Psychological Review

# Play in Predictive Minds: A Cognitive Theory of Play

Marc Malmdorf Andersen, Julian Kiverstein, Mark Miller, and Andreas Roepstorff

Online First Publication, June 16, 2022. http://dx.doi.org/10.1037/rev0000369

AMERICAN PSYCHOLOGICAL ASSOCIATION

Psychological Review


ISSN: 0033-295X

https://doi.org/10.1037/rev0000369

# Play in Predictive Minds: A Cognitive Theory of Play

Marc Malmdorf Andersen[1, 2], Julian Kiverstein[3], Mark Miller[4, 5], and Andreas Roepstorff[1, 2]
[1] Interacting Minds Centre, Aarhus University
[2] School of Culture and Society, Aarhus University
[3] Department of Psychiatry, Amsterdam University Medical Centre
[4] Center for Human Nature, Artificial Intelligence and Neuroscience, Hokkaido University
[5] Centre for Consciousness and Contemplative Studies, Monash University

In this article, we argue that a predictive processing framework (PP) may provide elements for a proximate model of play in children and adults. We propose that play is a behavior in which the agent, in contexts of freedom from the demands of certain competing cognitive systems, deliberately seeks out or creates surprising situations that gravitate toward sweet-spots of relative complexity with the goal of resolving surprise. We further propose that play is experientially associated with a feel-good quality because the agent is reducing significant levels of prediction error (i.e., surprise) faster than expected. We argue that this framework can unify a range of well-established findings in play and developmental research that highlights the role of play in learning, and that casts children as Bayesian learners. The theory integrates the role of positive valence in play (i.e., explaining why play is fun); and what it is to be in a playful mood. Central to the account is the idea that playful agents may create and establish an environment tailored to the generation and further resolution of surprise and uncertainty. Play emerges here as a variety of niche construction where the organism modulates its physical and social environment in order to maximize the productive potential of surprise.

*Keywords:* play, learning, predictive processing, surprise, niche construction



Why do humans play? For well over 100 years, this question has attracted the attention of researchers from a wide range of disciplines. This may be because play, despite its omnipresence, is one of the few human universals that does not seem to have an obvious immediate benefit to the player visible to outside observers (Martin & Caro, 1985). In spite of this mystery and the longstanding scientific scrutiny it has attracted, play has yet to become a central topic in the field of child development (Lillard, 2015; Pellegrini, 2011a). This may be attributable both to the lack of a unifying theoretical framework for play, and the lack of well-developed methodologies for approaching the phenomenon in general. By its very nature, play is difficult to study: It is spontaneous, and it exists in endless and highly diversified forms (e.g., Sutton-Smith, 1997; Zosh et al., 2018). Historically, this has not only made play very challenging to capture and define (Burghardt, 2011), but has also seriously hampered efforts to systematically study play through well-controlled research paradigms (Gopnik, 2016).

Despite such difficulties, there is overall consensus on a series of play-related issues. For instance, play is generally understood to be a spontaneous, internally motivated behavior exclusively initiated by individuals who are free from sickness, stress, and hunger (Burghardt, 2005) and, typically, it is experientially associated with positive feelings (Bateson & Martin, 2013). Interspecies biological comparisons have shown that the most playful animal species tend to mature more slowly, and have larger brains, increased intelligence and good learning abilities (Gopnik, 2016). Furthermore, there is widespread agreement that young individuals tend to play more than older individuals (e.g., Bateson & Martin, 2013).

Theories abound as to why humans (and a series of other highly intelligent, often social, animals with prolonged childhoods) play. Many of these theories are evolutionary in nature, and propose ultimate causes for the development of play. For this reason, most of these theories concern how various aspects of play increase the individual's odds of surviving and reproducing. Most such theories assume that because play requires organisms to spend energy and, in many cases, to engage in behavior which is risky and sometimes outright dangerous, play must enhance fitness in other ways (Bateson & Martin, 2013).

Accordingly, the dominant themes across most evolutionary accounts of play are based on the widely held assumption that play helps young animals (including humans) to acquire the skills they need to become more efficient adults. For example, it has variously been hypothesized that play expedites the development of adult musculature (Groos, 1898), improves physical balance (Fagan, 1981), practices coordination and complex movements (Baldwin & Baldwin, 1977), assists in the acquisition of communication skills (Poirier & Smith, 1974), helps to construct a working knowledge of the environment (Bateson, 2017), trains the organism for unexpected situations (Spinka et al., 2001), and helps develop crucial social skills necessary for maintaining social relationships (Bekoff, 1976). Nonadaptive theories also exist: Burghardt's Resource Surplus Theory, for instance, suggests that play may have emerged as a by-product

Marc Malmdorf Andersen https://orcid.org/0000-0001-8228-899X
Julian Kiverstein https://orcid.org/0000-0003-3428-8367
Andreas Roepstorff https://orcid.org/0000-0002-3665-1708

This work was supported by the Lego Foundation, The Horizon 2020 European Union ERC Advanced Grant XSPECT (DLV-692739), The H2020 ERC starting grant (679190), and the Netherlands Scientific Organisation grant.

The authors have no known conflict of interest to disclose.

Correspondence concerning this article should be addressed to Marc Malmdorf Andersen, School of Culture and Society, Aarhus University, Room 423, 4th floor, Building 1483, Jens Christian Skous Vej 4, 8000 Aarhus C, Denmark. Email: mana@cas.au.dk

of surplus resources, including metabolisms capable of sustained activity, copious food supplies, and a surfeit of parental protection (Burghardt, 2005).

In addition to such ultimate evolutionary accounts of play and its possible benefits (for a review, see Baldwin & Baldwin, 1977; Bateson & Martin, 2013; Burghardt, 2005), there are also several cognitive and proximate accounts of why children play. For example, it has variously been hypothesized that pretend play is a manifestation of a developing ability to think counterfactually (Gopnik, 2009; Lillard, 2001), of a developing capacity for metarepresentation (Leslie, 1987), or that pretend play assists and develops the imagination and a range of cognitive functions (Singer & Singer, 1990). In recent decades, the *theory theory*, the idea that everyday knowledge has similar properties to scientific theories, has been particularly influential. Here it has been suggested that play is a form of informal experimentation (e.g., Gopnik & Wellman, 2012) that allows children to optimize information gain and learn more about themselves and the world around them (e.g., Bonawitz et al., 2012; Cook et al., 2011). In most of these cognitive accounts of play, the explanation for why children play is the same: Children play because playing is fun and rewarding.

A consistent theme of this research is that children are motivated to play by their curiosity (Kidd & Hayden, 2015). Children play to actively learn, seeking experiences for themselves that allow them to gain new information. Play is therefore *intrinsically* motivating: The information the child gains is valued as a good in itself, not as a means to some other valued or rewarding end. What makes this information valuable is the progress it enables the child to make in its learning (Gottlieb et al., 2016; Oudeyer et al., 2007; Oudeyer & Smith 2016). Some theorists understand this learning progress in terms of theory construction. Infants, it has been argued, playfully explore when their intuitive theories of how the world works are violated (Stahl & Feigenson, 2019) and children's exploratory play supports causal learning (Gweon & Schulz, 2011; Schulz et al., 2007; Schulz, 2012). What is less clear from these cognitive accounts of play as an intrinsically rewarding behavior is why play should be fun? After all, while formal educational settings abound with facilitated learning opportunities for children, boredom among students is still a very frequently observed phenomenon. What is it about information gain and uncertainty reduction in play that accounts for it being so much fun?

In a recent account of human play, it has been argued that information gain cannot be the whole explanation of why children play (Chu & Schulz, 2020). In play, children often create imaginary problems for themselves they have no obvious need to solve, yet children will expend a good deal of energy with no obvious payoff for doing so. Chu and Schulz contend that "children's propensity to adopt idiosyncratic goals may be what distinctively human play is all about" (p. 327). They argue that what is distinctive about human play is the way in which children intervene on their own utility functions, fixing their own rewards in setting novel goals for themselves. In doing so they are able to creatively explore a space of hypotheses, inventing new ideas and plans that would otherwise never occur to them. The value of this kind of play lies in the potential it offers for innovation (Chu & Schulz, 2020, p. 329). Still, this account of distinctively human play fails to account for why the activity of setting arbitrary goals is so much fun.

In this article, we argue that a recent neurocognitive and computational framework, commonly referred to as "predictive processing," is consistent with, but also brings important new insights into, the field of play research. In its most ambitious form, the predictive processing framework (PP) attempts to explain perception, action, emotion, cognition, and their intertwined relationships via a single mechanism of prediction error minimization, whereby the brain attempts to reduce the mismatch between how it predicts the world to be and how the world actually is (Clark, 2013; Friston, 2010; Hohwy, 2013). We argue that the predictive processing framework may provide elements for a proximate cognitive theory of play that can help explain the widespread occurrence of play across form, age, and context. The universal occurrence of play across such a wide range of behavioral forms (e.g., playful object handling, playful running, playful eating, and so on) could be taken to suggest that play may be linked to domain-general cognitive processes rather than to highly specific tasks and domains. The predictive processing framework describes a domain-general neurocognitive architecture that holds the promise of providing a unifying explanation of the rich variety of forms of play in children.

Utilizing this framework, we propose that *play is a behavior in which the agent, in contexts of freedom from the demands of certain competing cognitive systems, deliberately seeks out or creates surprising situations that gravitate toward sweet-spots of relative complexity with the goal of resolving surprise. We further propose that play is experientially associated with a feel-good quality because the agent is reducing significant levels of prediction error (i.e., surprise) faster than expected.* Such a strategy of seeking and creating surprising situations, we argue, is in many ways optimal for learning in that it not only maximizes the speed at which learning takes place, but also enables optimized learning strategies, even in instances where opportunities to learn may be scarce.

We argue that this framework can unify a range of well-established as well as seemingly contradictory perspectives on play. This includes play as a behavior aiming to maximize information gain as well as play as a behavior where individuals incur unnecessary costs in pursuit of seemingly pointless goals. Furthermore, the theory integrates the role of positive valence in play, that is, it explains why play is fun; and it expands on the relationship between emotions and mood states, that is, playfulness, as they often occur in the context of play.

Finally, we argue that this understanding of play may cast light on an understudied aspect of predictive processing: It not only identifies play as a particular behavioral and cognitive strategy allowing the organism to seek out and reduce uncertainty, but further adds that the organism may create and establish an environment tailored to the generation and further investigation of surprise and uncertainty. Play can thus be described as a variety of niche construction where the organism modulates its physical and social environment in order to maximize the productive potential of surprise.

## Play and Surprise

A consistent theme in cognitive theories of play is that children are motivated to play to make progress in learning, reducing their uncertainty, and allowing them to better predict the effects of their actions on the world (Chu & Schulz, 2020; Gottlieb et al., 2013; Kidd & Hayden, 2015; Wang et al., 2021). The motivation to seek new and surprising information that, in turn, reduces uncertainty is by no means exclusive to humans. It has been known for some time that a wide range of different animals forgo immediate reward in order to gain information (e.g., Nissen, 1930). There is widespread evidence that animals value information as a good in itself, and not only instrumentally to maximize longer term gains (Blanchard et al., 2015; Gottlieb & Oudeyer, 2018; Pellegrini et al., 2007; Spinka et al., 2001; Vasconcelos et al., 2015). The curiosity of humans and other animals is sparked by specific questions that promise to dispel uncertainty thereby closing a gap in knowledge and understanding (Loewenstein, 1994). Through their own activity, humans and animals selectively sample the environment in search of useful information that offers the potential to reduce uncertainty and resolve surprises. An estimate of high expected information gain motivates them to sample only the information that is relevant to closing a knowledge gap. Closing such gaps is functionally important both for humans and animals as it allows them to learn a model of the causal structure and workings of the world. In other words, organisms assign value to specific changes in cognitive states independent of instrumental or extrinsic reward (Gottlieb & Oudeyer, 2018). In artificial intelligence it has been shown that approximating such curiosity-driven, active learning can allow a robot to learn tasks in which rewards are unknown and scarce (Barto et al., 2013; Friston, Lin, et al., 2017; MacKay, 1992; Oudeyer et al., 2007; Pathak et al., 2017; Schmidhuber, 1991, 2006, 2013; Sun et al., 2011).

The motivation to gain new information that reduces overall uncertainty in play suggests that children should be attracted toward novelty, ambiguity, and surprise in play. One contemporary account, authored by Spinka et al. (2001), proposes a functional hypothesis of play in mammals which emphasizes the deliberate cultivation of unexpected situations. These authors argue that play fighting and locomotor play are forms of "training for the unexpected," and that they allow mammals to develop flexible motor responses and emotional coping strategies for unexpected situations. Spinka et al argue that mammals "actively seek and create unexpected situations in play through self-handicapping; [ . . . ] actively putting themselves into disadvantageous positions and situations" (Spinka et al., 2001, p. 141). We are very much in agreement, and we will suggest later that in humans these practices of deliberate self-disadvantaging extend far beyond play fighting and locomotor play.

In recent decades, a series of experimental studies on exploratory play have further explored the relationship between surprise, uncertainty, and play. Bonawitz et al. (2012) conducted a study in which children were allowed to explore an asymmetrically weighted beam designed to balance on a fulcrum. The fulcrum was designed in such a way that hidden magnets were able to hold the asymmetrical beam in place, even at times where the beam should have normally tipped over (Bonawitz et al., 2012). Children were assigned to one of two conditions where the balance beam was either consistent with, or in violation of, the children's beliefs about balance relationships. The experimenter then found a novel toy and placed both the balanced beam and the novel toy in front of the child and left the child to play on its own. The researchers found that children that had their beliefs confirmed exhibited the standard novelty preference and played more with the new toy than the balance beam. The children that had their beliefs violated, however, did not exhibit this novelty preference, and instead played more with the balance beam than the novel toy. In other words, children in both conditions played with the object that showed the greatest potential to violate their beliefs (i.e., to surprise them).

