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The dynamics of emotion and speech in early caregiver-child interactions

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Princeton, NJ : Princeton University

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THE DYNAMICS OF EMOTION AND SPEECH IN EARLY CAREGIVER-CHILD INTERACTIONS

Mira Lyudmilova Nencheva

A DISSERTATION

PRESENTED TO THE FACULTY

OF PRINCETON UNIVERSITY

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Abstract

From their first interactions with caregivers, infants begin to make sense of a complex and dynamic world brimming with sounds, words, sensations, and feelings. Two dimensions of this social world - speech and emotion - offer infants a unique window into the minds of others and a way to communicate their own internal states and needs. The studies in this dissertation demonstrate that emotion and language are dynamically coupled across multiple timescales. First, I show that developmental changes in emotion transitions relate to both general and specific emotion vocabulary during the first five years of life. Second, I demonstrate that there are dynamic, moment-to-moment links between affect, communication, and word learning in children's home environments. Finally, I examine how children use the distribution of positive and negative words across utterances in order to learn emotion labels. Together, the studies in this dissertation advance our understanding of how language and emotion are intertwined in children's lives, spanning milliseconds and years. The emphasis on children's everyday, dynamic communicative experience can spark new interdisciplinary directions at the interface of cognitive development and clinical affective science, with the translational goal of supporting children's learning and long-term well-being.

Acknowledgments

Dissertations reflect many social interactions in a dynamic environment. Since I have been known to take an ill-fitting metaphor too far, this work is the product of...

Academic caregivers

The work in this dissertation is a direct product of the extremely generous and brilliant collaborators and advisers I had the honor of working with. I would like to thank my collaborators - Casey Lew-Williams, Diana Tamir, Erik Nook, Mark Thornton, Hannah Van Dusen, and Erin Watson. My committee - Asif Ghazanfar, Erik Nook, and Adele Goldberg, and most of all, my advisers - Casey Lew-Williams and Diana Tamir. I could fill the whole length of this dissertation with all the ways each of these mentors has supported me. They gently nudged me beyond what I thought I was capable of, continuously revealed new ideas and connections, got me unstuck when I was stuck, and built a model of the kind of mentor I want to be. I can only hope to pay forward a small fraction of what they have given me.

Academic environment

In addition to the support from my direct "academic caregivers," the various stages of my training have taken place in supportive academic environments. There are too many names to list here, but I hope you can recognize yourselves in these brief notes.

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Chapter I: Introduction

From their first interactions with caregivers, infants begin to make sense of a complex and dynamic world brimming with sounds, words, sensations, and feelings. Two dimensions of this social world - speech and emotion - offer infants a unique window into the minds of others and a way to communicate their own internal states and needs. Housed within largely separated fields, the study of emotion development and language development have traditionally been disconnected even though infants experience these signals concurrently. By connecting these fields, this dissertation showcases how emotion and speech permeate each other both in the moment and throughout development. This approach allows us to ground our understanding of how children learn about language or emotions in the dynamic and multifaceted context of their real-world experiences.

The first years of life are formative for emotion and language development. During this time, children learn their first words and multiword phrases (Caselli et al., 1995; Frank et al., 2017; Goldfield & Reznick, 1990; Reznick & Goldfield, 1992), and they learn how to express abstract concepts, such as emotions, with words (Baron-Cohen et al., 2010). At the same time, children learn to differentiate and categorize emotion displays (Widen & Russell, 2003, 2008, 2010; Woodard et al., 2022; Wu et al., 2022) and adapt their behavior in response to emotional information (Meltzoff et al., 2023; Sorce et al., 1985; Walden & Ogan, 1988). They build knowledge about which emotional states others are likely to experience in the future (Nencheva et al., 2024; Repacholi, Meltzoff, Hennings, et al., 2016; Repacholi, Meltzoff, Toub, et al., 2016). They also experience new types of emotions (Bafunno & Camodeca, 2017; Ferguson & Stegge, 1995; Stipek, 1995) and emotion regulation strategies (Morales et al., 2018; Ratcliff et al., 2021).

Over the course of development, language and emotion are tightly linked, as revealed by a range of correlation-based studies. For example, toddlers begin to accurately categorize facial displays of emotion at the same time that they learn to produce the labels for those emotions (Wu et al., 2022). Further, there are robust correlations between both general and emotion-specific vocabulary and various markers of emotion understanding from childhood to adolescence and beyond (Nook, Sasse, et al., 2017; Pons et al., 2003; Sidera et al., 2021; Streubel et al., 2020). For example, Nook et al. (2017) demonstrated that larger vocabularies among children and adolescents were associated with their capacity to depict abstract emotion dimensions. Specifically, increasing vocabulary size accounted for the transition from a unidimensional valence-based representation to a bi-dimensional valence- and arousal-based representation between the ages of 6 and 25. In younger children, Sidera et al. (2021) found that toddlers who produced more emotion labels were also better at simulating those emotions, suggesting better understanding. There is also evidence that language ability relates to the development of healthy socio-emotional experiences in early childhood (Cole et al., 2010; Eisenberg et al., 2005; Fabes et al., 2001; Roben et al., 2013). The more emotion words preschoolers use in conversation, the better liked they are by their peers (Fabes et al., 2001). In a longitudinal study, Roben et al., (2013) found that individual differences in young children's language skills predicted a decrease in anger and an increase in adaptive emotion regulation strategies. Despite the extensive correlational links between emotion and language, previous work connecting these two fields has largely measured the interaction between these highly dynamic processes as static snapshots. In reality, language and emotion unfold over time, with rich temporal structure reflecting their dynamics from one moment to the next, as well as changes over development.

Emotional experiences are known to be highly dynamic. For example, adults transition between multiple emotions per day and, while doing so, follow a predictable structure of going between similar emotions (e.g., sad, angry) more often than between dissimilar ones (e.g., sad, happy; Thornton & Tamir, 2017). Applying a dynamic approach to the study of emotion has been fruitful in uncovering how adults organize and conceptualize emotional experiences (Thornton et al., 2022, 2023; Thornton & Tamir, 2020). For example, adults tend to perceive two emotions as more similar if there's a greater likelihood of a transition between those emotions (Thornton et al., 2023) and the same dimensions (such as valence, rationality, and social impact) that predict the likelihood of a transition between two emotions also organize how adults think about emotions (Thornton & Tamir, 2020). Further, focusing on the dynamic aspects of emotion has resulted in the discovery of new predictors of mental health outcomes in adults, children, and adolescents (Reitsema et al., 2019; Kuppens et al., 2010; Somers et al., 2020; Somers & Luecken, 2022; Dejonckheere et al., 2019; Nelson et al., 2020; Shin et al., 2022). For instance, increased variability in positive and negative emotions has been associated with greater mental health problems in both children and adolescents (Reitsema et al., 2019). Similarly, variability in infants' negative affect was linked to parental stress and predicted behavioral problems in later childhood (Somers & Luecken, 2022).

Likewise, children's linguistic experiences unfold over time, and frameworks that focus on dynamics have revealed important insights into children's language learning. The sounds and units of language follow an organized temporal structure. Infants' ability to track this temporal structure (for example, in the transitional probabilities of syllables in a language) enables them to segment speech into words (Saffran et al., 1996) and eventually connect those words to meanings (Lany & Saffran, 2010). Also, the timing of word or phrase repetitions (Brodsky & Waterfall,

2007; Hills, 2013; Schwab et al., 2018; Schwab & Lew-Williams, 2016), the patterns among words in close temporal proximity (Fernald et al., 2009; Horowitz & Frank, 2015; Lany & Saffran, 2010; Peters et al., 2021; Schwab & Lew-Williams, 2017; Schwab & Lew-Williams, 2020; Wojcik & Saffran, 2015), and the temporal structure of acoustic and structural features of speech (Nencheva et al., 2021; Nencheva & Lew-Williams, 2022; Nencheva, Fausey & Lew-Williams, in prep) each shape children's learning. At longer timescales, there is structure in children's language input over the course of the day. For example, caregiver and child vocalizations in a North American sample were clustered throughout the day at multiple hierarchically nested timescales (Abney et al., 2017). Clustered bursts of child-directed speech were also found in communities where caregivers rarely address infants (Casillas et al., 2020). Children's language input is also organized around their daily routines. Children hear words for body parts during bath time and for fruits or vegetables during lunchtime (Custode & Tamis-LeMonda, 2020; Tamis-LeMonda et al., 2019), and talk about objects is typically clustered in short bursts (Slone et al., 2023). The distinctiveness of the spatial and temporal contexts in which children hear these words has also been associated with age of acquisition (Roy et al., 2015).

