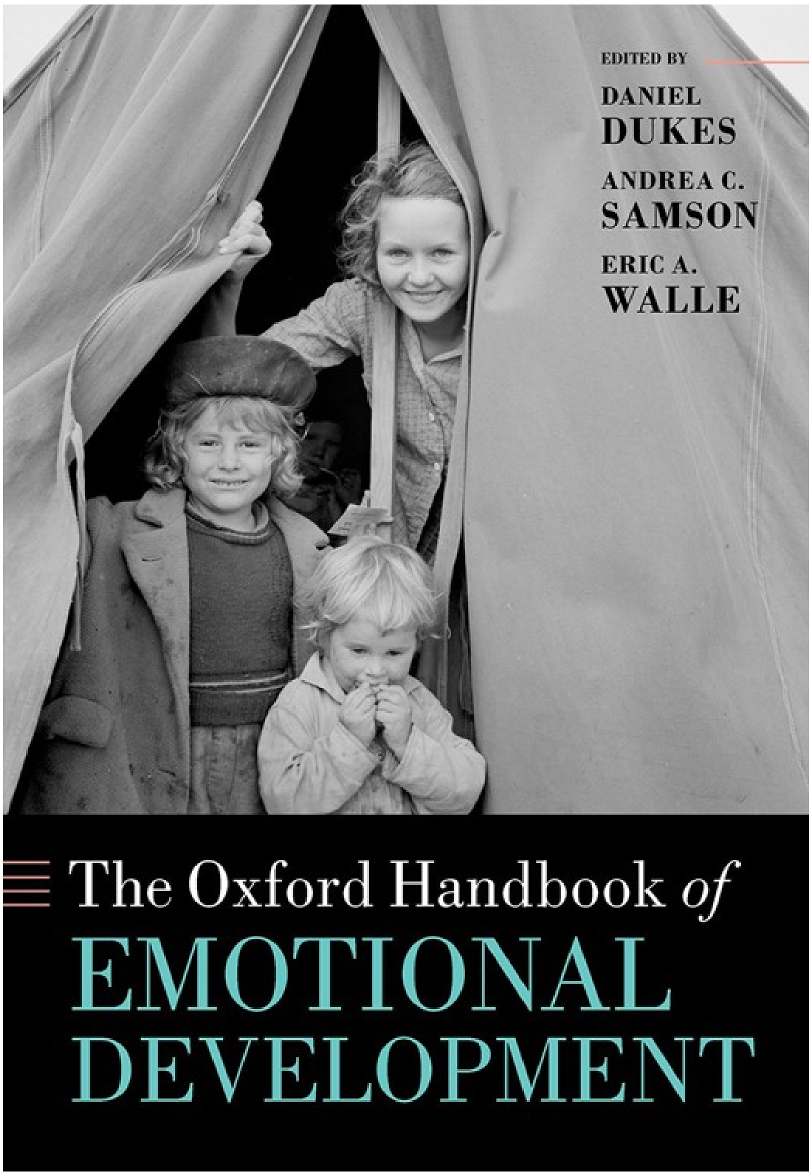

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CHAPTER

6 Statistical Learning in an Emotional World

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Abstract

Children face myriad challenges in navigating the emotional world, including discerning the emotions of others and making predictions based on emotional cues. How well children respond to these challenges can influence overall social competence and functioning. This chapter explores the contribution of statistical learning—a learning mechanism long used to understand knowledge acquisition in cognitive development—to emotional development. The authors propose that the statistics of socioemotional input in children's environments guide what children learn about emotions by allowing them to attend to regularities in the structure of input they receive. Statistical learning could be a mechanism through which children's early learning environments shape emotional development and may underlie differences in how children extract and use emotional information.

Keywords: statistical learning, emotion, emotional development, emotional cues, learning mechanism, psychopathology, prediction

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Introduction

THE study of child development presents a paradox: while children are generally less competent than adults, there are domains in which young children can outperform older individuals. As children mature, they increasingly express themselves more clearly, control their bodies more skillfully, and make better judgments and decisions. Yet infants generally acquire language more efficiently than adults, and preschoolers can construct abstract categories and reason about causation in ways that are disproportionately advanced given their early and relatively immature cognitive development. This seeming inconsistency has been resolved by mounting empirical evidence that very young children are powerful learners, who benefit from flexibility and openness to exploration, which are actually enhanced, rather than constrained, by their lack of knowledge (Gopnik et al., 2015, 2017; Walker et al., 2016; Newport, 1990). Not being overly constrained by existing knowledge allows the developing child to efficiently track and use associations in their environments (e.g., patterns and co-occurrences between stimuli and outcomes) to form expectations that guide behavior. Here we propose that psychological mechanisms that underlie children's cognitive development are similarly used to promote socioemotional development. We review evidence consistent with the view that general cognitive learning principles play a role in how children make inferences about how others are feeling and use emotion-relevant information to predict behaviors.