In another study by Schulz and Bonawitz (2007) using a free-play paradigm, 64 preschoolers (mean: 57 months) were presented with a toy box with two levers on it. One lever caused a small fuzzy duck figure to appear out of hole in the top of the box and the second lever caused a small puppet to emerge. In the experiment, some children were assigned to a "confounded condition" in which the causal structure of the toy box was confounded. Controlling for various artifacts such as the number of trials and number of lever presses, the remaining children were assigned to different versions of an "unconfounded condition," all of which enabled the children to learn which lever was connected to the duck and which was connected to the puppet. In both conditions, the experimenter then presented the child with a second, novel toy box with only one lever, placing both the old and the new toy box in front of the child and leaving her to play alone. The study found that children on a variety of measures were more likely to play with the familiar toy in the confounded condition than in the unconfounded conditions (Schulz & Bonawitz, 2007). Again, this supports the idea that one of the guiding principles in children's exploratory play is to seek out toys associated with uncertainty and attempt to reduce that uncertainty during play.

Similarly, Schulz et al. (2008) across four studies demonstrated that preschoolers, in their play, selectively engaged in exploration when evidence about objects' causal properties conflicted with inductive generalizations from the objects' kind to their causal powers. In other words, children who were surprised with objects, which should belong to a certain category but did not work in the same manner as other objects within the category, spent more time playing with those objects compared with objects that acted in a manner consistent with their category. While such studies nicely illustrate how children optimize their chances of discovering novel information by flexibly shifting from inductive inference to trial-and-error learning, these studies also highlight again the basic idea that children will play more with objects that are somehow associated with violation of belief (i.e., surprise).

Other experiments have shown similar effects of belief violation (i.e., surprise) on young children's play. For example, using a shadow play paradigm, van Schijndel et al. (2015) introduced children to a shadow machine, where children could place differently sized puppets at different distances from a light source, resulting in differently sized shadows on a screen. In this study, results revealed that children who were surprised by the sizes of the shadow figures were more likely to perform an unconfounded informative experiment in the beginning of their play, compared with children who were not surprised. In two studies, Butler and Markman (2010) investigated the effects of pedagogical cues on 3- to 4-year-old children's explorative playful behavior and found evidence to suggest that children build stronger expectations when intentionally instructed on an object's causal property by an adult than when the same causal property is demonstrated by accident. In turn, children were more surprised when encountering conflicting evidence to such intentional demonstrations, resulting in more and deeper forms of exploratory play (Butler & Markman, 2010).

Similar findings have been documented as early as infanthood. Indeed, in their seminal work, Stahl and Feigenson (2015) showed 11-month-old infants events that violated expectations about object behavior and nearly identical events that did not violate expectations. They found that infants who had previously seen an object behave in an unexpected way were more likely to explore that object in their ensuing play. Intriguingly, the infants seemed to not only explore these objects in broad manners, but in ways that were specific to the violation they had just witnessed. Moreover, Stahl & Feigenson were able to demonstrate, while controlling for overall attention that the infants were more likely to learn a new sound associated with an object if that object had acted in a surprising manner. Stahl & Feigenson argue that such surprises are a driver that "propels children—even infants—to form and test new hypotheses about surprising aspects of the world" (Stahl & Feigenson, 2019). Crucially, this drive seems mediated by the goal of forming and testing new hypotheses in order to resolve surprise. Indeed, Perez & Feigenson recently demonstrated that while infants increase exploratory play when encountering surprising objects, this surprise-induced exploration is abolished if the infants are provided with an explanation about why the object was behaving in a surprising manner (Perez & Feigenson, 2020).

In adults, a recent study on playfulness involved presenting adult participants with a building task using LEGO bricks (Heimann & Roepstorff, 2018). Participants were provided with five sets of six LEGO bricks, and instructed to build a small duck. Participants were assigned to two conditions: A playful condition in which they were asked to build ducks in a way that felt playful to them, and a nonplayful condition in which participants were asked to build ducks in a way that did not feel playful at all. While participants created a multitude of different ducks in the playful condition, they tended to reproduce similarly designed ducks in the nonplayful condition. Using the microphenomenological interview approach, a novel methodology for eliciting past experiences in a well-controlled manner (Petitmengin, 2006), the study found that participants in the nonplayful condition generally reported feelings of stress, obligation, and boredom, while participants in the playful condition reported feeling autonomy and, interestingly, feelings of surprise over the ducks they had ended up building (Heimann & Roepstorff, 2018). The study showcases a somewhat counterintuitive phenomenon, namely that individuals can surprise themselves during solitary play with objects.

In sum, belief-violation, ambiguity and novelty provide children with learning opportunities to improve their intuitive theories of the world and its causal workings. Children often sample information selectively when they play with the aim of updating their beliefs to resolve novel or surprising observations. In the next section, we explore the proposition that learners are attracted to surprising and novel information that tends to gravitate toward a sweet spot of complexity that is neither too simple, nor too complex given what they already know.

## The Right Surprise?

While play entails unpredictable elements of variation and creativity (Bateson & Martin, 2013; Burghardt, 2005; Spinka et al., 2001), it is also often characterized by fixed rules of conduct and stereotyped behavior (e.g., Burghardt, 2005). Such considerations suggest that there may be certain constraints on just how surprising play should be. Intuitively speaking, it seems likely that overly predictable play is boring and overly unpredictable play chaotic.

Several lines of research have suggested that both children and adults in general prefer stimuli which somehow hit what might be described as a "sweet spot" of surprise (e.g., Bloom, 2010, 2020; Dember & Earl, 1957; McCall & McGhee, 1977). Such sweet spots are typified by only moderate differences between any given stimuli and the observer's prior knowledge of that stimuli (Mather, 2013). Infants, for example, seem to be guided by the so-called "Goldilocks principle" in their preference for visual stimuli which are neither too simple nor too complex, but instead contain just the right amount of complexity (Kidd et al., 2012).

There is evidence to suggest that a Goldilocks principle could also be identified in play. The immersive experience of "flow," characteristic of playful states, tends to occur during tasks which are *just* within reach of one's ability (Bateson & Martin, 2013; Csikszentmihalyi, 1997). Similarly, play frequently involves self-handicapping behavior, like hopscotch, where individuals deliberately make already learned tasks harder and thus more surprising for themselves (Bateson & Martin, 2013). Indeed, Singer and Singer argue that

> most forms of play involve situations of moderate challenge, novelty, or incongruity. Playful interactions between self and others (or, in the case of pure fantasy play, self, and symbolic others) or between self and objects usually result in a somewhat reduced level of novelty or incongruity that evokes joy. [ ... ] [W]ithin the defined structures of play one can continue to experience moderate challenge along with a further reduction in incongruity (1990, p. 40).

Such sweet spots of moderate challenge and surprise have been observed in infant play studies. In peek-a-boo, one of the most universal forms of social play between adults and infants, a parent will repeatedly cover his or her face and, at various brief intervals, "reappear" to the infant, causing her to smile or laugh. The game always contains four basic stages—initial contact, disappearance, reappearance, and reestablishment of contact—but there are plentiful small variations that can be deployed within these stages (Bruner & Sherwood, 1976), ensuring only mild violation of expectations in the infant. Indeed, an experimental study by Parrott and Gleitman (1989) demonstrated that too large deviations from the game, such as an adult reappearing elsewhere or swapping with someone else, reduced infant smiling and laughing. Thus, successful peek-a-boo may depend on fine-tuned interactions between parent and infant, where parents tune in to the expectations of infants and attempt to deviate only slightly from them. Bruner and Sherwood (1976) observed just such sensitivity in their peek-a-boo studies, where they were "struck by the skill of mothers in knowing how to keep the child in an anticipatory mood, neither too sure of outcome nor too upset by a wide range of possibilities" (p. 283).

Along the same lines, Arco and McCluskey (1981) investigated the salience of maternal temporal style in mother–infant free play and found that a natural maternal temporal style of play rather than a faster or slower pace led to the most positive interactions between parent and infant. Furthermore, young children have been shown to dislike highly unpredictable objects and toys, such as a jack-in-a-box (Scarr & Salapatek, 1970). Indeed, it has been argued that for infants, one might "wonder how much of a violation of expectation is a good thing. Infants do not always prefer information that is more surprising or more complex: They appear to like things that they think they can learn" (Schulz, 2015, p. 43).

In preschool children, it has been found that individuals engaging in risky play, such as playing with heights, playing with speed, and rough-and-tumble play, seek heightened states of arousal, although too much arousal will result in a withdrawal from the activity (Sandseter, 2010). Such findings suggest that the experiential attractiveness of just-right doses of uncertainty and surprise applies to interoceptive as well as exteroceptive signals. Such ideas are supported in a recent study on play and fear, where older children and adult visitors to a haunted attraction were equipped with heart rate monitors and asked to report on their experience (Andersen et al., 2020). Results revealed that participants thought of the experience as a form of play, and that self-reported enjoyment had an inverted U-shaped relationship with self-reported fear. Similarly, results from the physiological data demonstrated an inverted U-shaped relationship between heart rate changes during moment-to-moment encounters and enjoyment, suggesting that enjoyment is related to just-right forms of arousal dynamics.

Work on curiosity and information-seeking in children tells a similar story. Indeed, in his seminal work, Loewenstein (1994) suggested that curiosity is piqued not by maximally novel or surprising information, but by moderately novel or surprising information. Similarly, Jirout and Klahr (2012) define children's curiosity as *the threshold of desired uncertainty in the environment that leads to exploratory behavior*, or, as they also formulate it: "children's level of preferred uncertainty" (p. 150). In support of such ideas, Wade and Kidd (2019) in a recent study demonstrated that a strong driver of curiosity is the learner's metacognitive estimates of their own prior knowledge, meaning that learners will have their curiosity piqued when they *think* that they are close to knowing the answer to a question (*see also*, Kang et al., 2009). Wade and Kidd (2019) suggest that "[c]uriosity may serve as a metacognitive signal that indicates when there's a match between the presented learning material and the learner's readiness to encode it" (p. 1382).[1] Such accounts suggest that individuals make estimates of the relative uncertainty associated with the difference between their own prior knowledge and encountered stimuli, and that they are attracted to situations that are characterized by estimated sweet-spots of relative complexity.

In recent years, cognitive and computational neuroscience have witnessed the rise of a highly influential framework for how the brain processes information. This framework is commonly referred to as "predictive processing." Reconciling play research with the predictive processing framework holds promise for a number of reasons. It may provide play researchers with a plausible neurocognitive and computational framework that can be formulated mathematically and mechanistically, and which can account for both exploratory and exploitative behavior. Furthermore, the framework is highly compatible with recent accounts suggesting that children are Bayesian learners (e.g., Gopnik & Tenenbaum, 2007; Gopnik & Wellman, 2012; Schulz, 2012; Sobel et al., 2004; Tenenbaum et al., 2011; Ullman & Tenenbaum, 2020).[2] The predictive processing framework can explain why play is often characterized by situations that hold a "just-right" amount of uncertainty for the playing individual; and why play is so fun and rewarding. The questions of why play is fun and why children are attracted to just the right kind of uncertainty and surprise have largely been left unanswered by previous cognitive accounts of play, and PP supplies promising solutions to both of these questions.

## Predictive Minds

For the last decade, predictive processing has been revolutionizing cognitive science. This theory portrays the human brain as a statistical organ that revolves around a core mechanism of prediction error minimization. Predictive processing differs from earlier accounts of perception and cognition in the emphasis it places on the process of knowledge-driven prediction (Clark, 2013, 2015; Friston, 2010; Friston & Kiebel, 2009; Friston & Stephan, 2007; Hohwy, 2013; Wiese & Metzinger, 2017). The brain uses prior knowledge to form top-down predictions, which are then compared to bottom-up sensory input. Mismatches between predictions and sensory input elicit *prediction error signals*, which the brain continuously attempts to minimize.

Predictions are thought to occur at multiple hierarchically organized levels which simultaneously operate across different spatiotemporal scales. This can be conceptualized as a hierarchical generative model (Friston, 2008; Parr & Friston, 2018)[3] where lower levels deal with states of affairs happening at faster time scales and are good for handling detail, whereas higher levels deal with regularities operating at slower time scales, which are usually more general and abstract in nature (Hohwy, 2013). When prediction error signals are elicited, they are communicated upward within this neuronal hierarchy, forcing levels above to change predictions that subsequently descend back down again to lower levels in the hierarchy. Through this simple mechanism, and by constantly aiming to reduce the overall level of prediction error signals, the brain can compare multiple hypotheses about the state of the world and, over time, approximate exact Bayesian inference[4] (e.g., Clark, 2015; Hohwy, 2013; Kanai et al., 2015).

When mismatches between predictions and sensory input arise, the organism has two main options available to minimize the overall level of prediction error. It can either update predictions to better account for the sensory input through *perception* (also referred to as "perceptual inference") or, alternatively, use *action* (also referred to as "active inference") to make the world align with its predictions, sometimes preventing the errors from arising in the first place (Feldman & Friston, 2010; Friston, 2009; Friston et al., 2010). Imagine, for example, that you are waiting for your partner at a designated meeting place. As you see your partner approaching from afar, you eagerly wave. As your "partner" approaches, however, your prediction errors start to increase, forcing your internal model to rapidly update. Suddenly, you realize that you have been waving at a complete stranger. Conversely, it may be the case that your partner is sitting on a bench with their back turned to you. Since you are still not entirely sure that it is in fact your partner sitting there, you attempt to reduce your prediction error through action: You move around the bench, trying to find a better angle from

[1] Recent studies on children's memory and learning similarly indicate a cognitive optimum for surprising stimuli that facilitate cognitive encoding (e.g., Banerjee et al., 2013; Hopkins & Lillard, 2021).