Children navigate these patterns in emotion and language at multiple timescales – from milliseconds to minutes and hours to the multi-year timescale of development (Piazza et al., 2021). In the domain of emotion, a child can experience or observe micro-changes in the intensity of an emotional experience at the level of seconds (Verduyn & Lavrijsen, 2015), transitions between emotions over the course of the day (Thornton & Tamir, 2017), multi-day patterns in mood (Clark et al., 2018), and developmental changes in emotional experiences that emerge over the course of years (Bafunno & Camodeca, 2017; Morales et al., 2018; Ratcliff et

al., 2021; Stipek, 1995). In language, children may experience meaningful subsecond patterns in the pitch of a word (Nencheva et al., 2021) that indicate its role in the sentence, multi-utterance patterns that indicate distinct or related discourse topics (Chang & Deák, 2019) or a narrative arc in a story, and changes in the language used by their caregivers as they develop over months and years (e.g., Schwab et al., 2018). These patterns can be independent or hierarchically nested (e.g., moving from syllables to words, sentences to stories). At the longest timescale - development - children aggregate many such experiences to learn how communication unfolds over time, enabling them to predict and seamlessly navigate their social world (Piazza et al., 2021; Tamir & Thornton, 2018).

Importantly, children's emotional and linguistic experiences unfold simultaneously across time. In light of the successful efforts in characterizing the dynamics of individual modalities like speech or emotion, there is a need to understand how these features of children's environment interact to give rise to learning (Kosie & Lew-Williams, 2023). Early linguistic communication is inevitably fused with the emotional experiences of both caregivers and children. Adults experience one or more emotions for 90% of their waking hours (Trampe et al., 2015), and the same is likely true for infants and young children, suggesting that both caregivers and children almost constantly experience emotions during verbal interactions. Likewise, early emotional experiences are often social and accompanied by communication with caregivers (Fields-Olivieri & Cole, 2022). How do the dynamics of emotion and language interact in children's early lives across timescales?

This dissertation examines three ways that emotion and language permeate each other, from single moments in time to the accumulation of these moments across months and years. First, over the course of children's first years of development, changes in language and emotion

abilities mutually reinforce each other, an idea I expand upon in Chapter II. In prior work, developing emotion skills have been shown to lead to higher quantity and quality of social interactions, which in turn can expose children to increasingly diverse language input (Fabes et al., 2001; Fields-Olivieri et al., 2020; Fields-Olivieri & Cole, 2019). For example, on average, toddlers who express less negative affect receive more speech input from caregivers (Fields-Olivieri et al., 2020; Fields-Olivieri & Cole, 2019). On the other hand, the ability to use language can give children richer information about the emotions of others during communication. These cross-domain abilities can explain the parallel development and mutually reinforcing nature of emotion and language. In Chapter II, I probe this hypothesis by focusing on the temporal organization of emotion dynamics and examining developmental links with children's expanding vocabularies (Nencheva, Nook, et al., under review).

Second, during a typical day, how children experience language depends in part on how they feel. Adults have been shown to have better semantic memory when they experience positively valenced or moderately high arousal states (Gilet & Jallais, 2011) and worse semantic memory when they experience more negative (vs. neutral) moods (Guo et al., 2018; Miller et al., 2018). Similarly, toddlers are more likely to learn novel words if they experience heightened physiological arousal after the word-learning task (Outters et al., 2023). Further, adults and children communicate differently based on their emotional state. Adults talk less to each other (daSilva et al., 2021) and their children (Ellwood-Lowe et al., 2022; Roby & Scott, 2022) on days when they are more stressed. Similarly, higher physiological arousal results in more infant vocalizations (Wass et al., 2022), whereas negative affect in toddlers is associated with fewer verbalizations (Fields-Olivieri et al., 2020). Chapter III extends this prior work by focusing on how the dynamics of language input and affect over the course of a typical day predict children's

word knowledge (Nencheva, Van Dusen, et al., under review). Importantly, the reverse directionality is also at play: the language used in emotional situations can change emotional experiences. Although this dissertation does not directly examine this direction of influence, prior work has shown that the use of more distant language, such as last or future tense, or second vs. first-person pronouns, can decrease the intensity or change the nature of emotional experiences (Kross et al., 2014; Moser et al., 2017; Nook, 2023; Nook et al., 2023; Nook, Schleider, et al., 2017; Orvell et al., 2021). These findings suggest that emotion and language shape one another dynamically during children's typical days with their families, and these experiences influence the words that children learn.

Third, on the timescale of months, children use the semantic content of their language input from caregivers to construct the meanings of emotion labels. Controlled experiments and theoretical work suggest that emotion labels help children extract common elements from emotional situations in a way that allows them to form emotion categories (Hoemann et al., 2019; Ogren & Sandhofer, 2022; Ruba et al., 2020; Woodard et al., 2021). Chapter IV extends this work by examining instead how real-world semantic context can help children construct the meaning of emotion labels (Nencheva, Tamir, et al., 2023). Importantly – although not explored in this dissertation – emotions provide context for language use. Past work shows that emotions allow infants to interpret the social and physical world as it unfolds in time (Wu et al., 2021). Emotions can also mark discourse topics that help build semantic networks. For example, a child's sadness may invite discourse about other related events and the common vocabulary that describes them (Nook et al., 2023). This prior work, in combination with Chapter IV, suggests that infants can track the statistics of co-occurrences between emotional and linguistic contexts to extract rich meaning and predictions about the social world.

The present studies

This dissertation investigated the links between dynamic aspects of emotion and language at multiple timescales. Chapter II examined how the temporal structure of children's emotions changes between 0 and 5 years and how these developmental changes relate to children's growing vocabularies. This work was foundational in characterizing the temporal structure of children's emotional experiences and establishing whether there is a mutually reinforcing link between language development and the dynamics of emotional experiences. In this series of studies, I collected caregiver reports on how children transition between emotional experiences using a combination of surveys and a 10-day ecological momentary assessment study. I found that children's emotion transitions started as more idiosyncratic early on in development and gradually converged toward the mature adult pattern of emotion transitions. This shift was related to children's general and emotion-specific vocabularies.

In Chapter III, I investigated how the dynamics of emotion over two days of a child's life relate to moment-to-moment fluctuations in communication and learning. This work provided a window into the effects of emotional experiences on how children interact with language in their home environment. To answer these questions, I combined day-long audio recordings of the child's language environment with ecological momentary assessment of the child's emotional environment. I found that moments of positive valence or high arousal were associated with more dense caregiver-child communication and a higher likelihood of word learning.

Finally, in Chapter IV, I examined how children aggregate over the local multi-utterance dynamics of language to learn emotion labels. This allowed us to probe how in-the-moment linguistic context can contribute to children's understanding of emotion. In a large corpus of caregiver-child interactions, I used sentiment analysis tools to extract the emotional content of

the language surrounding emotion labels in these interactions. I found that in the utterances preceding and following an emotion label, caregivers used words that matched the positive or negative valence of the label. A longitudinal analysis revealed that the extent to which caregivers followed this pattern predicted children's use of emotion labels in context.

Together, the studies in this dissertation advance our understanding of how language and emotion are intertwined in children's lives, spanning milliseconds and years. The emphasis on children's everyday, dynamic communicative experience can spark a variety of new interdisciplinary directions at the interface of cognitive development and clinical affective science, with the translational goal of supporting children's learning and long-term well-being.

Chapter II: The emergence of organized emotion dynamics in childhood[1]

Emotions are dynamic experiences. For example, when we feel excited, this experience often lasts for a finite amount of time before transitioning to a different emotion, such as happiness. Babies can be excited by a rattle at one moment and then cry from hunger the next. Prior developmental work on emotion dynamics has focused on individual differences in the ways emotions unfold over time (e.g., emotion inertia, network density, and differentiation, etc), and has found important implications for mental health outcomes from infancy through adolescence and beyond (Reitsema et al., 2019; Somers et al., 2020; Somers & Luecken, 2022; Dejonckheere et al., 2019; Nelson et al., 2020; Shin et al., 2022). Yet, we know little about the development of the typical patterns of how long emotions last and the way they transition from one to the other. The current investigation focuses on two aspects of how the emotional experiences of young children unfold over time: the duration of an emotion (i.e., how long someone feels excited) and the structure of their transitions (i.e., what emotion someone is likely to feel next). Longer emotion duration (Scherer & Wallbott, 1994; Verduyn, et al., 2009; Verduyn & Lavrijsen, 2015) and predictable emotion transitions (Thornton & Tamir, 2017) are a hallmark of adults' emotion experiences. In the current investigation, we examined how these two features evolve over early development. Based on emerging arguments that language shapes emotion, we also tested whether linguistic development might explain age-related changes in these emotion processes (e.g., Cole et al., 2010; Eisenberg et al., 2005; Fabes et al., 2001; Hoemann et al., 2019; Nook et al., 2017; Plate et al., 2019; Woodard et al., 2021).