When learning about emotion, children are faced with myriad challenges. Perhaps most basically, they must p. 79 be able to surmise how a social partner is feeling. However, ↳ this is not necessarily a straightforward task (Barrett et al., 2019). Social partners may feel multiple emotions at once, change how they are feeling, or feel emotions that are multifaceted and complex. Social partners also convey their feelings in different ways, and the way an emotion is conveyed may be influenced by the context. Other areas of emotional learning stem from this task of estimating another's feelings. Learning involves not only recognizing cues to emotion, but also predicting how others might feel given different outcomes in different situations. Children must be able to anticipate the actions of others, and emotions often provide clues about how another will behave. If a child spills juice on the carpet, their caregiver's emotional response may help the child predict whether they will get in trouble. Or, a social partner's emotional response to a situation might help a learner predict whether that individual might make a good friend. Here we will focus on these two tasks: identifying emotions and making predictions, though emotional development certainly involves many other skills.

When emotional development proceeds well, children's skill acquisition can seem so seamless that it could appear that little in the way of complex learning is even necessary for rudimentary emotion understanding. Many have argued that emotion concepts are invariant, universal, and evolutionarily constant (e.g., Ekman, 1992). However, disruptions in children's early social environments reveal cascading effects on children's emotional development, including the flexibility to adapt to emotions in the face of changing social contexts (Pollak & Kistler, 2002). Therefore, there is mounting evidence that our conceptions of emotion emerge *through* learning (e.g., Barrett, 2017), and, increasingly, research and theory are focusing on the underlying learning mechanisms through which maturational changes in emotional competence emerge (Pollak et al., 2019).

Theorists have debated whether early knowledge about emotions is innate or the result of learning. Now, emerging experimental research incorporates conceptual frameworks and techniques from the field of cognitive development to understand the role of learning in emotional development (e.g., Van de Cruys, 2017). While we expect that multiple learning mechanisms underlie emotional development (including learning through explicit instruction and using one's own emotional experiences to understand others), here we focus on the application of one particular learning mechanism—statistical learning—to the domain of emotion. We focus on the construct of statistical learning because this type of mechanism is likely to allow learners to sort through vast and complex input (e.g., in language, naïve physics). Therefore, statistical learning might be particularly well suited to making sense of the multifaceted, varied, and uncertain emotional input that characterizes the social world. Additionally, we have a robust understanding of how statistical learning supports cognitive development, which affords access to established methods and theoretical frameworks with which we can begin to ask questions about its application to emotional development.

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Statistical Learning Guides Meaning Extraction

Learning refers to knowledge or skills that one gains through experience. Learning allows individuals to gather information about their world, and individuals use what they learn to direct action. Children must acquire an incredible amount of information in order to successfully navigate the social world. For instance, they must discern who will care for their needs, how to make and maintain friendships, what might make others upset, and how to respond to the myriad complex emotions that social partners can, and do, convey. To tackle these, and many other learning challenges, children take advantage of powerful approaches, including supervised learning (i.e., receiving direct instruction or feedback) and unsupervised learning (i.e., learning in the absence of direct instruction or feedback) (Love, 2002). Supervised learning plays an important role in socioemotional development, including school-based curricula to teach social, emotional, and communication skills (e.g., Durlak et al., 2011). For instance, children's storybooks may draw attention to and label how characters are feeling, and adults might provide labels for emotions in order to guide children's understanding of nonverbal interpersonal interactions (Gordon, 1991; Pollak & Thoits, 1989). Child-focused materials (e.g., books, toys), parent–child interactions, and school settings are replete with examples of supervised emotion teaching and learning, and parental scaffolding of emotional content is associated with increases in prosocial behavior in toddlers and young children (Brownell et al., 2013; Drummond et al., 2014; Gross et al., 2015). Yet, supervised learning requires time, resources, and direct instruction. For example, in order to learn about sadness via supervised learning, a child might need to be explicitly exposed to, and guided through, instances of sadness-inducing situations, with facial cues to sadness labeled and described by a scaffolding social partner. Additionally, while this sort of pedagogy can promote learning, it can come at the cost of children discovering new ideas or possibilities through their own exploration (Bonawitz et al., 2011). As such, unsupervised learning, which happens without explicit instruction, might be a useful tool to help children learn in domains in which there is a large amount of varying information.