[2] Bayesian theorists understand development as an abductive process of learning a probabilistic generative model. Children learn by combining richly structured abstract knowledge with statistical inference to form hypotheses about unobserved variables that map the causal structure of the world. This abstract knowledge is taken to be encoded in a probabilistic generative model that maps systematic relationships between causal structures that give rise to the child's sensory observations. Bayesian models describe an optimal solution to a problem posed by the environment in terms of belief update according to Bayes rule, but they do not characterise the neurocognitive mechanisms that implement this problem solving. The PP framework is by contrast a neurocognitive framework that explains both how Bayesian inference could be approximated by neural processes, and what the relationship is between the pleasure of play and uncertainty reduction.

[3] For a heuristic illustration of a hierarchical generative model, see Clark, 2015.

[4] Bayesian inference is a computational method for weighting new evidence against existing knowledge (for an introduction, see Wiese & Metzinger, 2017).

which to catch a glimpse of the face of the person sitting there. Finding that it is in fact your partner, you have now successfully aligned the world with your predictions. In most real-world situations of course, both processes are likely to be recruited, with perception and action working closely and dynamically in tandem to minimize prediction error.

When faced with predictions errors a key question the brain must settle is whether the error signal is a reliable carrier of information, or whether to place more confidence in its prior predictions. This question is resolved by a second-order precision mechanism that decides how much weight should be assigned to prediction error signals relative to its predictions (Feldman & Friston, 2010; Friston, 2009). When faced with prediction error estimated to be imprecise, the brain will treat its predictions as precise, and pay less heed to its error signals. By contrast, error estimated to be highly precise calls for action that can take the form of either updating the predictions that generated error, or by changing the sensory states the agent samples to match predictions. Importantly, such estimates of precision vary according to contextual information to which the agent has become habituated. For example, during development we quickly learn that well-lit contexts typically afford reliable sensory input. Our predictions in, say, a brightly lit bedroom, will be in a state of constant correction because errors in such a context are estimated to be highly precise (causing us to quickly detect environmental changes—a moved bed, for instance). Conversely, in a dark bedroom error signals would be estimated to be imprecise, and we would find ourselves forced to rely more on top-down prediction to find our way to the bed (and perhaps crashing unexpectedly to the floor should someone have moved it).

This notion of precision applies to action as well. The precision estimation of actions in a given context can similarly be thought of as a second-order process, where the brain estimates how confident it is that certain actions will generate certain outcomes (Friston, 2010; Friston et al., 2014). Precision estimates for action will increase when actions bring about predicted outcomes, whereas precision estimates will decrease when actions do not lead to predicted outcomes. To put this another way, our confidence in certain actions grows as we learn that they reliably produce expected outcomes. One corollary of this is that actions that are expected to be highly precise and yet fail to bring about the desired outcome will trigger stronger prediction error signals than actions associated with low precision. For example, if we were to approach our front door with our key at the ready, and then suddenly found that the key we had selected from the bunch would not unlock the door, we would experience a greater sensation of surprise than if we were attempting to unlock a hitherto unentered door with an unfamiliar bunch of keys. This is because, having unlocked our front door innumerable times down the years, we have grown to have great automatic confidence in it.

Sequences of actions are selected based upon a set of rules referred to as "action policies." As with individual actions, such policies are selected on the basis of how well they are expected to reduce prediction error (Friston, FitzGerald, et al., 2017; Friston et al., 2015). Certain policies that have proven their worth in reducing prediction error time and time again can therefore oftentimes become utterly habituated, such is our confidence that they will do the job. This high confidence in an action policy means that the policy in question is believed to have high precision. A series of actions that brings about expected changes increases in precision, whereas a sequence that fails to do so decreases in precision.

In sum, predictive processing "depicts perception, cognition, and action as the closely woven products of a single kind of inferential process" (Clark, 2018, p. 1), and the goal of this process is the continuous long-term reduction of prediction error signals. At the outset, it may seem entirely counterintuitive to apply this picture of the brain as an utterly conservative error minimization machine to something like play, which is traditionally characterized precisely by variation, exuberance, and surprise (e.g., Spinka et al., 2001). When children are well fed, warm, and healthy, they do one thing above all: play. It seems quite clear that when they do so, they thoroughly enjoy exploration, experimentation, and surprise. But why? Why do children engage in surprise-inducing activities such as pretend, play-fight or hopscotch if their brains are fundamentally designed to reduce prediction errors? Why would a brain on an eternal quest to minimize predictions errors dabble in something as anarchic as play where unpredictability and error abound (Sun & Firestone, 2020)?

## The Puzzle of Play

The most basic response to this puzzle has been to point out that there is no immediate inconsistency between searching for surprises and prediction error minimization (Hohwy, 2013; Van de Cruys et al., 2020). This is essentially because *surprise, understood as short term, significant increases in prediction errors*, may result in long-term error minimization. Children may, for example, experience surprise in the short term when playing with the bathroom faucet (signifying that their predictions have been violated), but this may reduce the amount of prediction errors associated with using the faucet in the long term. Schwartenbeck and colleagues argue along these lines, advancing the claim that "minimizing surprise naturally leads to concepts such as exploration" (Schwartenbeck et al., 2013, p. 1). The very imperative to reduce prediction error in the long term may be what stands behind the motivation and curiosity seen in most novelty seeking and explorative behavior. This is because the overall objective of active inference is to reduce prediction error over time, and sometimes meeting this objective calls for an agent to gain new information so as to reduce its uncertainty. This means that novel or ambiguous stimuli, which may at the point of first encounter be some what unpredictable, are also rendered instantly attractive,[5] because they represent "expected surprise" or "uncertainty"[6] and, in turn, an *opportunity* to reduce prediction error over the longer term (Parr & Friston, 2017; Veissière et al., 2020). In other words, active inference concerns choosing the right kinds of behavior that reduce the prediction error expected after committing to that behavior. In short, prediction error minimization through action is the minimization of uncertainty that underwrites exploration and curiosity.

In other words, the predictive processing framework proposes the radical suggestion that all explorative behavior, from the exploration of novel or ambiguous stimuli to curiosity-driven dealings with expectancy-violating stimuli, can be explained with reference to a single cognitive mechanism: Actual or expected prediction error minimization. Naturally, explorative behavior will oftentimes be characterized by an alternation over time between expected and actual prediction error minimization, such that agents will identify

[5] Unless they are overwhelmingly uncertain/unpredictable, in which case they may elicit aversive behaviour (see below).

[6] Expected surprise and uncertainty are used synonymously in literature on predictive processing (e.g., Friston et al., 2018).

expected surprise in the environment, bring these surprises about in order to resolve them, which, in turn, may prompt new explorative forms of behavior as a response to newly encountered forms of expected surprise.

Formulated in terms of actions and action policies, when novel or ambiguous stimuli, objects or contexts are encountered, agents will in all probability only have action policies available with a fairly low precision. For instance, when a child encounters a new toy, it does not yet know how to interact with it. The child does not have an action policy or scheme ready in which it has a high confidence in the predicted consequences of the said action. Scenarios such as these should prompt exploratory behavior in the child, because such behavior would enable the child to update the precision of some of its action policies. This means that as the child plays with the toy, it has the opportunity to grow more confident about the predicted consequences of its interactions with the object in question. In this way, encounters that are associated with low precision action policies and, in turn, the expectation of surprise, are precisely the kinds of situations to which people feel ineluctably drawn. In other words, expected surprise summons up an irresistible desire to explore, to handle, and to experiment—in short, to play.

A predictive processing account of play is supported by recent ideas of childhood as an evolutionary solution to explore-exploit trade-offs—the problem of finding the right balance between keeping your options open, and committing to a particular option (Gopnik, 2020). This evolutionary perspective argues that cognition works differently in childhood as compared to adulthood. Whereas child cognition is characterized by a desire to learn through exploration, adult cognition is characterized by a desire to exploit what is already known to plan and make things happen. The child's motivation for active exploration and play is in tension with adult cognition that is characterized by "attentional focus, inhibition and executive function and behaviors like long-term, goal-directed planned action" (Gopnik, 2020, p. 2).

These different styles of cognition are described using the metaphor of "temperature," a concept utilized in a technique for solving optimization, search, and inference problems, called *simulated annealing* (Gopnik et al., 2017; Gopnik, 2020; Kirkpatrick et al., 1983; Lucas et al., 2014). In simulated annealing, a low temperature search of a space of hypotheses will be narrow. In predictive processing terms, this corresponds to the agent assigning high precision to its prior beliefs, only adjusting these beliefs when confronted with evidence estimated to be particularly strong. Compared with children, adult cognition is characterized by this kind of conservative, low temperature search. Children's cognition is, by contrast, generally characterized by a wider, high-temperature search over a broader space of hypotheses. In predictive processing terms, this corresponds to the child's brain assigning low precision to their prior beliefs, frequently adjusting them when encountering new evidence, allowing the child to sample and test a wider space of hypotheses (Gopnik, 2020).

Importantly, this general feature of childhood cognition may explain why children are inherently neophilic and curious, and why they are so active when it comes to exploration and play. These ideas are all highly compatible with the predictive processing framework and share the attractive feature of being applicable across play forms, age, and context. The predictive processing framework can, in addition, further contribute to this overall narrative by explaining why it is that play and curious exploration can be so fun and rewarding.

## The Joy of Surprises

Recent developments in predictive processing and emotional experiences provide resources for explaining why the experience of play is deeply associated with positive, "feel-good" experience. In this literature the valence of emotional experiences is hypothesized to correspond to the rate of prediction error reduction (Hesp et al., 2021; Joffily & Coricelli, 2013; Kiverstein et al., 2019; Van de Cruys, 2017). It is hypothesized that the agent is not only sensitive to prediction error reduction, but also sensitive to the *rate* at which prediction errors are reduced over time (Hesp et al., 2019, 2020; Kiverstein et al., 2019). On the basis of its prior knowledge, the agent is constantly estimating the pace at which prediction errors *should* be reduced and comparing this expected rate to the *actual* rate at which prediction error is being reduced. This comparison is essentially what makes it possible for the agent to determine if its current action policies are working to efficiently reduce prediction error or not. Crucially, when prediction error is being reduced *faster than expected*, the associated experiences will be positively valenced. When prediction error is being reduced *slower than expected*, the associated experiences will be negatively valenced.

The predictive processing account of valence entails that when play is fun (i.e., positively valenced), it is because the learner is reducing prediction errors at a faster than expected rate. Play activities will thus be fun if the activity allows the agent to make better than expected progress in prediction error reduction. In essence, the good feeling one gets from play is thus tantamount to inferring that "I am doing well." Another way of phrasing this is to say that, on a rudimentary level, play feels good because one does better than expected at transforming an unpredictable reality into a predictable one.

The predictive processing account of emotional valence highlights the intricate role of error dynamics when organisms adapt and optimize their responses to the unexpected. An agent, which also keeps track of the rate of change in error, is much more sensitive to how effective its strategies are; hence it can continuously improve its strategies by tuning its precision-weighting "on the fly" (Kiverstein et al., 2019, p. 15). An unexpected deceleration in error reduction informs the organism that a belief in an action policy should be assigned lower confidence. An unexpected acceleration in error reduction informs the organism that things are going better than expected, and it should continue on its existing path. This drive for continual optimization means that humans are forever on the lookout for better-than-expected slopes of error reduction.

Recent evidence from AI and developmental robotics supports the idea that error dynamics can motivate an agent to play and explore (Oudeyer & Smith, 2016; Schillaci et al., 2021). Oudeyer and colleagues designed a robot to engage in curiosity-driven exploration. The robot was equipped with a module that kept track of the evolution of prediction error as the robot learned to predict the sensory consequences of its own actions. The module tracked how well the robot did at predicting and controlling its actions, by constantly comparing the expected change in prediction error with the actual change in prediction error. The mismatch between the expected and actual prediction error reduction corresponds to error dynamics—the change in the rate of error reduction—in predictive processing terms.

Actions were selected by the robot based on the heuristic of maximizing the decrease in prediction error. The robot kept track of improvements in prediction and the control of action, and was rewarded when it made progress. Reward was thus an internal quantity that is proportional to decrease in prediction error (Oudeyer & Smith, 2016, p. 495). By seeking to continuously do better than expected in its predictions, the robot was able to make incremental progress in its learning, shifting from easier to more difficult tasks. The robot avoided activities that it was already able to predict, focusing instead on activities with the fastest improving learning rate (i.e., activities with the most potential for decrease in prediction error, or acceleration in error reduction). When these activities became well-learned, it switched to the next challenge. This behavior can be understood as the robot using error dynamics to approach tasks with the right level of complexity for the robot to optimize progress in learning and prediction error reduction. By using the rate of error reduction to select actions, the robot was attracted toward a sweet spot of complexity, where error was neither unmanageable nor so easily accommodated that there was nothing further for the robot to learn.

Agents that use valence to weigh precision will naturally seek situations where prediction error is consistently being reduced, preferably *faster* than the agent expected. Agents will tend to gravitate toward certain sweet spots of relative complexity where prediction error signals have a higher likelihood of being reduced more swiftly than expected. This is because situations that are neither too simple, nor too complex, are most often the ones that afford the richest opportunities for improving the rate of prediction error minimization (Oudeyer et al., 2007).[7] Such sweet-spots are an expression of agents optimizing their predictive grip on the world, and maximizing their own learning rate (Kiverstein et al., 2019).