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[1] This work was carried out in collaboration with Erik Nook, Mark Thornton, Casey Lew-Williams and Diana Tamir, and a version of this work has been released as a preprint: https://osf.io/preprints/psyarxiv/4hbz3. In addition, parts of this work were presented at the 2020 Society for Personality and Social Psychology Convention Emotion Preconference, the 2021 Society for Research in Child Development Biennial Meeting, and the 2022 International Congress on Infant Studies.

How long one experiences the same emotion (i.e., emotion duration) is an important part of emotion dynamics (Frijda et al., 1991; Verduyn, 2021; Verduyn et al., 2015; Verduyn, et al., 2009a). Adults' emotion experiences typically last from several minutes to hours (Scherer & Wallbott, 1994; Thornton & Tamir, 2017; Verduyn, et al., 2009a, 2009b; Verduyn & Lavrijsen, 2015). For example, in an experience sampling study, participants were likely to continue experiencing the same emotion over multiple consecutive data points, collected 3 hours apart (Thornton & Tamir, 2017). Different emotions have reliably different relative durations; for example, sadness and joy typically last longer than fear and anger (Scherer & Wallbott, 1994; Verduyn, et al., 2009; Verduyn & Lavrijsen, 2015). Children's emotion experiences, in contrast, are short: tantrums typically last only a few minutes (Potegal et al., 2003), far shorter than the typical duration of anger or sadness in adults of several hours (Verduyn & Lavrijsen, 2015). However, beyond this finding, it is unknown whether the duration for all emotions or relative differences in duration between specific emotions varies systematically across ages.

A second important component of emotion dynamics is the pattern of transitions between emotions. Adults tend to transition between emotions in predictable ways (Prasetio et al., 2020; Thornton & Tamir, 2017). Specifically, they are likely to transition to an emotion similar to the one they are currently experiencing. According to the 3d Mind Model (Thornton et al., 2022; Thornton & Tamir, 2020), similarity along several social, cognitive, and affective dimensions shapes adults' emotion transition patterns. The most prominent of these dimensions is valence (i.e., the relative positivity or negativity of an emotion; Thornton & Tamir, 2017). For example, adults, on average, are more likely to go from feeling happy to feeling calm (a positive emotion) than to feeling angry (a negative emotion; Thornton & Tamir, 2017). We refer to the extent to which one's emotion transitions follow this pattern as organization by valence. Do young

children show such organization by valence from infancy, or is this a pattern they gradually converge on during development?

Language is a key factor that may relate to the development of adult-like emotion dynamics. According to the theory of constructed emotion (Barrett, 2017), how people label emotion experiences influences how they categorize, understand, and communicate feelings. Further, emotion development may support language by allowing children to break into the structure of the social interactions in which they experience language. These links between emotion and language have been found in adult emotion dynamics (Barrett, 2006; Thornton et al., 2020; Thornton & Tamir, 2017). In development, verbal abilities relate to the emergence of emotion understanding (Nook et al., 2017), and children start matching labels and facial expressions correctly at around the same age that they produce emotion labels (i.e., 2 years of age; Frank et al., 2017; Wu et al., 2022). However, it is unknown whether language shapes the development of *dynamic* features of emotions or vice versa, or whether they co-emerge as the result of other developmental processes. Likely, language and emotion bidirectionally permeate each other on a microscale over the course of development. If this is the case, we would predict that as children learn more emotion-related words, their emotion dynamics will more closely match those of adults, and vice-versa. Previous scholars (e.g., Nook, 2021) have identified a critical need for investigating how the early development of emotion dynamics from infancy through early childhood interacts with language during this formative period when children's vocabularies are rapidly expanding (Goldfield & Reznick, 1990).

Although most adults follow a shared pattern of emotion durations and transitions (Scherer & Wallbott, 1994; Thornton & Tamir, 2017; Verduyn, et al., 2009; Verduyn & Lavrijsen, 2015), we know little about how this organization develops. While emerging work

shows that language relates to other aspects of emotion development, researchers have not determined how language relates to the development of dynamic emotional experiences. Here we addressed these gaps to advance a theoretical understanding of emotion and its development that is grounded in the dynamic nature of emotions and their interactions with other cognitive processes. We first described the development of children's emotion dynamics (duration and transitions) through the lens of their caregivers' perceptions. We then related this emotion development to children's language development. We hypothesized that, between the ages of 0 and 5, children's emotion duration and transitions would become more similar to those of adults. Further, we predicted that a child's emotion vocabulary would relate to the structure of their emotion experiences. We measured children's emotion transitions using a combination of methods. In studies 1-3, parents estimated their child's emotion duration and transitions. In Study 4, we recorded parent and child emotions multiple times per day for 10 days using ecological momentary assessments (EMA). Studies 1-4 all described the shift to an adult-like pattern of emotion dynamics between the ages of 0 and 5 years. Studies 3 and 4 additionally examined whether emotion duration and emotion transition organization follow a similar developmental trajectory. Finally, Studies 3 and 4 probed whether emotion language predicts the maturity of a child's emotion dynamics. This multi-part investigation allowed us to carry out preregistered replications across studies and methods.

1. Method

1.1. Transparency and openness

1.1.1. Compliance with Ethical Standards. This research was approved by the Institutional Review Board at Princeton University, and parents provided informed consent prior

to participating in all online studies. On behalf of all authors, the corresponding author states that there is no conflict of interest.

1.1.2. Availability of data and code. Data and analysis code for all studies can be found here: https://osf.io/hku68/?view_only=f330c97d6ce944caa814b15a5f534fac.

1.1.3. Preregistration and exploratory analyses. Preregistration for studies 1b and 3 can be found here: https://aspredicted.org/blind.php?x=64a3xr, and the preregistration for Study 4 can be found here: https://aspredicted.org/DTG_GJH.

Originally Study 1b and Study 3 were preregistered to be part of the same sample that would replicate findings from Study 1a and test novel hypotheses. However, when including all questionnaires in the same study, the study duration became too long to obtain reliable responses from participants (likely due to fatigue). Therefore, we conducted the study by collecting two separate samples: Study 1b was a direct replication of Study 1a, and Study 3 tested novel hypotheses. We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study.

1.2. Participants

1.2.1. Recruitment and exclusion criteria. Studies 1-3 recruited parents on Amazon Mechanical Turk (MTurk). We used MTurk's built-in recruitment filters, considering participants' responses to demographic questions about the age of their children. Because these questions did not precisely ask for date of birth, some caregivers provided responses for children older than five. Even though this extended the age range beyond what was originally preregistered, we chose to include those responses. In order to ensure that the participants were truthfully reporting their parenting status, participants filled out a short survey prior to the main part of the study, where they were asked (among other questions) if they are the primary

caregiver for a child under 5. Depending on their response, they were given the option to complete the survey for their child for a bonus payment. Importantly, if they answered ‘no’ to this question, they still received the base payment, meaning that payment was not contingent on parenting status. Study 4 recruited parents from the Princeton Baby Lab database, based out of a relatively high socio-economic-status area in central New Jersey.

Participants were excluded if they reported a lack of English proficiency. Additionally, in the preregistered Studies 1b and 3, participants were instructed to skip one of the pre-survey questions as an attention check and were excluded if they failed to do so. Attention checks were not included for Studies 1a and 2, as data collection for these studies served as pilot data. As preregistered, Study 4 participants were excluded if they did not complete the pre-study survey, or if they filled out fewer than five surveys over the course of the study. We did not collect demographic information for the children in Studies 1-3; however, general information about the demographics of MTurk workers can be found in Shaw and Hargittai (2021). More female (vs. male) caregivers completed the surveys (S1a: 60%F, 40%M; S1b: 54%F, 46%M; S2: 65%F, 35%M; S3: 66%F, 34%M). In Study 4, 52% of children were female, 48% were male. Race was not reported for 47% of Study 4 participants, 8% were Asian, 2% Black, 4% Hispanic, 3% Mixed race, and 35% White. Maternal education was unknown for 49% of Study 4 participants, 3% reported high school as their highest education level, 12% Bachelor’s, 31% Master’s, 4% doctorate.