However, relatively little attention has been devoted to understanding the role of unsupervised learning, including statistical learning, in emotional development. The term "statistical learning" refers to tracking relations between stimuli, for instance tracking that frowns and crying often occur together. Notably though, statistical learning extends beyond operant conditioning in which stimuli and outcomes are paired to attention to the overall statistical composition of a sample (e.g., Altvater–Mackensen et al., 2017; Maye et al., 2002; Xu & Garcia, 2008). Statistical learning is described as "modality-, domain-, and species-general" (Aslin, 2017), meaning that the system is not specialized for a certain class of stimuli. For example, while the majority of research on statistical learning focuses on language acquisition (e.g., infants use of
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statistical ↳ co-occurrences between sounds distinguishes words from nonwords; Saffran et al., 1996), statistical learning supports learning of other types of input as well (e.g., patterns of shapes; Kirkham et al., 2002). Statistical learning of streams of input can occur—and be enhanced—when the input is emotional (Everaert et al., 2020). Recently, computational accounts are emerging as another way to formalize how children's use of statistical evidence translates to knowledge, expectations, and behavior in emotional development (see Rudrauf et al., this volume); many of these accounts are predicated upon a developing child first recognizing associations or patterns of social input.

The emotional input in one's environment could vary along numerous dimensions including the emotions being conveyed, the number of emoters available and their expressive style, the predictive power of emotion cues, and how well the emotions match the context. We propose that statistical learning helps children organize and integrate this information. Given that statistical learning allows for extraction of meaningful information in multifaceted, noisy learning situations, it may be particularly well suited for the complexity of emotional content.

Statistical Distribution of Emotion Input Influences Emotion Categories

Adults and children perceive facial emotions categorically (e.g., Cheal & Rutherford, 2011; Etcoff & Magee, 1992). There are linear and continuous perceptual muscular changes that occur as an emoter goes from facial configurations of one emotion to another. However, perceivers see facial configurations that cross an emotion boundary (e.g., between happy and angry) as more different from each other compared to facial configurations that are within an emotion boundary (e.g., two angry faces) *even if* the perceptual change is the same (Calder et al., 1996; Pollak & Kistler, 2002). Perceiving emotions categorically serves a social function: one needs to decide how to respond when faced with a social partner conveying an emotion. Having a perceived boundary between emotion categories provides a convenient shortcut for determining how to act. Yet, little is understood about how learning and statistical information may influence these categories.

Typically developing infants see a large amount of facial input in the first three months of life, but this input is primarily provided by a relatively small number of individuals, suggesting that conceptions of emotion are generated and generalized from a small sample (Jayaraman et al., 2015). Emotions, when being conveyed by social agents, are also noisy. Emoters are individualized in their emotive style. For example, emoters may vary in the intensity of emotions conveyed such that some individuals are highly expressive and others are more muted in how they express emotions. Additionally, some emoters regularly convey certain emotions more than others. Expressive style also varies based on context: emoters will behave

differently if interacting in a library versus at a ↳ party, or at home versus out with strangers, and how emotional cues are produced can be influenced by the cultural context (Niedenthal et al., 2017). There may even be instances when emoters seem stochastic or random. One example might be if the emoter has information that the perceiver does not, such as the emoter concealing upsetting information and therefore acting sad during a seemingly happy occasion.

As described above, emoters influence the type of emotion input that children see; however, environments also influence or constrain the availability and type of emotion input. For example, infants' acquisition of motor abilities facilitates a new visual perspective (see Smith et al., 2018 for a review). Whereas infants see a lot of faces in their first three months of life, facial content is drastically reduced when infants begin to crawl. For crawling infants, objects comprise a larger amount of their visual input instead of faces. Additionally, different early experiences and environments influence what input children see. For instance, children with a history of physical abuse encounter more anger expressions from caregivers than children who have not experienced abuse (Plate et al., 2019). These variations in input constitute the emotional statistics that learners encounter: emotions varying according to frequency (e.g., the amount and types of emotions learners see), intensity (e.g., whether emotions are muted or more expressive), and predictability (e.g., how well emotional content predicts other information in the environment). Using experimental approaches to manipulate these factors in the lab, we can unpack how the statistical features influence emotion learning.