In this way, the predictive processing framework provides an answer to the question of why play is rewarding and fun. In play the agent is drawn to new surprising information that is neither too complex and chaotic, nor too simple as to promise only meager, uninteresting advances in learning. Surprising situations that fall within this sweet spot will allow the agent to do better than expected at reducing error, which, in turn, feels good. This is because positive valence corresponds with doing better than expected at error reduction. Importantly, as mentioned, prediction error reduction can be achieved in two ways in play. Over the course of play an agent can find their way to novel, ambiguous or and surprising information and reduce their associated uncertainty in ways that allow the agent to make better predictions in the future. Alternatively, in play, agents may attempt to make the surprising reality conform to their predictions. In short, play is fun because it allows for the discovery of new and improved strategies for rapid prediction error reduction either through learning and forming new predictions or by making the world conform to our predictions.[8] As prediction error minimizing agents what we want and enjoy is to make progress in prediction.

Crucially, an agent that is motivated in this way has a quite profound trick up its sleeve. In order to enjoy prolonged periods of fun and enjoyment, the playful agent may purposefully *design and create* situations characterized by an estimated just-right amount of surprises with the purpose of resolving such surprises.

## Slope Chasing & Slope Building: How to Get the Just-Right Surprise

A predictive processing account of play suggests that play is an active process of seeking out or creating surprising situations that gravitate toward a sweet-spot of relative complexity. In this account of play it is the metacognitive sensitivity to the valence of the situation that mediates the attraction toward situations of just-right complexity. Again, this is because situations that are neither too simple, nor too complex, are the ones that afford the richest opportunities for improving the rate of prediction error minimization, giving rise to situations where individuals are reducing prediction error faster than expected. Andy Clark has recently dubbed this "slope-chasing" (Kiverstein et al., 2019, p. 19), and we believe this characterizes a fundamental aspect of play: The tireless pursuit of just-right surprises.[9] The PP framework allows us to define more precisely what is meant by "just-right-surprise." "Surprise" in predictive processing is often described in terms of prediction error minimization, where a sensory experience that was not fully predicted evokes significant levels of prediction error. However, this is not the kind of surprise we are talking about here. The pursuit of just-right surprise pertains to the consequences of action; it is driven by an estimate of significant information gain afforded by some sensory outcome that has yet to be realized.[10]

Importantly, we argue that humans in general, and children in particular, not only seek surprises from the environment, but also alter the environment itself in such a way that surprises can potentially be extracted from it. While current schemes of predictive processing hold that certain actions become attractive if they are associated with "expected surprise" (i.e., if they represent opportunities to reduce prediction error—Veissière et al., 2020), these schemes may have

[7] A situation with the right level of complexity can also be understood in PP terms as providing epistemic affordances; namely, a situation that offers the right degree of unpredictability for resolving uncertainties—but that is not so unpredictable as to preclude any information gain or learning. In short, the right kind of 'predictable unpredictability' (see Friston, Lin, et al., 2017).

[8] There may of course be many additional reasons for why play is fun, such as the freedom the agent has to make their own choices, or the possibility to engage their imagination in a variety of ways. The PP framework implies that what may connect these reasons is that they all describe conditions that contribute to the agent finding their way to surprising situations that facilitate rapidly transforming unpredictable realities into predictable ones.

[9] Importantly, it follows that there is an intimate relationship between the slope of decreasing prediction error and the emergence of precise beliefs about action policies. This follows because in predictive processing the rate of evidence accumulation is determined by the precision of the evidence accumulated. In the present setting, one can therefore think of slope chasing as seeking out situations that yield a progressive increase in confidence about the consequences of action during exploratory behavior.

[10] In the visual search literature, the relation between surprise and information gain is formalized using the notion of Bayesian surprise. Bayesian surprise is defined as the mismatch between prior and posterior beliefs about the world (Itti & Baldi, 2005; Mirza et al., 2019). This concept is closely related to a range of other terms; for example, salience, epistemic value, intrinsic motivation, and so on. Bayesian surprise can be mapped onto notions of salience, and epistemic value in the sense that cues are salient when they offer opportunities to make information gains, or resolve uncertainties (Parr & Friston, 2018). Visual search results in new observations that yield information gains when the result of the exploration of a scene is a mismatch between the agent's prior and posterior beliefs. Observations with high Bayesian surprise are salient—they grab the perceiver's attention. An interesting distinction arises when we consider the nature of the unknowns about which expected surprise and uncertainty is resolved. In active inference, this uncertainty can be about states of affairs in the world (e.g., what's he thinking?). Alternatively, it can be about contingencies that have to be learned (e.g., what happens when I do this?). The corresponding expected surprise relating to states and contingencies are known as salience and novelty, respectively (Parr & Friston, 2018). This means that the imperatives to reduce expected surprise lead naturally to curious, novelty seeking, behavior that is epitomized by play.

overlooked how agents manipulate their environment in order to create surprises out of nothing. For example, children may build a block tower to see what happens when they knock it over; they may transform a banal piece of asphalt into a hopscotch grid; and they may turn a dreary stack of blankets into a fort to defend the center of the living room. Through these means, in a hunt for positive valence, children create and establish an environment tailored to the generation and further investigation of surprise and uncertainty. One could say that play is not only about epistemic foraging, it is also about epistemic farming.

Thus, an overlooked aspect of play may be that playful agents are not just "slope-chasers," but also "slope-builders." That is, if the environment provides no immediate surprises or uncertainties, children and adults will combat boredom by creating and establishing an environment specifically tailored to the generation and further investigations of surprise and uncertainty. As they play, humans in general, and children in particular, sometimes deliberately forge error-inducing environments, in order to allow for the further exploration of productive surprises. This active construction of error reduction slopes can be observed in a variety of play forms, not least in the variety of ways children have been observed constructing toys and play spaces (e.g., Lew-Lewy et al., 2021; Marshall, 1976; Takada, 2020). The reason why children, in ways that might seem quite pointless, may actively create surprising situations and environments that they eventually find ways to resolve is because doing so feels good. Chu and Schulz (2020) have pointed out, as have many play researchers before them, that a good deal of human play seems pointless. Children create problems for themselves which they devote some effort to solving without any obvious payoff. Seemingly pointless play is fun because the child is creating slopes of error that they can often resolve at a better-than-expected rate.

A series of descriptive findings on the development of play can highlight some of the strategies children utilize across development to ensure they are neither too surprised nor too bored while playing.

## Physical Forms of Play

While most forms of play continue to be present throughout childhood, many forms of play typically show an inverted U-shaped curve with certain peaks at different points during childhood (for a review, see Lillard, 2015). Such generic developmental trajectories, we argue, may showcase inherent knowledge and skill-based constraints in the seeking and creation of surprising situations. Before a child can crawl and move about, it is naturally inhibited from exploring much beyond itself and the immediate environment. This greatly curbs the range of surprises it can seek out. At the same time, the limited knowledge of an infant means that even within such a restricted environment, surprises still abound. Limited prior knowledge in conjunction with limited possibilities for exploration may explain why infants seek surprises primarily in *sensorimotor play* (Uzgiris, 1967).

As children develop their first rudimentary motor skills, opportunities to seek out surprise increase. As such, early forms of *locomotor play* may provide a unique window into what children do as their options expand. Locomotor play, which peaks at around 6 months of age, is the first form of play yielding observable evidence that play is often performed repeatedly in a similar, but not rigidly stereotyped, form (Bateson & Martin, 2013; Burghardt, 2005; Pellegrini, 2009, 2011b; Thelen, 1980). Often, this involves repeated rapid movements, such as "kicking, rocking, bouncing, swaying, waving, banging, rubbing, and scratching" (Thelen, 1980, p. 141), albeit with slight variations. Such slightly varied repetitions in motor behavior might precisely constitute moderate prediction violations. The child, by keeping large parts of the behavior constant, only varies subsets of certain action patterns, thereby ensuring that large parts of action patterns remain predictable, with prediction violations restricted to a small subsection of the behavioral routine. This principle seemingly continues in *exercise play*, a form of locomotor play that emerges around the 1-year mark and has its peak at around 4 or 5 years of age, which similarly also includes slightly varied repetitive action patterns, such as hopping, running, and swinging (Pellegrini, 2009, 2011b).

*Exploratory play* emerges and overlaps with sensorimotor and locomotor play. It refers primarily to activities where children play with novel or poorly understood objects (Bornstein, 2007; Lillard, 2015). As mentioned, some experimental studies already suggest that children are drawn to and play more with objects that are surprising or that they expect will be surprising (e.g., Baldwin et al., 1993; Bonawitz et al., 2012; Schulz & Bonawitz, 2007). At the same time, some objects can be too surprising. Indeed, multiple studies have found that infants and young children become startled and upset when they encounter highly unpredictable objects that create sudden or intense forms of stimulation, such as loud noises (e.g., a toy pistol) or sudden movements (e.g., jack-in-a-box; e.g., Scarr & Salapatek, 1970). Not surprisingly, children may over time associate such objects with unpleasantness and consequently shy away from them, effectively avoiding highly unpredictable and surprising stimuli.

Exploratory play has been the subject of some controversy within play research, because it has not always been clear how to meaningfully separate play from exploration more generally. One suggestion has been to differentiate the two based on the proposition that standard exploration is characterized by a close-ended approach ("What does this object do?"), whereas exploratory play is characterized by an open-ended approach ("What can I do with this object?"; Hutt et al., 1989). Such a distinction is compatible with the observation that the exploration of objects tends to occur when children first encounter a novel object, whereas play tends to occur once children have familiarized themselves with it (Lillard, 2015). Our model would characterize the distinction between exploration and play differently: To "explore" may be seen as an example of *seeking* out (and resolving) surprise, whereas to "play" may be seen as an example of *creating* (and also resolving) it.

*Rough-and-Tumble Play (R&T)* often takes the form of play-fighting or wrestling. It follows an inverted U-shaped curve and peaks at around 8–10 years, during middle childhood (Pellegrini & Smith, 1998). This behavior is characterized by high energy "exaggerated movements, and soft, open-handed hits or kicks" (Pellegrini, 2006, p. 84), and players often reciprocally switch "attacking" and "defending" roles. Another striking feature of R&T is that it is very often characterized by some form of self-handicapping behavior, especially in cases involving unequally strong partners (Pellegrini, 2006). For example, when an adult and a child play-fight, the adult may sit on his knees and maybe keep one arm behind his back to further equal the playing field. It has been suggested that this maximizes motivation in players through minimizing boredom from limited role enactment (Pellegrini, 2006, p. 84), but self-handicapping also allows the stronger player to create unexpected situations for themselves in the R&T interaction (Spinka et al., 2001).

In other words, self-handicapping may help ensure that both players can surprise each other during the interaction. Besides being playful signals (Pellegrini, 2006), the exaggerated movements often seen in R&T may also constitute a way for the players to telegraph their intent and thereby curb highly unpredictable elements in the interaction. This stands in stark contrast to real fights where, for obvious reasons, opponents strive for maximal unpredictability.

## Mischief, Imposed Challenges, and Pretend Play

From as early as 4 months, children will begin engaging in clowning and teasing behaviors in order to elicit novel responses from caregivers and siblings. In doing so, children will often violate norms, act profanely or even deliberately knock over things that other children have carefully built (Reddy & Mireault, 2015). Such clowning and teasing can take endless forms, but what these forms share is a violation of normal expected patterns of social life. In infants, it seems to occur "as a play on any newly developed skill or social arrangement" (Reddy & Mireault, 2015, p. 22). For instance, a 9-month-old may jiggle an object in order to attract the attention of a caregiver, then offer the caregiver the object, only to teasingly withdraw it as soon as she reaches for it (Reddy & Mireault, 2015). Such teasing entails that the child predicts large parts of the action pattern of the caregiver, in this case that the caregiver will reach out her hand and expect the object to be released. Through teasing, the child violates the expectations of the caregiver at the last moment, eliciting a novel variation on the caregiver's usual action pattern. The fact that these sorts of behavior emerge from *newly* developed skills or social arrangements may be interpreted as examples of creating, yet keeping within the bounds of, moderate surprises.

Older children often impose needless challenges and costs upon themselves in their play. As already mentioned, self-handicapping is a frequent behavior observed in rough-and-tumble play, but this behavior is also often observed in other forms of physical play. Children may, for instance, decide to walk backwards around the living room; blindfold themselves with a towel; or play hopscotch, forcing themselves to rely on one leg. In these ways, children actively surprise themselves and one another by manipulating previously acquired sensory-motor skills (Spinka et al., 2001). Such self-imposed challenges may be seen as a way to induce moderate surprises when none are to be immediately found.

Indeed, across four studies Chu & Schulz elegantly demonstrated that 4- to 5-year-old children not only infer playful behavior from observed violations of rational actions, but take on unnecessary costs themselves and perform inefficient actions during play, despite understanding and valuing efficiency in nonplayful instrumental contexts (Chu & Schulz, 2020). Chu & Shulz speculate that such seemingly pointless play may serve an important learning function allowing the child to search a space of hypotheses, generating innovative, new ideas that the children would not otherwise be able to identify. What is distinctive about human play, they argue, is that it allows the child to make progress, not only in terms of information gain, but also in "thinking and planning," meaning that children are able to come up with novel hypotheses and plans that helps them understand the larger structure of a problem. The experimental data shows that children will deliberately form idiosyncratic goals and even make some tasks a bit harder for themselves during playful behavior as opposed to nonplayful instrumental behavior. Such findings are thus also compatible with the notion that (enjoyable) play will gravitate toward sweet-spots of relative complexity and that such surprising conditions may often be deliberately facilitated by children themselves.

