case for guided methods of instruction. *American Psychologist, 59,* 14–19. http://dx.doi.org/10.1037/0003-066X.59.1.14

Needham, A. (2000). Improvements in object exploration skills may facilitate the development of object segregation in early infancy. *Journal of Cognition and Development, 1,* 131–156. http://dx.doi.org/10.1207/S15327647JCD010201

Nelson, J. D. (2005). Finding useful questions: On Bayesian diagnosticity, probability, impact, and information gain. *Psychological Review, 112,* 979–999. http://dx.doi.org/10.1037/0033-295X.112.4.979

Perfors, A., Tenenbaum, J. B., Griffiths, T. L., & Xu, F. (2011). A tutorial introduction to Bayesian models of cognitive development. *Cognition, 120,* 302–321. http://dx.doi.org/10.1016/j.cognition.2010.11.015

Piaget, J. (1954). *The construction of reality in a child*. New York, NY: Basic Books. http://dx.doi.org/10.1037/11168-000

Roskos, K., Christie, J. F., Widman, S., & Holding, A. (2010). Three decades in: Priming for meta-analysis in play-literacy research. *Journal of Early Childhood Literacy, 10,* 55–96. http://dx.doi.org/10.1177/1468798409357580

Samuelson, L. K. (2002). Statistical regularities in vocabulary guide language acquisition in connectionist models and 15–20-month-olds. *Developmental Psychology, 38,* 1016–1037. http://dx.doi.org/10.1037/0012-1649.38.6.1016

Sarama, J., & Clements, D. H. (2009a). Building blocks and cognitive building blocks: Playing to know the world mathematically. *American Journal of Play, 1,* 313–337.

Sarama, J., & Clements, D. H. (2009b). "Concrete" computer manipulatives in mathematics education. *Child Development Perspectives, 3,* 145–150. http://dx.doi.org/10.1111/j.1750-8606.2009.00095.x

Schulz, L. E., & Bonawitz, E. B. (2007). Serious fun: Preschoolers engage in more exploratory play when evidence is confounded. *Developmental Psychology, 43,* 1045–1050. http://dx.doi.org/10.1037/0012-1649.43.4.1045

Seo, K.-H., & Ginsburg, H. P. (2004). What is developmentally appropriate in early childhood mathematics education? Lessons from new research. In D. H. Clements, J. Sarama, & A.-M. DiBiase (Eds.), *Engaging young children in mathematics: Standards for early childhood mathematics education* (pp. 91–104). Mahwah, NJ: Lawrence Erlbaum.

Shipley, E. F. (1993). Categories, hierarchies, and induction. *Psychology of Learning and Motivation, 30,* 265–301. http://dx.doi.org/10.1016/S0079-7421(08)60299-6

Sim, Z., & Xu, F. (2015). Toddlers learn with facilitated play, not free play. In D. C. Noelle, R. Dale, A. S. Warlaumont, J. Yoshimi, T. Matlock, C. D. Jennings, & P. P. Maglio (Eds.), *Proceedings of the 37th Annual Meeting of the Cognitive Science Society* (pp. 2200–2205). Austin, TX: Cognitive Science Society.

Simons, D. J., & Keil, F. C. (1995). An abstract to concrete shift in the development of biological thought: The insides story. *Cognition, 56,* 129–163. http://dx.doi.org/10.1016/0010-0277(94)00660-D

Singer, D., Hirsh-Pasek, K., & Golinkoff, R. M. (2009). *Play=learning: How play motivates and enhances children's cognitive and social-emotional growth*. New York, NY: Oxford University Press.

Smith, L. B. L., Jones, S. S., Landau, B., Gershkoff-Stowe, L., & Samuelson, L. (2002). Object name learning provides on-the-job training for attention. *Psychological Science, 13,* 13–19. http://dx.doi.org/10.1111/1467-9280.00403

Sobel, D. M., & Kirkham, N. Z. (2006). Blickets and babies: The development of causal reasoning in toddlers and infants. *Developmental Psychology, 42,* 1103–1115. http://dx.doi.org/10.1037/0012-1649.42.6.1103

Sobel, D. M., & Sommerville, J. A. (2010). The importance of discovery in children's causal learning from interventions. *Frontiers in Psychology, 1,* 176. http://dx.doi.org/10.3389/fpsyg.2010.00176

Stahl, A. E., & Feigenson, L. (2015). Observing the unexpected enhances infants' learning and exploration. *Science, 348,* 91–94. http://dx.doi.org/10.1126/science.aaa3799

Sylva, K., Bruner, J., & Genova, P. (1974). The role of play in the problem-solving of children 3–5 years old. In J. S. Bruner, A. Jolly, & K. Sylva (Eds.), *Play: Its role in development and evolution* (pp. 244–257). Harmondsworth, UK: Penguin.

Tenenbaum, J. B., Griffiths, T. L., & Niyogi, S. (2007). Intuitive theories as grammars for causal inference. In A. Gopnik & L. E. Schulz (Eds.), *Causal learning: Psychology, philosophy, and computation* (pp. 301–322). New York, NY: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780195176803.003.0020

Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. *Science, 331,* 1279–1285. http://dx.doi.org/10.1126/science.1192788

Vygotsky, L. S. (1978). The role of play in development. In M. Cole (Trans.), *Mind in society* (pp. 92–104). Cambridge, MA: Harvard University Press.

Walker, C. M., & Gopnik, A. (2014). Toddlers infer higher-order relational principles in causal learning. *Psychological Science, 25,* 161–169. http://dx.doi.org/10.1177/0956797613502983

Weisberg, D. S., Hirsh-Pasek, K., & Golinkoff, R. M. (2013). Guided play: Where curricular goals meet a playful pedagogy. *Mind, Brain and Education, 7,* 104–112. http://dx.doi.org/10.1111/mbe.12015

Weisberg, D. S., Hirsh-Pasek, K., Golinkoff, R. M., & McCandliss, B. D. (2014). Mise en place: Setting the stage for thought and action. *Trends in Cognitive Sciences, 18,* 276–278. http://dx.doi.org/10.1016/j.tics.2014.02.012

Wellman, H. M., & Gelman, S. A. (1992). Cognitive development: Foundational theories of core domains. *Annual Review of Psychology, 43,* 337–375. http://dx.doi.org/10.1146/annurev.ps.43.020192.002005

Xu, F., Dewar, K. M., & Perfors, A. (2009). Induction, overhypotheses, and the shape bias: Some arguments and evidence for rational constructivism. In B. M. Hood & L. R. Santos (Eds.), *The origins of object knowledge* (pp. 263–284). New York, NY: Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780199216895.003.0011

Xu, F., & Kushnir, T. (2012). *Advances in child development and behavior: Rational constructivism in cognitive development*. Waltham, MA: Elsevier.

Xu, F., & Kushnir, T. (2013). Infants are rational constructivist learners. *Current Directions in Psychological Science, 22,* 28–32. http://dx.doi.org/10.1177/0963721412469396

Received December 8, 2015
Revision received November 8, 2016
Accepted November 16, 2016 ■