1.2.2. Sample size. Information about sample size and exclusion is included in Table 1, and histograms of the age distribution for each study can be found in Supplementary Figure 1.

In the exploratory Studies 1a and 2, sample size was modeled after prior studies on the development of emotion concepts in older children (e.g., Nook et al., 2017, 2018). The sample

sizes in Studies 1b, 3, and 4 were preregistered to achieve power of 80% in the analyses of interest based on an independent pilot sample using the simr package in R for power analyses in mixed effect models. In Studies 1b and 3, we computed power based on the effect of age on valence organization of transitions in an independent pilot sample of 150 participants. In Study 4, we computed power based on the effects of (1) age, (2) vocabulary size, and (3) knowledge of the label based on an independent pilot sample of 20 participants. To ensure an equal number of participants in each of the five age groups (0-5 years) and address the uneven sampling of different age ranges resulting from broader recruitment, we expanded the sampling beyond the initially planned sample size. The decision to continue data collection was made prior to any data analysis and was purely based on achieving approximately even sampling across the age range.

Table 1.

Study	**Final sample**	**Preregistered**	**Age range**	**Excluded participants**
Study 1a	148 children; 129 parents 110 reported on 1 child 19 - reported on 2 children	N/A	0 to 5;0 years*	41 total excluded 41 English proficiency
Study 1b	255 children and parents	170	0;2 to 7;1 years*	121 total excluded 113 attention check 8 English proficiency
Study 2	161 children; 134 parents 108 reported on 1 child 25 - reported on 2 children 1 - reported on 3 children	N/A	0;0 to 5;0 years*	0
Study 3	239 children	170	0;2 to 7;0 years*	66 total excluded 51 attention check 15 English proficiency
Study 4	99 children 80 reported on 1 child 8 - reported on 2 children 1 - reported on 3 children	70	0;1 to 4;11 years*	5 total excluded 4 missing pre-study survey 1 fewer than 5 surveys

* The reported ages follow the format *years; months*

1.3. Measures

1.3.1. Emotion-intensity profile questionnaire. In Studies 2 - 4, parents reported how the intensity of each emotion (e.g., 'surprise') changes from its onset (0 s) to two hours after its onset (i.e., the emotion's intensity profile; Sonnemans & Frijda, 1994; Verduyn, Van Mechelen, et al., 2009) for their child (and in Study 2 for themselves as well). At each trial, they saw a graph where the y-axis represented the intensity of the emotion (with 100% being the peak intensity and 0% the lowest), and the x-axis had time intervals from zero seconds, marking the onset of the emotion, to 2 months after the onset of the emotion (see Figure 3a). Participants indicated the emotion intensity at each time by dragging the points on the graph up and down with their cursor.

1.3.2. Emotion-transition likelihood questionnaire. In Studies 1a, 1b, and 3, parents reported how likely they (1a and 1b) and their child (1a, 1b, and 3) were to transition between 70 pairs of emotions. For example, participants might estimate the likelihood of HAPPY → SAD, which means if they were feeling happy (the first emotion in the pair), how likely would they be to feel sad (the second emotion) next? They reported this likelihood using a slider with continuous values from 0 (extremely unlikely) to 100 (extremely likely). We selected a subset of emotion states (*happy*, *irritated*, *calm*, *interested*, *sad*, *stressed*, *serious*, *confused*, *surprised*, and *disgusted*) from Thornton and Tamir (2017) that spanned the 3-dimensional affective space (including rationality and social impact in addition to valence) described by Thornton & Tamir (2017) and Tamir et al., (2016). Based on adult norms from 1,205 participants in Tamir et al., (2016), half of the states we selected were positive, and half were negative, and each valence category had equal numbers of high vs. low rationality and social impact states (Supplementary Table 2).

Vocabulary and emotion-label production. In Studies 3 and 4, parents completed a vocabulary questionnaire for their child. They reported whether their child "understands" or "understands and says" (i.e., produces) a set of 64 words. This included 19 emotion labels (including the 10 used in previous tasks) and 45 other words from the English Words and Sentences MacArthur-Bates Communicative Development Inventory (Fenson, 2007). The latter were evenly split across neutral, negative, and positive valence and were matched on child production at the midpoint in the age range of the study (2;6 years), based on data from WordBank (Frank et al., 2017; see Supplementary Figure 2). In Studies 3 and 4, vocabulary size refers to the count of words the child can produce.

Additionally, we marked each child's production of the 10 emotion labels whose transition likelihood and duration we measured. This measure allowed us to relate emotion label production to emotion dynamics across tasks. Additional preregistered analyses about the contents of children's vocabularies can be found in the Supplement.

1.3.4. Ecological Momentary Assessment. In Study 4, parents were prompted to report how their child felt 6 times per day for 10 days at random intervals (normally distributed around 2 hours between surveys, with a standard deviation of 15 minutes). This time interval matches the typical intervals used for ecological momentary assessment studies in adults (Thornton & Tamir, 2017). A transition was marked as any consecutive surveys in a given day. Prior work has shown that the structure of emotion transitions is relatively stable across varying time intervals: transitions which are more likely over short intervals also tend to be more likely over longer ones (Thornton & Tamir, 2017). Some participants missed a few surveys, and some chose to complete the survey a few additional times. On average, participants completed 55.78 surveys (sd = 4.92; min = 41, max = 64).

Each survey began by asking the parent if, in the past 15 minutes, they were present with their child and their child was awake. If not, the survey ended. Otherwise, the parent selected all emotions (out of 10) their child was currently experiencing, with the option to select multiple (or no) emotions if applicable. Parents were asked to give their best estimate of their child's feelings.

1.3.5. Other measures. In Studies 1b and 3, we collected responses on the caregiver's emotion expressivity and child duration of orienting for exploratory purposes. Analyses and details of these measures are included in the Supplementary Materials.

1.3.6. Study Plan, Procedure, And Order. The measures included in each study and the order of presentation is outlined in Table 2. In Studies 1a, 2, and 4, some caregivers reported on multiple children (the exact breakdown is available in Table 2)

Table 2.

	Study 1a	**Study 1b**	**Study 2**	**Study 3**	**Study 4**
Emotion-transition likelihood questionnaire	Parental report on self and child	Parental report on self and child	-	Parental report on child	-
Emotion-intensity trajectory questionnaire	-	-	Parental report on self and child	Parental report on child	Parental report on child
Vocabulary and emotion-label production	-	-	-	Parental report on child	Parental report on child
Ecological Momentary Assessment	-	-	-	-	Parental report on child
Presentation order	Parent, then child	Order counterbalanced	Parental report on self first, then child	Order randomized	The intensity trajectory and vocabulary questionnaires were completed in a pre-study survey

1.4. Analysis

1.4.1. Quantifying transition likelihood. The likelihood of a transition between two emotions was quantified in three ways. In Studies 1-3, it was measured as the likelihood rating provided by caregivers in the emotion-transition likelihood questionnaire.

In Study 4, transitions were registered as a sliding window across two consecutive timepoints in the study (i.e., two consecutive surveys completed by the parent). We marked that a transition occurred if the caregiver checked off the first emotion of the transition in the first survey, and the second emotion in the next survey. For example, if a caregiver reported that the child was happy on a survey completed at 9:36 am and sad on the next survey they completed at 11:24 am, we marked that a transition between happiness and sadness occurred. Based on this definition, we computed two measures of transition likelihood. First, we measured the frequency of the transition as the total number of transitions between two emotions observed over the 6 days of the study. Because this measure did not control for the base frequency of each of the emotions in the transition, we computed a second measure of transition likelihood - a log odds ratio, which controlled for the base frequency of transitions that involved each of the emotions in the pair. This measure was computed using the `oddsratio` function in the 'epitools' package in R (Aragon, 2020), based on the frequency of the transition between the two emotions of the pair (e.g. happiness and sadness), the frequency of transitions between each of the emotions in the pair and other emotions (e.g. between happiness and any other emotion, not including sadness), and the frequency in transitions between emotions that are not in the pair (e.g. any two emotions that are not happiness or sadness).