The most widely studied form of play, pretend play, may also be seen as a way that children modify their environment to yield more surprises. Pretend play can be seen as early as 12–18 months where children initiate object substitution, but pretend play in its more elaborate form peaks around 3–5 years (Lillard, 2017; Piaget, 1962). This form of play is characterized by simulation, nonliterality, and "as-if" behavior (Fein, 1981), where children pretend that objects, persons, or places are different to what they actually are. Although many early forms of play seem to be beneficial to distinct aspects of development, researchers have struggled to find causal evidence of any benefit resulting from pretend play (For an extended review, see Lillard et al., 2013).

In 2001, Lillard proposed the "Twin Earth model" of pretense, in which she argues that pretend play is much like the imaginary world "Twin Earth," a concept that philosophers sometimes use in their thought experiments (Pessin & Goldberg, 1996). Twin Earth tends to be formulated as a place which is exactly like real Earth except for just a few carefully chosen parameters. While Lillard's model was originally developed to address the much-debated relationship between pretend play and theory of mind, its scope goes well beyond that by pointing to a crucial central structure in pretend play, namely that children will keep most parameters of reality predictably constant, changing only a few as they go about immersing themselves in moderately surprising imaginary worlds: "The child has become the mother, but mothers are the same, how mothers respond to babies is the same, the fact that pie is eaten after lunch is the same, and so on" (Lillard, 2001, p. 516). Such behavior, as Singer & Singer puts it: "creates a novel stimulus field" that may sometimes be considered "as a characteristic response to an environment in which there is considerable redundancy" (1990, p. 145).

In this light, pretend play could be seen as an obvious solution for an agent who has but one goal in mind: Enjoying just the right doses of relative complexity. By creating an imaginary world, which contains only few deviations from the real world, children effectively shape their environment to set themselves up for small surprises where none were to be found before. In other words, children readily introduce uncertainty into environments that are lacking it in an effort to combat boredom. This view helps us understand why children not only pretend and reenact real-life scenarios like playing house, school or restaurant, things which might prepare them for similar situations later in life, but also unrealistic scenarios like pretending to be Spiderman or a Pippi Longstocking (Weisberg & Gopnik, 2013). While the specific content of counterfactual scenarios such as simulating how to climb a skyscraper or to lift a horse with one hand may be novel and surprising to the individual child, it will not necessarily be relevant for predicting and navigating physical spaces later in life. Such scenarios may, however, all represent opportunities of exploring different strategies for error reduction, including social strategies for negotiation and making the world conform to the agent's expectations (e.g., "[W]ill you be the king, Dad? … No, you can't be the prince, cause there is no prince on Atecopia, so you can only be King", Andersen, 2022).

By contrast, the content of sensorimotor, locomotor, and exploratory play, where children seek, create, and resolve surprises immediately relevant to their own bodies, motor capabilities, and physical environment, are more likely to involve information gains relevant to predicting and navigating physical spaces. This is simply because over time, even a blind search for surprises within these areas will optimize sensory–motor skills and exploratory skills within a predefined set of embodied and environmental constraints. By analogy, Pathak et al. (2017) created a software agent designed to learn how to play *Super Mario Bros*, a computer game constrained by a preset digital world with linear gameplay. The software agent, which had no prior knowledge of Super Mario Bros, was equipped with a "blind" curiosity module that quickly optimized game performance simply by rewarding the agent every time it failed to predict the consequences of its own actions in the game (Pathak et al., 2017).

## Discussion

If play is, at its core, the deliberate seeking and creation of surprising situations, this has important implications for learning, niche construction; for current understandings of playfulness as a general mood state; as well as methodological implications for future research on play in humans.

### Play, Learning, and Niche Construction

Humans in general, and children in particular, play not only to chase slopes of error reduction but also to actively build and create such slopes of error reduction. This perspective may be relevant for recent work in evolutionary biology that addresses predictive processing and niche construction. Predictive processing extends to nonhuman animals as well because prediction error minimization is believed to be a universal biological process in which organisms attempt to keep themselves within expected sensory and physiological states given their species-specific prestructuring and the niche they inhabit (Friston, 2010). In evolutionary biology, niche construction refers to the process of organisms modifying their environment, thereby steering their own and others' evolutionary trajectory (Laland et al., 2015). Recent arguments suggest that the mathematics of predictive processing can be used to model the effect of niche construction on biological evolutionary processes (Constant et al., 2018).

From this perspective, niche construction is a way for organisms to efficiently minimize prediction error by manipulating the environment to conform to their own expected states. Thus, an organism's species-specific prestructuring may prompt it to build a nest or a burrow, ensuring that expectations about things such as wind speed or temperature are effectively met. Niche construction may therefore be seen as a form of active inference, where the organism manipulates the environment to fit its own expectations. In many cases, animals are born into an already altered environment fit to suit their species-specific prestructured expectations, for example, ants in an anthill; beavers in a lodge; or humans in a house (Constant et al., 2018). What this account may have overlooked, however, is that a handful of species, notably the most intelligent, regularly engage in playful behavior after their basic expectations have been met. Human children actively seek and create situations that they expect to be surprising in an effort to reduce uncertainty. When the environment offers no uncertainty, children will readily modulate it in such a way that it *becomes* error-inducing.

It is an open question as to whether this may also be the case for certain nonhuman species famous for their playful inclinations. Dolphins, for instance, can often be seen creating bubble rings by exhaling air through their blowholes, which they subsequently play with in a variety of ways. Some dolphins have even been observed to produce multiple rings that they then join together, or push one through another (Janik, 2015). Similarly, several populations of Bornean orangutans have been documented building nests for social play, and object-substitution and pretend play have been documented in both chimpanzees and gorillas (Jensvold & Fouts, 1993; Ramsey & McGrew, 2005). The motivation for such behaviors is not obvious from the perspective of existing work on niche construction in the predictive processing framework, because these behaviors do not involve the identification and resolution of preexisting environmental uncertainties. Rather, we speculate that these behaviors could result from efforts to create uncertainty and surprise in environments in which they are lacking.

Interestingly, there is an apparent cross-species relationship between playfulness and the capacity for culture. Some of the most playful species, including dolphins, great apes, crows, monkeys, and, of course, humans, show highly diverse culturally patterned practices (e.g., Hunt & Gray, 2003; Kuczaj & Highfill, 2005; Whiten et al., 1999). While we recognize that this relationship is likely to be mediated by intelligence and general cognitive capacity among other things, we speculate that proneness to boredom and a proclivity to play may act as a creative stimulus for cultural innovation. Numerous researchers have already argued that human play facilitates creativity and innovation (e.g., Bateson & Martin, 2013; Russ, 2014). Whether this argument can be extended to other playful species remains to be seen. If these species modulate the environment so that surprises may be extracted from it, this could galvanize the emergence of new behaviors which, if they persisted over time and were transmitted between individuals, could be added to the cultural repertoires of their populations.

### Play, Playfulness, and Mood

In addition to elegantly integrating emotion, cognition, and perception, recent predictive processing accounts have also emerged to include overall mood states into the framework (Clark et al., 2018; Kiverstein et al., 2020). Moods are often described as "generalized emotions," emotions that are directed at the world as a whole rather than any one particular object (Solomon, 1993, 71). Moods are further distinguished from emotions by being longer in duration, providing a persistent "background" feeling tone to our transitory, short-lived emotional experiences (Ekman & Davidson, 1994). Like feelings, moods are also believed to structure our experiences by way of anticipation-fulfillment dynamics (Kiverstein et al., 2020; Ratcliffe, 2008).

From a predictive processing perspective, affective valence acts as a metacognitive signal within the predictive system, informing it of how well or poorly it is predicting in some specific local context. Moods by contrast are global background expectations about the slopes of error reduction the agent is likely to encounter. A positive mood, then, can be understood as the product of a series of experiences where the organism has reduced error faster than expected. This in turn leads to a general upward biasing of our expectations of positive valence going forward. In other words, agents that are in a good mood expect error slopes to incrementally improve (Kiverstein et al., 2020; cf. Clark et al., 2018; Eldar et al., 2016, 2021; Rutledge et al., 2014).

Playfulness has previously been recognized as a positive mood state that is frequently manifested in observable behavior during play (Bateson & Martin, 2013). While this mood state is believed to often accompany play, it is also believed to sometimes facilitate it. In the predictive processing theory of mood, repeated experiences of better-than-expected error slopes improves mood (Rutledge et al., 2014), making the agent more optimistic, and expect attractive opportunities to reduce error (Cools et al., 2011; Niv et al., 2006; Somerville et al., 2013; Wang et al., 2013). This is supported by laboratory findings that positive mood has been shown to induce risk-taking behavior (Arkes et al., 1988; Isen & Patrick, 1983) as well as in real-world settings (Bassi et al., 2013; Edmans et al., 2007), in which positive mood has been shown to bias the expectation of future positive outcomes (Wright & Bower, 1992).

Notice the effect that this positive biasing can have in an environment like ours where opportunities for error reduction tend to rise and fall together. The upward biasing of the agent's expectations about the rate at which error is reduced makes it more likely for the system to expend energy to confirm predictions about error reduction slopes (Eldar et al., 2016). The optimistic agent is therefore more likely to find better than expected opportunities in their environment when they are available, which in turn perpetuates the positive mood. In this perspective, moods reflect a sort of emotional "momentum"—when the agent feels rewarded for doing better than expected, it increasingly expects such rewards to keep on coming (and conversely, when agents are doing worse than expected, it incrementally expects more bad times ahead, Eldar et al., 2016, 2021; Kiverstein et al., 2020; Rutledge et al., 2014).

Consider a child who has previously enjoyed a visit to a theme park. At the theme park, the child repeatedly experienced reducing error faster than expected where what is expected relates to the child's preferred states, the satisfactions of its needs and desires, and the fulfillment of its goals (e.g., eating ice creams and candy floss that increase glucose blood levels faster than expected; the roller coaster rides that create and resolve error faster than the family car). That child is likely to become in a good and playful mood when being told that the family again this year is going to visit the park on the weekend. According to the model, this is because the child anticipates encountering a plethora of attractive error reduction slopes when reaching the theme park. In other words, the child is in a good mood then because it expects to encounter rewarding possibilities and the good mood will be sustained as long as this expectation is fulfilled. Mood is therefore a form of generalized summary of expectations that relates to how well or badly the agent has been faring in the world as a prediction error minimizing organism, which in turn shapes its anticipation of the trend of rewards going forward.

However, as the opportunities to reduce error begin to fall away, as will inevitably happen in an environment offering finite resources, the agent's positive mood will likewise diminish. The theme park, for instance, offers a rich abundance of opportunities for the child to fulfill their desires until the park closes and a long drive home awaits them. Many studies suggest that a negative mood is associated with biasing of predictions for negative error slopes—anticipation of doing worse than expected in error reduction, biasing perception of negative outcomes (Badcock et al., 2017; Fabry, 2020; Kiverstein et al., 2020; Kube et al., 2020; Paulus et al., 2019; Ramstead et al., 2021). For instance, in depression, a state characterized by a persistent negative mood, there is a loss of confidence that any policy will succeed in reducing error (Badcock et al., 2017). This sometimes creates a perpetuating negative spiral, where the expectation of encountering worse than expected slopes for error reduction leads the agent to sample the environment for evidence, which in turn confirms and supports the negative belief. In that sense, playfulness as a mood can be thought of along the same lines as the famous words of Brian Sutton-Smith, who stated that the opposite of play is not work; it is depression (Sutton-Smith, 1997, p. 198)

## Further Implications and Future Directions

The central role of positive valence in a predictive processing account of play may provide important new directions for future studies. Methodologically, it implies that zooming in on surprise dynamics over time may allow play researchers to get an important and empirically well-founded picture of the cognitive and physiological fluctuations that happen when children and adults engage in playful activities. At the same time, this may also provide play researchers with an alternative to unrefined between-group designs, given that surprise by definition is a reflection of the knowledge of the given participant. The framework's emphasis and focus on predictions and prediction errors may lend itself to an increased focus on within-subject measures of agents' real-time patterns of prediction on various time scales in different play settings. Recent technological advances may help here. Mobile eye tracking, for instance, is a particularly strong candidate for gathering behavioral proxies for predictions in ecologically valid playful situations (e.g., Andersen et al., 2019), and pupil dilation has been shown to signal uncertainty and surprise (e.g., Lavín et al., 2014).

Some of these methodological approaches are already widespread in the study of infant cognition, but grow increasingly absent in research paradigms as children acquire language and motor skills. Indeed, one of the most widely used approaches to study infant cognition has been to treat surprise or its absence as the main measure by observing whether children express expectation or surprise in various experimental contexts (e.g., Baillargeon et al., 1985; Scherer et al., 2004; Werker et al., 1997). Using such measures, efforts to systematically map what types of predictions children make in different forms of play could prove beneficial. Other behavioral measures can serve as proxies or indicators for surprise as well, and one could, for instance, use pitch levels in verbal utterances (e.g., Ververidis et al., 2004) or facial expression (e.g., Cohn et al., 1998) as behavioral proxies for surprise. The same goes for physiological measures such as heart rate variability (Andersen et al., 2020; Sukalla et al., 2016), which nowadays can be easily measured in real-life settings in noninvasive ways.

Future studies may benefit from tracking the relationship between various slopes of actual and expected surprise reduction over time and their effects on valence and motivation in play. For example, researchers might utilize an unfamiliar toy type, such as a drone controlled by hand gestures, designed to respond to the playing individual with various levels of unpredictability controlled by the experimenter. By tracking the gaze and hands of the playing individuals as well as the ongoing changes in distance from the hands to the toy, which is already possible with available technology, researchers will be able to get measures of how well participants predict the movements of such a toy over time and how predictions improve or worsen. Such measures may be then related to measures of interest, such as enjoyment or motivational measures, which could be obtained by showing the participant the first-person view video of their play and continuously rating it for how fun or engaging it was.