One question that researchers have addressed is how the frequency of emotions encountered influences individuals' emotion categorization. In one series of experiments, the frequency of emotional information conveyed was manipulated to test whether the statistical distribution of emotional input would influence the placement of the boundary between emotion categories (Plate et al., 2019). Participants were asked to categorize faces as being either "upset" or "calm." The faces were sampled from a continuum of facial morphs between neutral and angry. Critically, some participants saw more angry faces, some saw more neutral faces, and some saw faces that were equally distributed across anger and neutral. Both school-age children and adults adjusted their emotion categories based on the frequency of the input. Those exposed to more angry faces increased their threshold for categorizing a face as angry (therefore narrowing their category of anger). Those exposed to more calm faces decreased their threshold for categorizing a face as angry. These shifts in categorization occurred through exposure, with no feedback given to participants about their responses. Children overall had more variability in their categorization choices, providing evidence that their emotion categories are less established compared to those of adults. More broadly, how frequent or common an emotion appears in one's environment influences the observer's conception of that emotion (Levari et al., 2018). As a result, individual differences in emotion categories may be influenced by early experience that differs according to emotional input. For example, having experienced maltreatment from a caregiver changes how young children discriminate salient emotions (e.g., anger; Pollak & Kistler, 2002). Taken together, this research illustrates one way—attention to the statistical features (e.g., frequency)—in which statistical learning influences emotional development.

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In addition to categorizing emotions, children can track information about emoters across contexts to learn more about the emoter's desires and emotional display rules. For example, when 7- to 10-year-olds were presented with illustrated stories that showed a character acting one way in front of their social partner (social context) and another way behind their back (nonsocial context), children were able to infer display rules in the situation. They interpreted the expression in the nonsocial context to represent what the emoter felt and the reaction in the social context as how the expresser wanted to display that emotion (Wu & Schulz, 2020). In sum, the statistical distribution of emotion input influences children's ability to track individual differences in expressivity, categorize emotions, and uncover social display rules.

Statistical Learning and Prediction

One powerful statistical learning approach that children use is Bayesian learning. Bayesian learners track statistical information and use that information to make rational inferences about their environment (Gopnik & Wellman, 1994; Gopnik & Bonawitz, 2015; Xu & Kushnir, 2013). These inferences take into consideration prior probabilities and current constraints on the hypothesis space given the context (Perfors et al., 2011). The Bayesian learning approach has been used in other areas of child development to explain young children's ability to infer causes of failed actions (Gweon & Schulz, 2011) and uncover the preferences of others (Kushnir et al., 2010). More recently, researchers have begun to focus more on how emotional development is also driven by this learning because emotion learning involves recognizing different cues to emotion *and* making predictions based on those cues. Here we review research that provides evidence for how children use emotional input in their environments to make predictions, such as predicting what preceded a social agent's action, new events based on how reliable a social agent's affective cues are, and how a social agent will feel in different situations. In considering the interplay between statistical learning and prediction in the emotion domain, we raise the possibility that these could be dissociable, albeit related, aspects of emotion development. To illustrate, a child may notice the co-occurrence of two stimuli, such as a parent scowling when they are doing laundry. However, we might wonder when the child can predict the behavior (doing laundry) from the facial cue alone (scowling) or vice versa.

Children show early forms of using the emotions of others to make predictions through social referencing. In the classic visual cliff paradigm, infants who observe their mother indicating joy will crawl across a transparent surface suspended above the ground (Sorce et al., 1985). However, they will not cross if their mother indicates fear. Infants similarly use affective auditory cues to make predictions about which toys would be safe to play with (Mumme et al., 1996) and about what actions to try themselves (Patzwald et al., 2018). Further, infants seek out emotional information from potential informants when assessing novel environments (Moses et al., 2001), suggesting ↳ that infants are using emotional cues to make predictions about how to best interact with their surroundings.
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As children get older, they use affective input to make predictions about what preceded a social agent's action. For example, children predicted that a vocalization of "deliciousness" (e.g., an "mmm" sound) was caused by cake, while a vocalization of "adorableness" (e.g., an "aww" sound) was caused by seeing a smiling infant (Wu et al., 2017). Therefore, children attended to the emotional information in an environment to understand the larger context of a social partner's experiences. Children can also use emotional behavior at one time point to predict the emotional informativeness of an individual in a different context. Children may look to the emotional reliability of a social partner to predict whether that partner's affective cues will be useful in new situations. When 4- and 5-year-old children heard speakers use emotional prosody that was incongruent with what was being said, children were unlikely to use that speaker's emotional prosody on a future trial. Specifically, if a speaker said "My dog ran away" in a positive (incongruent) intonation, children ignored the prosody of that speaker later on. They did not use negative intonation of the speaker saying "Look at the ball" to infer it was a deflated ball, and instead attended equally to a regular and deflated ball (Thacker, 2018). Taken together, these experiments demonstrate how children track the content of emotional input and use co-occurrences to extract rich emotional information.