1.4.2. Quantifying valence organization. Valence organization of emotion transition measures the extent to which a child (or an adult) is more likely to transition to a more (vs. less)

similar emotion. For each pair of emotions, we computed the absolute difference in valence score for each state. These scores reflect the average ratings made by 1,205 adults on a continuous 100-point scale (Tamir et al., 2016). In all studies, it was measured as the standardized regression coefficient of the similarity in valence (-ΔV; valence difference multiplied by -1) predicting the transition likelihood (likelihood ~ $\beta(-\Delta V)$). This quantity (β) is referred to as valence organization index (*VOI*) in the text.

1.4.3. Inferential statistics. In this investigation, we characterized how age, vocabulary, and emotion duration correlated with changes in valence organization. We expect in all cases that valence similarity will predict higher transition likelihood. We further predicted that this relation should be strongest if a variable of interest, like age, vocabulary size, etc., were high. In Studies 1a, 1b, and 3, we did so by constructing a regression model in which the predicted variable was the VOI, and the predictors were the corresponding variable of interest (as preregistered in Studies 1b and 3). In Study 4, we preregistered a slightly more sensitive regression model, in which we omitted the intermediate step of computing a summary VOI by participant. Instead, we quantified how the predictor of interest (e.g., age, vocabulary, etc.) modulated the effect of valence similarity on transition likelihood (captured by VOI in previous studies). The models used for Study 4 predicted the likelihood of the transition (i.e., the transition frequency or the log odds ratio), and included valence similarity, the variable of interest, and their interaction. In this model, we focused our analyses on the interaction term (valence similarity x predictor of interest). For the main analyses, we computed the shared effect across all studies. In those cases, just for the shared regression, we followed the model structure of Studies 1a, 1b, and 3. For all analyses, we used an alpha level of 0.05.

For all mixed-effect regressions in the manuscript, we used the lmerTest package, with a Satterthwaite approximation for the degrees of freedom and an alpha level of 0.05. We followed a shared rule for selecting the structure of the model. We always started with the most random model - including both random slopes and intercepts by the relevant factor(s) (e.g., by participant or emotion). If this most random model returned a convergence error, or a singular fit warning, we instead used a smaller model that only included random intercepts (and omitted random slopes).

2. Results

2.1. Developmental changes in emotion dynamics in early childhood

We characterized two aspects of children's emotion dynamics during the first five years of life: the duration and transition organization of children's emotion experiences as perceived by caregivers.

2.1.1. Emotion duration in early childhood. Studies 2, 3, and 4 examined the development of the duration of emotion experiences (i.e., the amount of time children spend in the same emotional state). We estimated a half-life for each emotion as the time between the onset of the emotion and the time when the intensity of the emotion returned to half of its peak intensity (as indicated by the caregiver).

Over the first five years, emotion half-life increased with age (S2: $\beta_{age} = 0.08$, 95% CI [0.02, 0.13], $t(1215) = 2.85$, $p = 0.004$; S3: $\beta_{age} = 0.1$, 95% CI [0.07, 0.16], $t(2039) = 5.31$, $p = 1.2\times10^{-7}$; S4: $\beta_{age} = 0.1$, 95% CI [0.04, 0.16], $t(863) = 3.1$, $p = 0.002$; Figure 3e). Combining the results from the three studies into a single regression model with a random intercept for study revealed an overall association between age and emotion half-life ($\beta_{age} = 0.1$, 95% CI [0.07, 0.13], $t(4130) = 6.8$, $p = 1.3\times10^{-11}$). Further, in Study 2, which measured both adult and child

emotion duration, children had significantly shorter emotion half-life than adults ($t(287) = 5.83$, $p = 1.5\times10^{-8}$; see Figure 1).

Even though the average emotion half-life increased with age, the relative order of half-lives across emotions between caregivers and children did not change. For example, both for adults and children, happiness lasted longer than surprise or irritation. We tested this by computing the rank-order Spearman correlation between each child's and their caregiver's emotion durations in Study 2. There was no significant association between the child's age and the magnitude of the correlation ($\beta_{age} = 0.03$, 95% CI [-0.14, 0.19], $t(143) = 0.35$, $p = 0.73$). Together, these results suggest that caregivers perceived children's emotion experiences to be reliably shorter than those of adults, and to increase in duration during the first five years of life. However, which emotions last longer or shorter remains similar to that of their caregivers across age.

2.1.2. Emotion transition organization in early childhood. In four studies, we characterized the organization of young children's emotion transitions, as perceived by caregivers. First, we tested whether valence organized emotion transitions at each age. A one-sample *t*-test in each of the four studies showed that the valence organization index was significantly greater than zero at all ages, from zero to 7 years (see Figure 1 and Supplementary Table 1). This suggests that, even in infancy, emotion transitions are already organized, at least partially, by valence.

Second, we evaluated whether the level of organization by valence changes over development. In all four studies, we found that caregivers perceived the organization of children's emotion transitions by valence as increasing with age (Figure 1; Figure 2b). Children become increasingly likely to transition between similarly valenced emotions (e.g., from sad to

frustrated) and less likely to transition between differently valenced emotions (e.g., from sad to happy). Age predicted VOI in Studies 1a [Study 1a: $\beta_{age} = 0.17$, 95% CI [0.01, 0.33], $t(146) = 2.11$, $p = 0.037$]. In Studies 1 and 3, the effect was positive, but did not reach significance [Study 1b: βage = 0.12, 95% CI [-0.004, 0.24], t(248) = 1.9, p = 0.059; Study 3: $\beta_{age} = 0.11$, 95% CI [-0.02, 0.24], $t(237) = 1.68$, $p = 0.09$]. Finally, in Study 4's experience sampling data, children's emotion transitions also became more organized by valence with age. A preregistered analysis predicting the likelihood of a transition between two emotions revealed a significant interaction between how similar the valence of two emotions was and the child's age, such that valence similarity was a stronger predictor of valence transitions at older ages. This was true for both measures of transition likelihood [frequency: $\beta_{age \times valence\ similarity} = 0.04$, 95% CI [0.02, 0.06], $t(5{,}761) = 4.71$, $p = 2.52 \times 10^{-6}$; log odds ratio: $\beta_{age \times valence\ similarity} = 0.09$, 95% CI [0.06, 0.11], $t(5{,}682) = 7.42$, $p = 1.3 \times 10^{-13}$]. Finally, we found a shared effect of age on valence organization across studies using a mixed effect model with random slopes and intercepts for study [$\beta_{age} = 0.14$, 95% CI [0.06, 0.25], $t(4.76) = 3.56$, $p = 0.017$]. Together, these retrospective and *in vivo* measures provide converging evidence that over the first five years of life, children's emotion transitions become increasingly organized by valence. Through early childhood, children become more likely to transition between emotions that are similar in valence and less likely to transition between emotions that are different in valence.

In an exploratory analysis, we arbitrated between two patterns that are consistent with an increase in valence organization of emotion transitions: (1) children's emotion transitions are initially idiosyncratic (i.e., each child may transition in unique ways), or (2) young children follow a consistent pattern that is simply less organized by valence (i.e., all children may transition in similar ways). In Study 1a, the consistency in emotion transition likelihoods,

quantified as the average rank-order correlation between the transition likelihoods for all emotion pairs of same-aged children in the sample, increased with age (see Figure 2a; $\beta_{age} = 0.13$, 95% CI [0.09, 0.16], $t(2,219) = 6.13$, $p = 1.02 \times 10^{-9}$). Infants' emotions were highly idiosyncratic, and over time, these idiosyncratic patterns converged into a shared mature pattern of emotion transitions - one organized by valence.