Simpler setups may also work. For instance, Doan and colleagues presented 4-year-olds with a puzzle that they were told was either easy or hard (or, in the baseline condition, where they received no information). When the 4-year-olds completed the puzzle that they were told was hard (i.e., presumably completed the puzzle faster than expected), they spent more time exploring and attempted more different interventions with a subsequent novel toy compared to when they were told that the puzzle was easy or at baseline when no difficulty information was provided. Thus, experimenters may take advantage of the possibility to manipulate the relationship between expected and actual surprise reduction over time. They could also investigate the effects of encountering several such instances, where agents do better than expected, which is hypothesized to positively affect their playful mood and overall risk taking.

For pretend play, researchers may consider taking advantage of the rise in popularity of online streamed tabletop roleplaying games, where older children and adults pretend to be characters in fictional settings. Through the use of automated voice recognition software, some of which is already implemented in larger online platforms (e.g., YouTube), researchers have access to vast datasets of dialog in the form of subtitles from pretend settings. Through the use of natural language processing (NLP) methods (e.g., Jurafsky & Martin, 2000), it is possible to characterize the moment-to-moment development of variables such as novelty and recurrence, syntactic complexity and narrative arc, while relating these measures to proxies for enjoyment like popularity, view count, or positive sentiment in language use in viewers of the stream. This, in other words, allows researchers to look at proxies for surprise/renewal and enjoyment and their intertwined relationships as they unfold over time whilst being completely in the sphere of imaginary forms of play.

Future studies may also investigate how the seeking, creating, and resolving of error slopes in play is mediated and modulated during playful interactions with other agents. We know from other studies of playful parent–child interaction, for example, that parents actively guide and manipulate expectations by signaling surprise to their children at appropriate moments. Mothers of toddlers have been shown to increase their mean fundamental frequency and use a wider pitch range in playful situations compared to nonplayful situations (Reissland & Snow, 1996). Similarly, another study involving mothers and infants interacting together with a surprise-inducing toy found that the mothers' exclamations of surprise became more high-pitched when they noticed that their children did not react with surprise to the toy (Reissland et al., 2002). Along similar lines, Wu and Gweon (2021) introduced 3- to 4-year-old children to a novel toy with one salient casual function that the children first learned about. The children then saw an adult play with the toy. Intriguingly, children explored the toy more when the adult expressed surprise compared to when she expressed happiness, but only when the children knew that the adult already knew about the toy's salient function. As Wu & Gweon argues, these results suggest that "children consider others' knowledge and selectively interpret others' surprise as *vicarious prediction error* to guide their own exploration" (p. 862). Thus, it may be that when agents have fun together, they do so by collaboratively reducing error for each other.

## Conclusion

This article proposes a cognitive theory of why humans play based on recent insights from the predictive processing framework. This account of play provides researchers with a cognitively and neurobiologically plausible proximate framework that can be formulated mathematically and mechanistically and which lends support both to the notion that play helps children to learn and that children are Bayesian learners. The theory explains why play is fun and why play so often is characterized by just-right levels of relative complexity. Importantly, the role of valence in this account brings novel insights to the predictive processing community as well, by highlighting a new contribution of niche construction to error minimization. In play, the agent purposefully creates and resolves error, and in so doing finds their way to better than expected policies for reducing error going forward. In sum, the predictive processing account may offer a valuable proximate model of play, and help isolate key mechanisms and variables underlying one of the most universal yet open-ended behavioral categories. As a consequence, it may help to bring play research where it belongs; at the center of developmental research.

## References


Andersen, M. (2022). *Play*. Aarhus University Press/John Hopkins University Press.

Andersen, M., Nielbo, K. L., Schjoedt, U., Pfeiffer, T., Roepstorff, A., & Sørensen, J. (2019). Predictive minds in Ouija board sessions. *Phenomenology and the Cognitive Sciences*, *18*, 577–588. https://doi.org/10.1007/s11097-018-9585-8

Andersen, M. M., Schjoedt, U., Price, H., Rosas, F. E., Scrivner, C., & Clasen, M. (2020). Playing with fear: A field study in recreational horror. *Psychological Science*, *31*(12), 1497–1510. https://doi.org/10.1177/0956797620972116

Arco, C. M., & McCluskey, K. A. (1981). "A change of pace": An investigation of the salience of maternal temporal style in mother-infant play. *Child Development*, *52*, 941–949. https://doi.org/10.2307/1129098

Arkes, H. R., Herren, L. T., & Isen, A. M. (1988). The role of potential loss in the influence of affect on risk-taking behavior. *Organizational Behavior and Human Decision Processes*, *42*(2), 181–193. https://doi.org/10.1016/0749-5978(88)90011-8

Badcock, P. B., Davey, C. G., Whittle, S., Allen, N. B., & Friston, K. J. (2017). The depressed brain: An evolutionary systems theory. *Trends in Cognitive Sciences*, *21*(3), 182–194. https://doi.org/10.1016/j.tics.2017.01.005

Baillargeon, R., Spelke, E. S., & Wasserman, S. (1985). Object permanence in five-month-old infants. *Cognition*, *20*(3), 191–208. https://doi.org/10.1016/0010-0277(85)90008-3

Baldwin, D. A., Markman, E. M., & Melartin, R. L. (1993). Infants' ability to draw inferences about nonobvious object properties: Evidence from exploratory play. *Child Development*, *64*(3), 711–728. https://doi.org/10.2307/1131213

Baldwin, J. D., & Baldwin, J. I. (1977). The role of learning phenomena in the ontogeny of exploration and play. In S. Chevalier-Skolnikoff & F. E. Poirier (Eds.), *Primate bio-social development* (pp. 343–406). Garland.

Banerjee, K., Haque, O. S., & Spelke, E. S. (2013). Melting lizards and crying mailboxes: Children's preferential recall of minimally counterintuitive concepts. *Cognitive Science*, *37*(7), 1251–1289. https://doi.org/10.1111/cogs.12037

Barto, A., Mirolli, M., & Baldassarre, G. (2013). Novelty or surprise?. *Frontiers in Psychology*, *4*, Article 907. https://doi.org/10.3389/fpsyg.2013.00907

Bassi, A., Colacito, R., & Fulghieri, P. (2013). 'O Sole Mio: An experimental analysis of weather and risk attitudes in financial decisions. *Review of Financial Studies*, *26*(7), 1824–1852. https://doi.org/10.1093/rfs/hht004

Bateson, P. (2017). *Behaviour, development and evolution*. Open Book Publishers. https://doi.org/10.11647/OBP.0097

Bateson, P. P. G., & Martin, P. (2013). *Play, playfulness, creativity and innovation*. Cambridge University Press. https://doi.org/10.1017/CBO9781139057691

Bekoff, M. 1976. Animal play: Problems and perspectives. In *Perspectives in ethology* (pp. 165–188). Springer. https://doi.org/10.1007/978-1-4615-7572-6_4

Blanchard, T. C., Hayden, B. Y., & Bromberg-Martin, E. S. (2015). Orbitofrontal cortex uses distinct codes for different choice attributes in decisions motivated by curiosity. *Neuron*, *85*(3), 602–614. https://doi.org/10.1016/j.neuron.2014.12.050

Bloom, P. (2010). *How pleasure works: The new science of why we like what we like*. Random House.

Bloom, P. (2020). The paradox of pleasurable fear. *Trends in Cognitive Sciences*, *25*(2), 93–94. https://doi.org/10.1016/j.tics.2020.12.001

Bonawitz, E. B., van Schijndel, T. J., Friel, D., & Schulz, L. (2012). Children balance theories and evidence in exploration, explanation, and learning. *Cognitive Psychology*, *64*(4), 215–234. https://doi.org/10.1016/j.cogpsych.2011.12.002

Bornstein, M. H. (2007). On the significance of social relationships in the development of children's earliest symbolic play: An ecological perspective. In *Play and development* (pp. 108–136). Psychology Press.

Bruner, J. S., & Sherwood, V. (1976). Peekaboo and the learning of rule structures. In J. S. Bruner, A. Joly, & K. Sylva (Eds.), *Play: Its role in development and evolution*. Basic Books.

Burghardt, G. M. (2005). *The genesis of animal play: Testing the limits*. MIT Press.

Burghardt, G. M. (2011). Defining and recognizing play. In P. Nathan & A. D. Pellegrini (Eds.), *The oxford handbook of the development of play*. Oxford University Press.

Butler, L., & Markman, E. (2010). Pedagogical cues influence children's inductive inference and exploratory play. *Proceedings of the Annual Meeting of the Cognitive Science Society*, *32*(32). https://escholarship.org/uc/item/4jx5s52x

Chu, J., & Schulz, L. (2020). Exploratory play, rational action, and efficient search. *PsyArXiv*. https://doi.org/10.31234/osf.io/9yra2

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*(3), 181–204. https://doi.org/10.1017/S0140525X12000477

Clark, A. (2015). *Surfing uncertainty: Prediction, action, and the embodied mind*. Oxford University Press.

Clark, A. (2018). A nice surprise? Predictive processing and the active pursuit of novelty. *Phenomenology and the Cognitive Sciences*, *17*, 521–534. https://doi.org/10.1007/s11097-017-9525-z

Clark, J. E., Watson, S., & Friston, K. J. (2018). What is mood? A computational perspective. *Psychological Medicine*, *48*(14), 2277–2284. https://doi.org/10.1017/S0033291718000430

Cohn, J. F., Zlochower, A. J., Lien, J. J., & Kanade, T. (1998, April). Feature-point tracking by optical flow discriminates subtle differences in facial expression. In *Proceedings third IEEE international conference on automatic face and gesture recognition* (pp. 396–401). IEEE.

Constant, A., Ramstead, M. J. D., Veissière, S. P. L., Campbell, J. O., & Friston, K. J. (2018). A variational approach to niche construction. *Journal of the Royal Society, Interface*, *15*(141), Article 20170685. https://doi.org/10.1098/rsif.2017.0685

Cook, C., Goodman, N. D., & Schulz, L. E. (2011). Where science starts: Spontaneous experiments in preschoolers' exploratory play. *Cognition*, *120*(3), 341–349. https://doi.org/10.1016/j.cognition.2011.03.003

Cools, R., Nakamura, K., & Daw, N. D. (2011). Serotonin and dopamine: Unifying affective, activational, and decision functions. *Neuropsychopharmacology*, *36*, 98–113. https://doi.org/10.1038/npp.2010.121

Csikszentmihalyi, M. (1997). *Flow and the psychology of discovery and invention* (p. 39). HarperPerennial.

Dember, W. N., & Earl, R. W. (1957). Analysis of exploratory, manipulatory, and curiosity behaviors. *Psychological Review*, *64*(2), 91–96. https://doi.org/10.1037/h0046861

Edmans, A., García, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *The Journal of Finance*, *62*(4), 1967–1998. https://doi.org/10.1111/j.1540-6261.2007.01262.x

Ekman, P., & Davidson, R. J. (Eds.) (1994). *The nature of emotion: Fundamental questions*. Oxford University Press.

Eldar, E., Pessiglione, M., & van Dillen, L. (2021). Positive affect as a computational mechanism. *Current Opinion in Behavioral Sciences*, *39*, 52–57. https://doi.org/10.1016/j.cobeha.2021.01.007

Eldar, E., Rutledge, R. B., Dolan, R. J., & Niv, Y. (2016). Mood as representation of momentum. *Trends in Cognitive Sciences*, *20*(1), 15–24. https://doi.org/10.1016/j.tics.2015.07.010

Fabry, R. E. (2020). Into the dark room: A predictive processing account of major depressive disorder. *Phenomenology and the Cognitive Sciences*, *19*(4), 685–704. https://doi.org/10.1007/s11097-019-09635-4

Fagan, R.. 1981. *Animal play behavior*. Oxford University Press.

Fein, G. G. (1981). Pretend play in childhood: An integrative review. *Child Development*, *52*, 1095–1118. https://doi.org/10.2307/1129497

Feldman, H., & Friston, K. J. (2010). Attention, uncertainty, and free-energy. *Frontiers in Human Neuroscience*, *4*, Article 215. https://doi.org/10.3389/fnhum.2010.00215

Friston, K. (2008). Hierarchical models in the brain. *PLoS Computational Biology*, *4*(11), Article e1000211. https://doi.org/10.1371/journal.pcbi.1000211

Friston, K. (2009). The free-energy principle: A rough guide to the brain?. *Trends in Cognitive Sciences*, *13*(7), 293–301. https://doi.org/10.1016/j.tics.2009.04.005

Friston, K. (2010). The free-energy principle: A unified brain theory?. *Nature Reviews Neuroscience*, *11*(2), 127–138. https://doi.org/10.1038/nrn2787

Friston, K., FitzGerald, T., Rigoli, F., Schwartenbeck, P., & Pezzulo, G. (2017). Active inference: A process theory. *Neural Computation*, *29*(1), 1–49. https://doi.org/10.1162/NECO_a_00912

Friston, K., Fortier, M., & Friedman, D. A. (2018). Of woodlice and men: A Bayesian account of cognition, life and consciousness. An interview with Karl Friston. *ALIUS Bulletin*, *2*, 17–43.