Another prediction that children make from statistical information is about how a social agent will *feel*. Infants are able to match an actor's facial cues to an emotion-eliciting event, even distinguishing within-valence emotions (Ruba et al., 2019). Ten-month-old infants expect positive emotional reactions in response to achieving a goal (Skerry & Spelke 2014), and 12-month-olds are surprised by incongruent reactions to events, such as positive reactions to negative events (Reschke et al., 2017). Toddlers also take into account contextual factors and the emoter's epistemic state when making emotion-related predictions (Scott, 2017; Wu et al., 2018).

In a set of studies with older children, participants viewed the likelihood of receiving a particular type of gumball from a machine and used that probability of receiving a desired or rare outcome to predict the magnitude of another's feelings. If a gumball machine contained almost entirely black gumballs and an actor gets a red gumball, 7-year-old children inferred that they were more surprised by this event than by getting a red gumball when red and black gumballs were equally likely (Doan et al., 2018). Five- and 6-year-old children can also predict that less likely positive events make individuals happier than more likely positive events. However, 4-year-old children are unable to make these predictions, despite being able to infer the quality of the outcome (e.g., that an unlikely good event is better than a likely good event; Doan et al., 2020; see also Asaba et al., 2019).

It is possible that using the statistical information to infer the quality of an event might be a separate skill from using that information to predict an emotion or behavior. Additional support for this possibility comes from a modified Sally–Anne task, where a character that children have seen, Sally, leaves the room while another character, Anne, hides Sally's toy. Sally returns to the room either angry (implying she saw Anne p. 85 hide ↳ her toy and is upset) or happy (implying that she did not see Anne hide her toy). Four-year-old children knew whether Sally saw Anne hide her toy, but were unable to use this knowledge to predict Sally's action (e.g., whether Sally would look for her toy where Anne hid it, or where Sally placed the toy originally) until age 5 (Wu et al., 2018). These findings suggest that knowledge about an emotion state is not the only skill necessary for prediction about emotion behaviors.

One critical issue in the application of statistical learning to the emotion domain, as illustrated by the aforementioned research, is how and whether to distinguish between the role of statistical learning to *extract* information versus making *predictions* based on that information. Individuals may have intact statistical learning processes but deficits in using the statistical information to make predictions (Gomot & Wicker, 2012; Haebig et al., 2017), as might be the case for 4-year-old children in the Sally–Anne task: they extracted the correct information but did not translate that information into an accurate prediction (though see Reschke et al., 2017 for a discussion on how these skills may have some basis in infancy). Such skills may be difficult to distinguish in stable environments but may become dissociable in a changing environment

(Saffran, 2018), particularly when the probabilistic relation between action and outcome is not deterministic. This dissociation could explain whether differences in emotion-related skills stem from the use of statistics or in applying those statistics predictively.

Statistical Learning and Implications for Adaptive Behavior

Statistical learning may have implications for understanding how typical emotional development could get disrupted, and what interventions could be helpful. There is some evidence that associative learning—a subtype of statistical learning in which specific stimuli are paired probabilistically (i.e., pairing action A with outcome A 70% of the time and pairing action A with outcome B 30% of the time)—is impaired in children with a history of maltreatment. Specifically, children with a history of adversity have difficulty using such statistical associations to predict opportunities for reward (Hanson et al., 2017). Additionally, maltreated adolescents are slower to use observed co-occurrences to form specific associations and have difficulty updating these associations after contingencies change (Harms et al., 2018). Deficits in associative learning can both be *predicted by* the extent of early life stress (Harms et al., 2018) and *predictive of* later difficulties in social functioning (i.e., behavioral problems; Hanson et al., 2017). How individuals track and update statistical input to make sense of the emotional world may also be relevant for understanding mechanisms underlying symptoms of Autism Spectrum Disorder (ASD). The way in which individuals with ASD use statistical patterns to generate and update predictions provides insight into potential disruptions in the
p. 86 learning process (Van de Cruys et al., 2013, 2014). Specifically, there is evidence to ↳ suggest that individuals with ASD establish rigid initial expectations and have difficulty discerning when to update those expectations versus when to ignore noise in uncertain, not deterministic, environments.