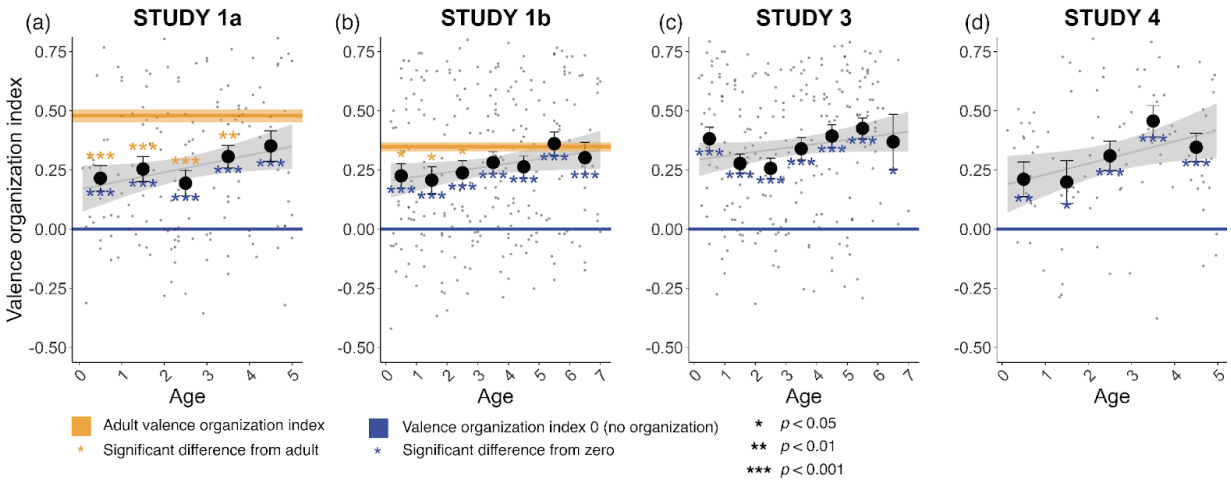

Figure 1. Organization of emotion transitions by valence for children between zero and seven years (a - d) for studies 1a, 1b, 3, and 4, respectively.

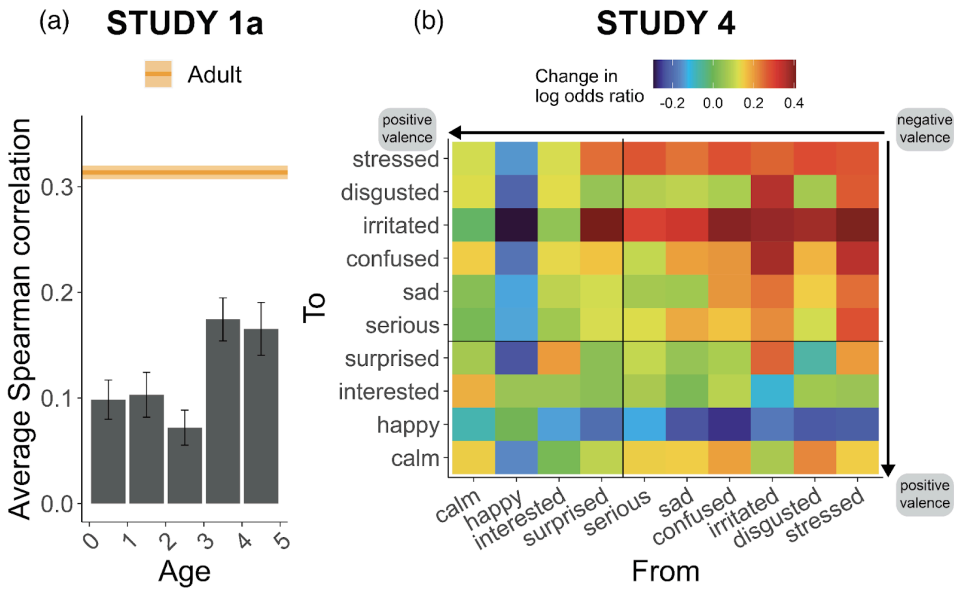

Figure 2. (a) The consistency in children's emotion transitions across individuals at a given age (computed as the average spearman correlation) is plotted on the y-axis. The error bars represent a 95% confidence interval. The shared orange line shows the Spearman correlation observed in adult caregivers. (b) The color of each cell represents the extent to which the likelihood of the transition (log odds ratio) from a given emotion (on the x-axis) to another emotion (on the y-axis) correlates with age. Red hues signal that the transition became more likely with age, whereas blue hues show a decrease in the likelihood of the transition. Green hues represent little or no change with age. The emotions listed on each axis are ordered by valence, with the black lines representing neutral valence (a value of 0). An increase in valence organization is marked by an increase in transition odds between similarly valenced states (between negative states in the top right quadrant and positive states in the bottom left quadrant) and a decrease in transition odds between other states.

2.2. Relation between emotion duration and emotion-transition organization

In Studies 3 and 4, we probed whether the duration of a given emotion relates to the organization of its transitions. In Study 3, the half-life of an emotion positively related to its valence organization index in a mixed regression with random intercepts per participant ($\beta_{\text{half-life}}$ = 0.09, 95% CI [0.04, 0.14], t(1930.56) = 3.8, p = 0.0001). This effect held after controlling for the child's age ($\beta_{\text{half-life}}$ = 0.09, 95% CI [0.04, 0.14], t(1938.52) = 3.74, p = 0.0002). In Study 4, half-life was related to the effect of valence similarity on transition likelihood, measured as frequency (captured by VOI in previous studies; β = 0.04, 95% CI [0.02, 0.06], t(4,916) = 3.18, p =0.001), even when controlling for age (β = 0.04, 95% CI [0.02, 0.06], t(4,916) = 3.18, p

=0.002). This effect was not significant with the log odds ratio measure of transition likelihood (β = -0.01, 95% CI [-0.03, 0.02], t(5,000) = 0.77, p =0.44).

Despite the divergent results between the two measures in Study 4, the results in Studies 3 and 4 suggest that the organization of children's emotion transitions is positively associated with the duration of their emotion experiences. That is, longer emotions tend to transition to more similarly valenced emotions.

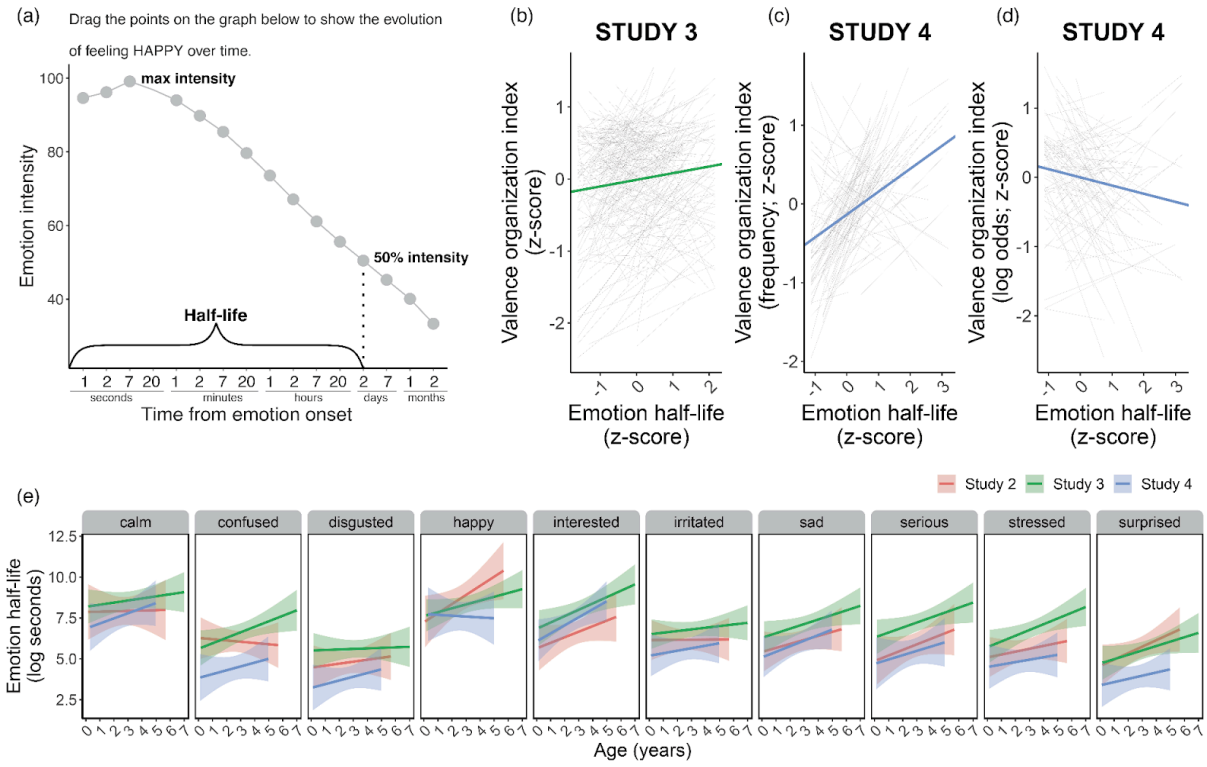

Figure 3. (a) Measuring emotion duration. In this example trial, a parent would drag the points on a graph using their mouse cursor to show how the intensity of the target emotion (e.g., happiness) changes over time from the onset of the emotion till two months after the emotion onset. Half-life is the time between the emotion onset and the time when the emotion reaches half of its maximum intensity. The correlation between emotion half-life and valence organization in Study 3 (b) and the two measures in Study 4 (c-d). The thin black lines show the regression line for each participant. The thick colored line (green for Study 3 and blue for Study 4) shows the fixed effect regression line from the mixed effects model with random intercepts by participant. (e) Changes in each emotion's half-life by age in Studies 2 (red), 3 (green), and 4 (blue).