Friston, K., & Kiebel, S. (2009). Predictive coding under the free-energy principle. *Philosophical Transactions of the Royal Society of London, Series B: Biological Sciences*, *364*(1521), 1211–1221. https://doi.org/10.1098/rstb.2008.0300

Friston, K., Rigoli, F., Ognibene, D., Mathys, C., Fitzgerald, T., & Pezzulo, G. (2015). Active inference and epistemic value. *Cognitive Neuroscience*, *6*(4), 187–214. https://doi.org/10.1080/17588928.2015.1020053

Friston, K., Schwartenbeck, P., FitzGerald, T., Moutoussis, M., Behrens, T., & Dolan, R. J. (2014). The anatomy of choice: Dopamine and decision-making. *Philosophical Transactions of the Royal Society of London, Series B: Biological Sciences*, *369*(1655), Article 20130481. https://doi.org/10.1098/rstb.2013.0481

Friston, K. J., Daunizeau, J., Kilner, J., & Kiebel, S. J. (2010). Action and behavior: A free-energy formulation. *Biological Cybernetics*, *102*(3), 227–260. https://doi.org/10.1007/s00422-010-0364-z

Friston, K. J., Lin, M., Frith, C. D., Pezzulo, G., Hobson, J. A., & Ondobaka, S. (2017). Active inference, curiosity and insight. *Neural Computation*, *29*(10), 2633–2683. https://doi.org/10.1162/neco_a_00999

Friston, K. J., & Stephan, K. E. (2007). Free-energy and the brain. *Synthese*, *159*(3), 417–458. https://doi.org/10.1007/s11229-007-9237-y

Gopnik, A. (2009). *The philosophical baby: What children's minds tell us about truth, love & the meaning of life*. Random House.

Gopnik, A. (2016). *The gardener and the carpenter: What the new science of child development tells us about the relationship between parents and children*. Macmillan.

Gopnik, A. (2020). Childhood as a solution to explore–exploit tensions. *Philosophical Transactions of the Royal Society B*, *375*(1803), Article 20190502. https://doi.org/10.1098/rstb.2019.0502

Gopnik, A., O'Grady, S., Lucas, C. G., Griffiths, T. L., Wente, A., Bridgers, S., Aboody, R., Fung, H., & Dahl, R. E. (2017). Changes in cognitive flexibility and hypothesis search across human life history from childhood to adolescence to adulthood. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(30), 7892–7899. https://doi.org/10.1073/pnas.1700811114

Gopnik, A., & Tenenbaum, J. B. (2007). Bayesian networks, Bayesian learning and cognitive development. *Developmental Science*, *10*(3), 281–287. https://doi.org/10.1111/j.1467-7687.2007.00584.x

Gopnik, A., & Wellman, H. M. (2012). Reconstructing constructivism: Causal models, Bayesian learning mechanisms, and the theory theory. *Psychological Bulletin*, *138*(6), 1085–1108. https://doi.org/10.1037/a0028044

Gottlieb, J., Lopes, M., & Oudeyer, P. Y. (2016). Motivated cognition: Neural and computational mechanisms of curiosity, attention, and intrinsic motivation. In *Recent developments in neuroscience research on human motivation*. Emerald Group Publishing. https://doi.org/10.1108/S0749-742320160000019017

Gottlieb, J., & Oudeyer, P. Y. (2018). Towards a neuroscience of active sampling and curiosity. *Nature Reviews Neuroscience*, *19*(12), 758–770. https://doi.org/10.1038/s41583-018-0078-0

Gottlieb, J., Oudeyer, P. Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: computational and neural mechanisms. *Trends in Cognitive Sciences*, *17*(11), 585–593. https://doi.org/10.1016/j.tics.2013.09.001

Groos, K. 1898. *The play of animals*. D. Appleton. https://doi.org/10.1037/12894-000

Gweon, H., & Schulz, L. (2011). 16-month-olds rationally infer causes of failed actions. *Science*, *332*(6037), 1524. https://doi.org/10.1126/science.1204493

Heimann, K. S., & Roepstorff, A. (2018). How playfulness motivates-putative looping effects of autonomy and surprise. *Frontiers in Psychology*, *9*, Article 1704. https://doi.org/10.3389/fpsyg.2018.01704

Hesp, C., Smith, R., Allen, M., Friston, K., & Ramstead, M. (2019). Deeply felt affect: The emergence of valence in deep active inference. *PsyArXiv*. https://doi.org/10.31234/osf.io/62pfd

Hesp, C., Smith, R., Parr, T., Allen, M., Friston, K. J., & Ramstead, M. J. (2021). Deeply felt affect: The emergence of valence in deep active inference. *Neural Computation*, *33*(2), 398–446. https://doi.org/10.1162/neco_a_01341

Hesp, C., Tschantz, A., Millidge, B., Ramstead, M., Friston, K., & Smith, R. (2020, September). Sophisticated affective inference: Simulating anticipatory affective dynamics of imagining future events. In *International workshop on active inference* (pp. 179–186). Springer.

Hohwy, J. (2013). *The predictive mind*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199682737.001.0001

Hopkins, E. J., & Lillard, A. S. (2021). The Magic School Bus dilemma: How fantasy affects children's learning from stories. *Journal of Experimental Child Psychology*, *210*, Article 105212. https://doi.org/10.1016/j.jecp.2021.105212

Hunt, G. R., & Gray, R. D. (2003). Diversification and cumulative evolution in New Caledonian crow tool manufacture. *Proceedings of the Royal Society of London, Series B: Biological Sciences*, *270*(1517), 867–874. https://doi.org/10.1098/rspb.2002.2302

Hutt, S. J., Tyler, S., Hutt, C., & Christopherson, H. (1989). *Play, exploration, and learning: A natural history of the pre-school*. Routledge.

Isen, A. M., & Patrick, R. (1983). The effect of positive feelings on risk taking: When the chips are down. *Organizational Behavior and Human Performance*, *31*(2), 194–202. https://doi.org/10.1016/0030-5073(83)90120-4

Itti, L., & Baldi, P. (2005). *Bayesian surprise attracts human attention* [Conference session]. Proceedings of the 18th International Conference on Neural Information Processing Systems 18, Cambridge, Massachusetts, United States.

Janik, V. M. (2015). Play in dolphins. *Current Biology*, *25*(1), R7–R8. https://doi.org/10.1016/j.cub.2014.09.010

Jensvold, M. L. A., & Fouts, R. S. (1993). Imaginary play in chimpanzees (Pan troglodytes). *Human Evolution*, *8*(3), 217–227. https://doi.org/10.1007/BF02436716

Jirout, J., & Klahr, D. (2012). Children's scientific curiosity: In search of an operational definition of an elusive concept. *Developmental Review*, *32*(2), 125–160. https://doi.org/10.1016/j.dr.2012.04.002

Joffily, M., & Coricelli, G. (2013). Emotional valence and the free-energy principle. *PLoS Computational Biology*, *9*(6), Article e1003094. https://doi.org/10.1371/journal.pcbi.1003094

Jurafsky, D., & Martin, J. H. (2000). *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition*. Prentice Hall.

Kanai, R., Komura, Y., Shipp, S., & Friston, K. (2015). Cerebral hierarchies: Predictive processing, precision and the pulvinar. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1668), Article 20140169. https://doi.org/10.1098/rstb.2014.0169

Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T. Y., & Camerer, C. F. (2009). The wick in the candle of learning: Epistemic curiosity activates reward circuitry and enhances memory. *Psychological Science*, *20*(8), 963–973. https://doi.org/10.1111/j.1467-9280.2009.02402.x

Kidd, C., & Hayden, B. Y. (2015). The psychology and neuroscience of curiosity. *Neuron*, *88*(3), 449–460. https://doi.org/10.1016/j.neuron.2015.09.010

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), Article e36399. https://doi.org/10.1371/journal.pone.0036399

Kirkpatrick, S., Gelatt, C. D., Jr., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, *220*, 671–680. https://doi.org/10.1126/science.220.4598.671

Kiverstein, J., Miller, M., & Rietveld, E. (2019). The feeling of grip: Novelty, error dynamics, and the predictive brain. *Synthese*, *196*(7), 2847–2869. https://doi.org/10.1007/s11229-017-1583-9

Kiverstein, J., Miller, M., & Rietveld, E. (2020). How mood tunes prediction: A neurophenomenological account of mood and its disturbance in major depression. *Neuroscience of Consciousness*, *2020*(1), Article niaa003. https://doi.org/10.1093/nc/niaa003

Kube, T., Schwarting, R., Rozenkrantz, L., Glombiewski, J. A., & Rief, W. (2020). Distorted cognitive processes in major depression: A predictive processing perspective. *Biological Psychiatry*, *87*(5), 388–398. https://doi.org/10.1016/j.biopsych.2019.07.017

Kuczaj, S. A., & Highfill, L. E. (2005). Dolphin play: Evidence for cooperation and culture?. *Behavioral and Brain Sciences*, *28*(5), 705–706. https://doi.org/10.1017/S0140525X05370129

Laland, K. N., Uller, T., Feldman, M. W., Sterelny, K., Müller, G. B., Moczek, A., Jablonka, E., & Odling-Smee, J. (2015). The extended evolutionary synthesis: Its structure, assumptions and predictions. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1813), Article 20151019. https://doi.org/10.1098/rspb.2015.1019

Lavín, C., San Martín, R., & Rosales Jubal, E. (2014). Pupil dilation signals uncertainty and surprise in a learning gambling task. *Frontiers in Behavioral Neuroscience*, *7*, Article 218. https://doi.org/10.3389/fnbeh.2013.00218

Leslie, A. M. (1987). Pretense and representation: The origins of" theory of mind. *Psychological Review*, *94*(4), 412–426. https://doi.org/10.1037/0033-295X.94.4.412

Lew-Lewy, S., Andersen, M. M., Lavi, N., & Riede, F. (2021). *Object play and tool use in hunter-gatherer societies: An ethnohistorical analysis*.

Lillard, A. (2001). Pretend play as twin earth: A social-cognitive analysis. *Developmental Review*, *21*(4), 495–531. https://doi.org/10.1006/drev.2001.0532

Lillard, A. S. (2015). The development of play. *Handbook of child psychology and developmental science, cognitive Processes* (pp. 425–468). Wiley.

Lillard, A. S. (2017). Why do the children (pretend) play?. *Trends in Cognitive Sciences*, *21*(11), 826–834. https://doi.org/10.1016/j.tics.2017.08.001

Lillard, A. S., Lerner, M. D., Hopkins, E. J., Dore, R. A., Smith, E. D., & Palmquist, C. M. (2013). The impact of pretend play on children's development: A review of the evidence. *Psychological Bulletin*, *139*(1), 1–34. https://doi.org/10.1037/a0029321

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychological Bulletin*, *116*(1), 75–98. https://doi.org/10.1037/0033-2909.116.1.75

Lucas, C. G., Bridgers, S., Griffiths, T. L., & Gopnik, A. (2014). When children are better (or at least more open-minded) learners than adults: Developmental differences in learning the forms of causal relationships. *Cognition*, *131*(2), 284–299. https://doi.org/10.1016/j.cognition.2013.12.010

MacKay, D. J. (1992). Information-based objective functions for active data selection. *Neural Computation*, *4*(4), 590–604. https://doi.org/10.1162/neco.1992.4.4.590

Marshall, L. (1976). *The! Kung of Nyae Nyae*. Harvard University Press. https://doi.org/10.4159/harvard.9780674180574

Martin, P., & Caro, T. M. (1985). On the functions of play and its role in behavioral development [Academic Press]. *Advances in the Study of Behavior*, *15*, 59–103. https://doi.org/10.1016/S0065-3454(08)60487-8

Mather, E. (2013). Novelty, attention, and challenges for developmental psychology. *Frontiers in Psychology*, *4*, Article 491. https://doi.org/10.3389/fpsyg.2013.00491

McCall, R. B., & McGhee, P. E. (1977). The discrepancy hypothesis of attention and affect in infants. In *The structuring of experience* (pp. 179–210). Springer. https://doi.org/10.1007/978-1-4615-8786-6_7

Mirza, M. B., Adams, R. A., Friston, K., & Parr, T. (2019). Introducing a Bayesian model of selective attention based on active inference. *Scientific Reports*, *9*(1), Article 13915. https://doi.org/10.1038/s41598-019-50138-8

Nissen, H. W. (1930). A study of exploratory behavior in the white rat by means of the obstruction method. *Pedagogical Seminary and Journal of Genetic Psychology*, *37*, 361–376. https://doi.org/10.1080/08856559.1930.9944162

Niv, Y., Joel, D., & Dayan, P. (2006). A normative perspective on motivation. *Trends in Cognitive Sciences*, *10*(8), 375–381. https://doi.org/10.1016/j.tics.2006.06.010

Oudeyer, P. Y., Kaplan, F., & Hafner, V. V. (2007). Intrinsic motivation systems for autonomous mental development. *IEEE Transactions on Evolutionary Computation*, *11*(2), 265–286. https://doi.org/10.1109/TEVC.2006.890271

Oudeyer, P. Y., & Smith, L. B. (2016). How evolution may work through curiosity-driven developmental process. *Topics in Cognitive Science*, *8*(2), 492–502. https://doi.org/10.1111/tops.12196

Parr, T., & Friston, K. J. (2017). Uncertainty, epistemics and active inference. *Journal of the Royal Society, Interface*, *14*(136), Article 20170376. https://doi.org/10.1098/rsif.2017.0376

Parr, T., & Friston, K. J. (2018). The anatomy of inference: Generative models and brain structure. *Frontiers in Computational Neuroscience*, *12*, Article 90. https://doi.org/10.3389/fncom.2018.00090

Parrott, W. G., & Gleitman, H. (1989). Infants' expectations in play: The joy of peek-a-boo. *Cognition and Emotion*, *3*(4), 291–311. https://doi.org/10.1080/02699938908412710

Pathak, D., Agrawal, P., Efros, A. A., & Darrell, T. (2017). *Curiosity-driven exploration by self-supervised prediction* [Conference session]. Proceedings of the 34th International Conference on Machine Learning, Sydney, Australia.

Paulus, M. P., Feinstein, J. S., & Khalsa, S. S. (2019). An active inference approach to interoceptive psychopathology. *Annual Review of Clinical Psychology*, *15*, 97–122. https://doi.org/10.1146/annurev-clinpsy-050718-095617

Pellegrini, A. D. (2006). The development and function of rough and tumble play in childhood and adolescence. In A. Göncü & S. Gaskins (Eds.), *Play and development: Evolutionary, sociocultural, and functional perspectives* (pp. 77–98). Erlbaum.