Statistical learning may also have implications for interventions, given its potential role in the development of differences in emotion perception and associative learning across populations. One intervention task that relies on associative learning is the modified visual probe or “Dot Probe” task (Bar–Haim et al., 2007; Fox et al., 2001; MacLeod et al., 2002; Mogg & Bradley, 1998). In this task (often referred to as attention bias modification), a contingency is made between a visual probe (e.g., an asterisk) and a threat-neutral stimulus that is presented alongside a threat-relevant stimulus (e.g., an angry face). The success of this intervention hinges on the learner’s ability to track and respond to this statistical association (Bar–Haim, 2010; Grafton et al., 2014). Indeed, statistical learning ability (as measured by the ability to track nonemotion visual associations) predicted treatment outcome in patients with social anxiety disorder who underwent attention bias modification (Alon et al., 2019). Understanding the relation between statistical learning and intervention efficacy could promote identification of individuals who would be best suited (or, alternatively, poorly suited) for attention bias modification as a treatment option.

Future Directions in the Application of Statistical Learning to Emotional Development

Discrimination among different emotion expressions does not imply that children have learned all there is to know about those emotions. Therefore, while statistical learning might help learners extract emotion information, it is less clear how that information is imbued with meaning. Consider an analogy to language: language learners must first extract units from speech streams (i.e., words), but then they must critically pair words with objects (or actions, etc.). Similarly, emotion learners must attach meaning to emotional content to inform interpersonal functioning. One way that learners might attach meaning to emotional content is through their own emotional experiences. How infants and children experience emotions themselves likely interacts with the environmental, statistical cues they observe (Walle et al., 2012).

Another critical issue in the application of statistical learning to the emotion domain is how learners balance stability (e.g., having stable emotion categories) and flexibility (e.g., adapting to emotional content in a particular environment). Through statistical learning, children acquire probabilistic information from the environment, allowing them to infer meaning and make predictions about how other social beings in the environment might act. Therefore, rather than facilitating the formation of simple ↳ associations, statistical learning influences complex emotion concepts. Thus, we might be interested in how the statistics of a learner's environment results in stable emotion concepts. For instance, we might ask questions such as whether learners need to be exposed to a certain *type* (e.g., particular emotions) or *amount* (e.g., how much emotional content is observed) of input. Alternatively, type and amount of input may not matter as much as the level of statistical variability across emoters or contexts. Certainly, this process could also be influenced by the salience of the stimuli (e.g., highly intense emotional response) or the salience to the learner (e.g., if a parent's angry voice is predictive of corporal punishment).

In addition, but related, is the question of how much flexibility learners maintain in their ability to update emotion representations based on statistical input of present (or future) environments in comparison to their previous experience. In the language domain, prior experience can interfere with the statistical learning of new information (Endress & Langus, 2017; Siegelman et al., 2018). Yet, children and adult learners remain nimble in their ability to update emotion category information (Plate et al., 2019). Additional flexibility in emotion categories may be necessary to adapt to situational or cultural norms or when transitioning between environments with very different emotional input. This flexibility may also underlie an individual's ability to become more emotionally similar to their host group when visiting a new culture (De Leersnyder et al., 2011).

Flexibility must be balanced with stability in emotion categories. For example, if a child reared with an abusive caregiver is moved to a foster home, then the emotional input of their surroundings may change significantly and being able to flexibly update these categories could be beneficial. However, maintaining some stability could be useful to avoid being overly influenced by single instances of skewed input—such as when a child encounters a caregiver having a bad day. Very little is known about how learners navigate the balance between stability and flexibility, and what balance of stability and flexibility is associated with social competence in the real world.

Conclusion

Taken together, there is increasing evidence of the role of statistical learning in emotional development, specifically in how children categorize emotions, reconcile emotions across contexts, and use emotional content to make predictions. This new perspective, which focuses on the role of learning underlying emotional development, has the potential to explain the mechanisms of change that inform how children acquire and update emotion understanding, and the mechanisms underlying socioemotional difficulties. This intersection of cognitive and emotional development promises adding a fruitful interdisciplinary perspective to the field of emotion.

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