2.3. Relation between emotion vocabulary and emotion dynamics

Next, we examined whether the dynamics of emotion relate to young children's growing vocabularies in Studies 3 and 4. We examined two preregistered predictions: (i) overall vocabulary size will relate to valence organization, measured across all emotions; and (ii) children's production of the label for a specific emotion will relate to the organization of that same emotion's transitions.

First, we tested the preregistered prediction that children with larger vocabularies will have emotion transitions more organized by valence. This was the case in Study 3 ($\beta = 0.18$, 95% CI [0.06, 0.30], $t(237) = 2.87$, $p = 0.004$; Figure 4a), and this effect remained significant after controlling for age ($\beta = 0.25$, 95% CI [0.05, 0.45], $t(236) = 2.46$, $p = 0.01$). Similarly, in Study 4, overall greater vocabulary size was related to greater valence organization [frequency: $\beta = 0.04$, 95% CI [0.02, 0.05], $t(5,761) = 4.16$, $p = 3.16 \times 10^{-5}$; log odds ratio: $\beta = 0.07$, 95% CI [0.04, 0.09], $t(5,761) = 5.56$, $p = 2.83 \times 10^{-8}$, Figure 4b], but the effect did not hold after controlling for age [frequency: $\beta = -0.02$, 95% CI [-0.05, 0.02], $t(5,759) = -0.95$, $p = 0.34$; log odds ratio: $\beta = 0.02$, 95% CI [-0.02, 0.07], $t(5,759) = 1.00$, $p = 0.32$]. It is important to note that age was highly correlated with vocabulary size, [$r = 0.85$, $t(97) = 16.02$, $p = 5.43 \times 10^{-29}$]. Together, these results suggest that children's growing vocabulary skills may be related to the organization of their emotion transitions. However, other developmental factors that increase with age likely also contribute to this relation.

Next, we tested the hypothesis that language and emotion dynamics will be related at the level of individual emotions. In Study 3, an exploratory mixed-effect regression (which included random slopes and intercepts by emotion) showed that when parents reported that their child produced the label for a given emotion, the way that their child transitioned from that emotion

was more organized by valence ($\beta_{\text{label production}} = 0.13$, 95% CI [0.04, 0.23], $t(6.63) = 2.78$, $p = 0.03$; Figure 4c). This effect did not remain significant when controlling for child age ($\beta_{\text{label production}} = 0.08$, 95% CI [-0.01, 0.21], $t(11.94) = 1.86$, $p = 0.09$). A preregistered analysis in Study 4 replicated this effect [frequency: $\beta_{\text{valence similarity} \times \text{label production}} = 0.08$, 95% CI [0.07, 0.14], $t(5{,}652.71) = 5.9$, $p = 3.3 \times 10^{-9}$; log odds ratio: $\beta_{\text{valence similarity} \times \text{label production}} = 0.11$, 95% CI [0.10, 0.2], $t(5{,}689.32) = 6.16$, $p = 7.68 \times 10^{-10}$; Figure 4c], which remained significant when controlling for the effect of age on valence organization [frequency: $\beta_{\text{valence similarity} \times \text{label production}} = 0.07$, 95% CI [0.04, 0.14], $t(5{,}761) = 3.36$, $p = 7.9 \times 10^{-4}$; log odds ratio: $\beta_{\text{valence similarity} \times \text{label production}} = 0.06$, 95% CI [0.005, 0.13], $t(5770) = 2.13$, $p = 0.03$]. Together, these results show that when a child experiences an emotion that they can name (as opposed to an emotion they cannot name), they are more likely to transition to similarly valenced emotions. However, given that this effect did not hold after controlling for age in Study 3, other developmental factors linked to age may also be at play.

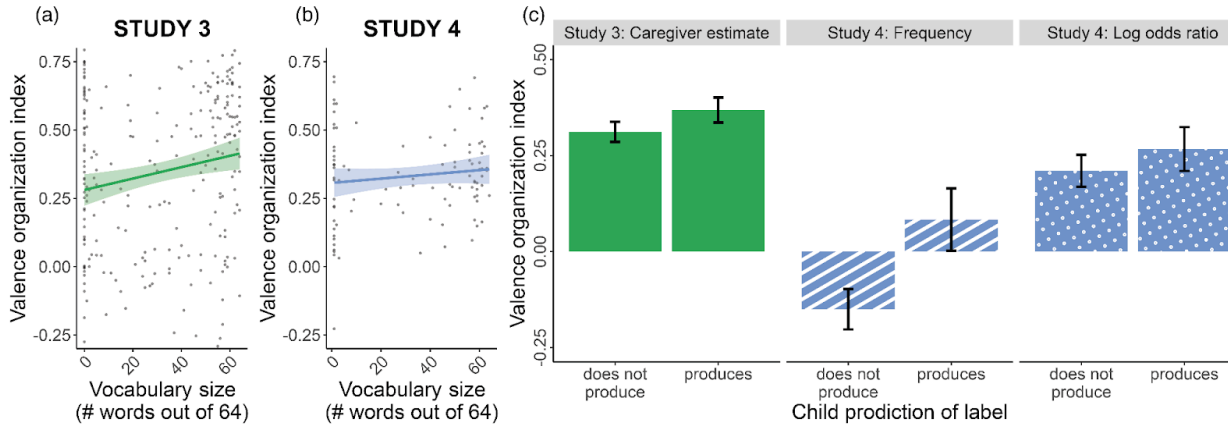

Figure 4. Vocabulary size related to valence organization in (a) Study 3 and (b) Study 4. (c) Valence more strongly organized the transitions of emotions that a given child can label (vs. ones the child cannot yet name) in Study 3 (green) and Study 4 (blue), using both log-odds-ratio (striped), and frequency (dotted). Error bars show a 95% confidence interval.

3. Discussion

The current investigation characterized the change in children's emotion dynamics over the first five years of life, as perceived by caregivers, and its relation to language development. Across four studies, we observed an increase in emotion duration and transition organization. These changes paralleled children's growing emotion vocabulary. Together, these results add to a rich literature showing that childhood is a formative period in emotion development, likely with bidirectional influence between emotion dynamics and early language development.

Caregivers reported that the duration and transition organization of children's emotions increased over development. Infants start with highly idiosyncratic emotion transitions, and over time,converge onto a canonical adult-like pattern. There are several ways in which children come to develop canonical emotion dynamics. During the first few years of life, children accumulate knowledge about emotion durations and emotion transitions by observing the statistics of others' emotion experiences. Extensive research in the field of statistical learning suggests that children readily learn statistical patterns such as the durations (Addyman et al., 2014) and transitions of complex events and actions (Lew-Williams et al., 2011; Monroy et al., 2017, 2019; Saffran & Kirkham, 2018). Studies have shown that children also extract statistics from emotion experiences. For example, older children (6-10 years) track the frequency of emotion facial configurations (Plate et al., 2019; Woodard et al., 2021), and young infants track the "emotional history" of individuals (Repacholi, Meltzoff, Hennings, et al., 2016; Repacholi, Meltzoff, Toub, et al., 2016). Collectively, these findings suggest that children may gradually develop adult-like patterns of emotion durations and transitions by observing socially relevant statistics in their environment.