Pellegrini, A. D. (2009). *The role of play in human development*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195367324.001.0001

Pellegrini, A. D. (2011a). Introduction. In A. Pellegrini (Ed.), *The oxford handbook of the development of play*. Oxford Library of Psychology.

Pellegrini, A. D. (2011b). The development and function of locomotor play. In A. Pellegrini (Ed.), *The oxford handbook of the development of play*. Oxford Library of Psychology.

Pellegrini, A. D., Dupuis, D., & Smith, P. K. (2007). Play in evolution and development. *Developmental Review*, *27*(2), 261–276. https://doi.org/10.1016/j.dr.2006.09.001

Pellegrini, A. D., & Smith, P. K. (1998). Physical activity play: The nature and function of a neglected aspect of playing. *Child Development*, *69*(3), 577–598. https://doi.org/10.1111/j.1467-8624.1998.tb06226.x

Perez, J., & Feigenson, L. (2020). Violations of expectation trigger infants to search for explanations. *Cognition*, *218*, Article 104942. https://doi.org/10.1016/j.cognition.2021.104942

Pessin, A., & Goldberg, S. (Eds.). (1996). *The twin earth chronicles*. M. E. Sharpe.

Petitmengin, C. (2006). Describing one's subjective experience in the second person: An interview method for a science of consciousness. *Phenomenology and the Cognitive Sciences*, *5*(3), 229–269. https://doi.org/10.1007/s11097-006-9022-2

Piaget, J. (1962). *Play, imitation and dreams in childhood*. Norton.

Poirier, F. E., & Smith, E. O. (1974). Socializing functions of primate play. *American Zoologist*, *14*(1), 275–287. https://doi.org/10.1093/icb/14.1.275

Ramsey, J. K., & McGrew, W. C. (2005). Object play in great apes. In A. D. Pelligrini & P. K. Smith (Eds.), *The nature of play: Great apes and humans* (pp. 89–112). Guilford Press.

Ramstead, M. J., Wiese, W., Miller, M., & Friston, K. J. (2021). *Deep neurophenomenology: An active inference account of some features of conscious experience and of their disturbance in major depressive disorder*. http://philsci-archive.pitt.edu/18377/

Ratcliffe, M. (2008). *Feelings of being: Phenomenology, psychiatry and the sense of reality*. Oxford University Press.

Reddy, V., & Mireault, G. (2015). Teasing and clowning in infancy. *Current Biology*, *25*(1), R20–R23. https://doi.org/10.1016/j.cub.2014.09.021

Reissland, N., Shepherd, J., & Cowie, L. (2002). The melody of surprise: Maternal surprise vocalizations during play with her infant. *Infant and Child Development: An International Journal of Research and Practice*, *11*(3), 271–278. https://doi.org/10.1002/icd.258

Reissland, N., & Snow, D. (1996). Maternal pitch height in ordinary and play situations. *Journal of Child Language*, *23*(2), 269–278. https://doi.org/10.1017/S0305000900008795

Russ, S. W. & American Psychological Association (2014). *Pretend play in childhood: Foundation of adult creativity* (pp. 45–62). American Psychological Association.

Rutledge, R. B., Skandali, N., Dayan, P., & Dolan, R. J. (2014). A computational and neural model of momentary subjective well-being. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(33), 12252–12257. https://doi.org/10.1073/pnas.1407535111

Sandseter, E. B. H. (2010). “it tickles in my tummy!” understanding children’s risk-taking in play through reversal theory. *Journal of Early Childhood Research*, *8*(1), 67–88. https://doi.org/10.1177/1476718X09345393

Scarr, S., & Salapatek, P. (1970). Patterns of fear development during infancy. *Merrill-Palmer Quarterly of Behavior and Development*, *16*(1), 53–90.

Scherer, K. R., Zentner, M. R., & Stern, D. (2004). Beyond surprise: The puzzle of infants’ expressive reactions to expectancy violation. *Emotion*, *4*(4), 389–402. https://doi.org/10.1037/1528-3542.4.4.389

Schillaci, G., Pico Villalpando, A., Hafner, V. V., Hanappe, P., Colliaux, D., & Wintz, T. (2021). Intrinsic motivation and episodic memories for robot exploration of high-dimensional sensory spaces. *Adaptive Behavior*, *29*(6), 549–566. https://doi.org/10.1177/1059712320922916

Schmidhuber, J. (1991). Curious model-building control systems. In *Proceedings of the 1991 IEEE international joint conference on neural networks* (pp. 1458–1463). IEEE.

Schmidhuber, J. (2006). Developmental robotics, optimal artificial curiosity, creativity, music, and the fine arts. *Connection Science*, *18*(2), 173–187. https://doi.org/10.1080/09540090600768658

Schmidhuber, J. (2013). PowerPlay: Training an increasingly general problem solver by continually searching for the simplest still unsolvable problem. *Frontiers in Psychology*, *4*, Article 313. https://doi.org/10.3389/fpsyg.2013.00313

Schulz, L. (2012). The origins of inquiry: Inductive inference and exploration in early childhood. *Trends in Cognitive Sciences*, *16*(7), 382–389. https://doi.org/10.1016/j.tics.2012.06.004

Schulz, L. (2015). Psychology. Infants explore the unexpected. *Science*, *348*(6230), 42–43. https://doi.org/10.1126/science.aab0582

Schulz, L. E., & Bonawitz, E. B. (2007). Serious fun: Preschoolers engage in more exploratory play when evidence is confounded. *Developmental Psychology*, *43*(4), 1045–1050. https://doi.org/10.1037/0012-1649.43.4.1045

Schulz, L. E., Gopnik, A., & Glymour, C. (2007). Preschool children learn about causal structure from conditional interventions. *Developmental Science*, *10*(3), 322–332. https://doi.org/10.1111/j.1467-7687.2007.00587.x

Schulz, L. E., Standing, H. R., & Bonawitz, E. B. (2008). Word, thought, and deed: The role of object categories in children’s inductive inferences and exploratory play. *Developmental Psychology*, *44*(5), 1266–1276. https://doi.org/10.1037/0012-1649.44.5.1266

Schwartenbeck, P., Fitzgerald, T., Dolan, R. J., & Friston, K. (2013). Exploration, novelty, surprise, and free energy minimization. *Frontiers in Psychology*, *4*, Article 710. https://doi.org/10.3389/fpsyg.2013.00710

Singer, D. G., & Singer, J. L. (1990). *The house of make-believe: Children’s play and the developing imagination*. Harvard University Press. https://doi.org/10.4159/9780674043688

Sobel, D. M., Tenenbaum, J. B., & Gopnik, A. (2004). Children’s causal inferences from indirect evidence: Backwards blocking and Bayesian reasoning in preschoolers. *Cognitive Science*, *28*(3), 303–333. https://doi.org/10.1207/s15516709cog2803_1

Solomon, R. C. (1993). *The passions: Emotions and the meaning of life*. Hackett Publishing.

Somerville, L. H., Wagner, D. D., Wig, G. S., Moran, J. M., Whalen, P. J., & Kelley, W. M. (2013). Interactions between transient and sustained neural signals support the generation and regulation of anxious emotion. *Cerebral Cortex*, *23*(1), 49–60. https://doi.org/10.1093/cercor/bhr373

Spinka, M., Newberry, R. C., & Bekoff, M. (2001). Mammalian play: Training for the unexpected. *The Quarterly Review of Biology*, *76*(2), 141–168. https://doi.org/10.1086/393866

Stahl, A. E., & Feigenson, L. (2015). Cognitive development. Observing the unexpected enhances infants’ learning and exploration. *Science*, *348*(6230), 91–94. https://doi.org/10.1126/science.aaa3799

Stahl, A. E., & Feigenson, L. (2019). Violations of core knowledge shape early learning. *Topics in Cognitive Science*, *11*(1), 136–153. https://doi.org/10.1111/tops.12389

Sukalla, F., Shoenberger, H., & Bolls, P. D. (2016). Surprise! An investigation of orienting responses to test assumptions of narrative processing. *Communication Research*, *43*(6), 844–862. https://doi.org/10.1177/0093650215596363

Sun, Y., Gomez, F., & Schmidhuber, J. (2011, August). Planning to be surprised: Optimal bayesian exploration in dynamic environments. In *International conference on artificial general intelligence* (pp. 41–51). Springer.

Sun, Z., & Firestone, C. (2020). The dark room problem. *Trends in Cognitive Sciences*, *24*(5), 346–348. https://doi.org/10.1016/j.tics.2020.02.006

Sutton-Smith, B. (1997). *The ambiguity of play*. Harvard University Press.

Takada, A. (2020). Children and play. In *The ecology of playful childhood* (pp. 57–68). Palgrave Macmillan. https://doi.org/10.1007/978-3-030-49439-1_4

Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. *Science*, *331*(6022), 1279–1285. https://doi.org/10.1126/science.1192788

Thelen, E. (1980). Determinants of amounts of stereotyped behavior in normal human infants. *Ethology and Sociobiology*, *1*(2), 141–150. https://doi.org/10.1016/0162-3095(80)90004-7

Ullman, T. D., & Tenenbaum, J. B. (2020). Bayesian models of conceptual development: Learning as building models of the world. *Annual Review of Developmental Psychology*, *2*, 533–558. https://doi.org/10.1146/annurev-devpsych-121318-084833

Uzgiris, I. C. (1967) Ordinality in the development of schemas for relating to objects. In J. Hellmuth (Ed.), *Exceptional infant: Vol 1. The normal infant* (pp. 317–334). Special Child Publications.

Van de Cruys, S. (2017). *Affective value in the predictive mind*. Johannes Gutenberg-Universität Mainz.

Van de Cruys, S., Friston, K., & Clark, A. (2020). Controlled optimism: Reply to Sun and Firestone on the dark room problem. *Trends in Cognitive Sciences*, *24*(9), 1–2. https://doi.org/10.1016/j.tics.2020.05.012

van Schijndel, T. J., Visser, I., van Bers, B. M., & Raijmakers, M. E. (2015). Preschoolers perform more informative experiments after observing theory-violating evidence. *Journal of Experimental Child Psychology*, *131*, 104–119. https://doi.org/10.1016/j.jecp.2014.11.008

Vasconcelos, M., Monteiro, T., & Kacelnik, A. (2015). Irrational choice and the value of information. *Scientific Reports*, *5*, Article 13874. https://doi.org/10.1038/srep13874

Veissière, S. P., Constant, A., Ramstead, M. J., Friston, K. J., & Kirmayer, L. J. (2020). Thinking through other minds: A variational approach to cognition and culture. *Behavioral and Brain Sciences*, *43*, 1–75.https://doi.org/10.1017/S0140525X19001213

Ververidis, D., Kotropoulos, C., & Pitas, I. (2004, May). Automatic emotional speech classification. In *2004 IEEE international conference on acoustics, speech, and signal processing* (Vol. 1, pp. I–593). IEEE.

Wade, S., & Kidd, C. (2019). The role of prior knowledge and curiosity in learning. *Psychonomic Bulletin & Review*, *26*(4), 1377–1387. https://doi.org/10.3758/s13423-019-01598-6

Wang, A. Y., Miura, K., & Uchida, N. (2013). The dorsomedial striatum encodes net expected return, critical for energizing performance vigor. *Nature Neuroscience*, *16*(5), 639–647. https://doi.org/10.1038/nn.3377

Wang, J. J., Yang, Y., Macias, C., & Bonawitz, E. (2021). Children with more uncertainty in their intuitive theories seek domain-relevant information. *Psychological Science*, *32*(7), 1147–1156. https://doi.org/10.1177/0956797621994230

Weisberg, D. S., & Gopnik, A. (2013). Pretense, counterfactuals, and Bayesian causal models: Why what is not real really matters. *Cognitive Science*, *37*(7), 1368–1381. https://doi.org/10.1111/cogs.12069

Werker, J. F., Polka, L., & Pegg, J. E. (1997). The conditioned head turn procedure as a method for testing infant speech perception. *Infant and*

*Child Development*, *6*(3–4), 171–178. https://doi.org/10.1002/(SICI)1099-0917(199709/12)6:3/4<171::AID-EDP156>3.0.CO;2-H

Whiten, A., Goodall, J., McGrew, W. C., Nishida, T., Reynolds, V., Sugiyama, Y., Tutin, C. E., Wrangham, R. W., & Boesch, C. (1999). Cultures in chimpanzees. *Nature*, *399*(6737), 682–685. https://doi.org/10.1038/21415

Wiese, W., & Metzinger, T. (2017). Vanilla PP for philosophers: A primer on predictive processing. In *Philosophy and predictive processing* (pp. 1–18). Frankfurt am Main: MIND Group.

Wright, W. F., & Bower, G. H. (1992). Mood effects on subjective probability assessment. *Organizational Behavior and Human Decision Processes*, *52*(2), 276–291. https://doi.org/10.1016/0749-5978(92)90039-A

Wu, Y., & Gweon, H. (2021). Preschool-aged children jointly consider others' emotional expressions and prior knowledge to decide when to explore. *Child Development*, *92*(3), 862–870. https://doi.org/10.1111/cdev.13585

Zosh, J. M., Hirsh-Pasek, K., Hopkins, E. J., Jensen, H., Liu, C., Neale, D., Solis, S. L., & Whitebread, D. (2018). Accessing the inaccessible: Redefining play as a spectrum. *Frontiers in Psychology*, *9*, Article 1124. https://doi.org/10.3389/fpsyg.2018.01124

Received July 2, 2021
Revision received February 23, 2022
Accepted February 27, 2022 ■