In addition to children's growing experience with emotion dynamics in the first years of life, children's advancing , language skills may help them learn how emotions unfold over time. Children with larger vocabularies had more canonical emotion transitions, controlling for age. Further, when children could label a specific emotion, their transitions for that emotion were more organized by valence. These findings align with prior work linking both general and emotion-specific language to emotion development (Fabes et al., 2001; Nook et al., 2017; Roben et al., 2013; Streubel et al., 2020). When emotion labels co-occur with observed or experienced emotions, they may help children connect different instances of the same emotion, in line with the theory of constructed emotion (Barrett, 2017; Hoemann et al., 2019). This could, in turn, enable them to extract fine-tuned statistics about each specific emotion, such as its average duration and its likelihood of transitioning to other emotions (Cole et al., 2010; Hoemann et al., 2019; Lindquist et al., 2015; Nook & Somerville, 2019; Ruba et al., 2022; Ruba & Repacholi, 2020; Shablack et al., 2020). Further, the broader ability to reason about and participate in real-world social situations through language can support both conceptual (Bowerman & Levinson, 2001) and emotional development (Nook & Somerville, 2019). Alternatively, children's emotion development may scaffold their emotion language (Vigliocco et al., 2009). Most likely, there are bidirectional links between emotion and language development, such that shifts toward the mature state in each domain reinforce each other across time.

The relation between language and emotion dynamics may also reflect the way that caregiver-child communication interacts with parental perceptions. As children communicate and think about their emotions in increasingly granular ways (Nook et al., 2017, 2020; Widen & Russell, 2008), caregivers may recognize more subtle emotion transitions in their child. For example, an infant may not experience a recognizable transition between sadness and anger,

instead expressing both states in non-specific ways, whereas an older child may both experience these transitions and communicate their experiences by labeling them explicitly. Further, caregivers can convey more information about emotion to their child as the child's emotion vocabulary increases. Indeed, in older children, caregivers and children mutually influence each other's emotional language (Nook et al., 2023). Over time, this increasingly sophisticated back-and-forth interaction may help children develop adult-like experiences, expressions, and understanding of emotion. It is important to note that the link between language and emotion dynamics did not reliably hold when controlling for age, which leaves open the possibility that other developmental processes may play a role, such as changes in children's memory, attention, and regulation abilities.

Limitations and future directions

A major strength of this line of work is that it captures patterns in emotion dynamics across a younger age range than previous studies, expanding our understanding of emotion processes in infancy and early childhood. However, these conclusions must be interpreted with several limitations in mind.

Our measures of children's emotional experiences were indirect, as caregivers reported on their child's emotion experiences. We chose this approach because: (1) young infants cannot self-report emotions, (2) physiological and behavioral measures of specific emotions (e.g., differentiating between different high arousal emotions) have not been validated with specificity in infants, and (3) adults have been shown to be quite good at estimating emotion transitions of close others (Zhao & Tamir, 2020). That said, subjective reports of others' emotions likely do not perfectly capture each child's experiences (Lagattuta et al., 2012; López-Pérez & Wilson, 2015). For example, even though caregivers reported their children experiencing each emotion, we do

not know the extent to which caregivers believed young children were capable of experiencing these emotional states in an adult-like way (Lozada et al., 2016). Parent reports were also likely biased by their own personal experiences of emotions and emotion transitions. Future research should examine how adults perceive children's minds and emotions more directly. Studies 1-3 asked caregivers to estimate the likelihood of transitions, which may further decrease accuracy. In order to mitigate this concern, we used an EMA approach instead in Study 4. As in previous work in adults, we found similar findings across these two methods (Thornton & Tamir, 2017), but future work would need to understand how different sampling intervals shape caregivers' reporting in EMA studies of children's emotions. The EMA approach comes with limitations as well, since it is not possible to sample emotion experiences continuously, and we may miss intermediate transitions between two-time points in the day. Moreover, future studies could use more ecologically valid measures of emotion experiences, such as facial or vocal expressions in videos of natural interactions, or measure self-reported emotions in older children.

Our work showing that children's language development relates to their emotion experiences is grounded in a North-American context. This limits our ability to generalize the findings across cultures and communities. How might language help infants tune into the emotion dynamics of their communities? There is evidence of common valence-based organization of mental-state language across cultures, as well as variability in the meanings of emotion labels (Jackson et al., 2019; Thornton et al., 2022). Thus, there is likely both consistency and variation in the specific structure of the emotions and emotion language that children experience in their home environment. Future work will be able to leverage these individual differences to understand how young children extract emotion-related regularities in diverse environments (Mesquita, 2022).

To understand how children's dynamic and complex emotional worlds change over development, it is important to understand how emotion changes over hours and days. The current investigation applies a dynamic lens to studying emotion development and how it relates to children's developing language skills.

Chapter III: The dynamic interaction of affect and language in children's home environments[2]

Children experience language in the context of activities, routines, feelings, and social interactions that change from one moment to the next. Affect is a particularly salient aspect of children's experiences that supports semantic memory (Guo et al., 2018; Miller et al., 2018; Outters et al., 2023), shapes communicative behaviors (daSilva et al., 2021; Fields-Olivieri et al., 2020; Wass et al., 2022), and provides a rich somatosensory context (Andrews et al., 2009; Nencheva et al., 2023). Yet, the natural fluctuations of affect are nearly unexplored as a factor in language learning (Doan, 2010). In this investigation, we examined how caregiver and child affect throughout the day dynamically relate to early communication and learning. To do so, we combined (1) ecological momentary assessment of caregivers' perceptions of their own and their child's affect, (2) natural day-long audio recordings of caregiver-child communication, and (3) caregiver reports of children's word knowledge.

Affective information has two components that have been theorized to support word learning: *experienced affect* (e.g., feeling down/low) and *displayed affect* (e.g., smiling, happy prosody, etc.; Andrews et al., 2009). However, prior research has overwhelmingly focused on displayed affect – particularly in lab settings – showing that children and adults prefer emotionally-charged (over neutral) affect in various domains, including speech (Singh et al., 2002), faces (Reider et al., 2022), and actions (Zieber et al., 2014). Lab experiments have also shown that infants better recognize words heard with happy (vs. neutral) prosody (Singh, 2008) and that toddlers learn novel words equally well when viewing angry, happy, or sad displays

[2] This work was carried out in collaboration with Hannah Van Dusen, Erin Watson and Casey Lew-Williams, and a version of this work has been released as a preprint: https://psyarxiv.com/wbsym/. In addition, parts of this work were presented at the 48th Annual Boston University Conference on Language Development.

(Ogren & Sandhofer, 2021). But little is known about how the real-world affective experiences in children's lives shape their word learning.

While experienced affect has received some attention as a factor in children's language learning, prior work has focused on internal states such as wakefulness and alertness (Axelsson et al., 2016; Werchan & Gómez, 2014). There is preliminary evidence that the dynamics of experienced affect throughout the day relate to children's vocabulary size (Nencheva et al., preprint). Further, positively valenced or moderately high arousal states in adults have been shown to support semantic memory (Gilet & Jallais, 2011), and negative (vs. neutral) moods are associated with worse recall of familiar and novel words (Guo et al., 2018; Miller et al., 2018). In toddlers, physiological arousal following episodes of word learning is associated with better learning (Outters et al., 2023). These findings hint toward the possibility that the child's affective states may dynamically guide learning throughout the day.

What can explain this link? There are two key ways that children's affective displays and experiences can shape language development.

First, how children and caregivers feel may broadly shape how they communicate. Infants produce more vocalizations in moments of higher physiological arousal (Wass et al., 2022), and toddlers who display more negative affect produce and receive fewer verbalizations (Fields-Olivieri et al., 2020). Caregivers' affect is also known to shape their own behavior. For example, in moments of heightened stress, adults talk less to each other (daSilva et al., 2021) and to their children (Ellwood-Lowe et al., 2022; Roby & Scott, 2022), and global differences in caregiver affect (e.g., depression) alter communicative behavior (Field, 2010; Herrera et al., 2004). If caregivers and toddlers engage in less communication in moments of more negative valence or lower arousal, this will likely result in overall less speech input and turn-taking (i.e.,

contingent back-and-forth utterances between caregivers and children), which has been shown to be an important catalyst of language learning (Donnelly & Kidd, 2021; Feurstein et al., 2023; Romeo et al., 2018). Together, these findings suggest that children's and caregivers' affective states may shape learning by modifying when caregivers and children engage in high-quality communication.

A second and more specific way in which affect may shape language is by creating contexts that guide children's learning of new words across time. Word learning is known to unfold over time in diverse communicative contexts, spanning people, spaces, and routines (Roy et al., 2015), and the child learner must integrate their experiences to determine meanings. Some words they encounter may appear in consistent affective contexts, but others may not appear in any organized fashion. Given this variability, are words more learnable if they appear in variable or stable contexts? Variable contexts may support children's learning by exposing them to the full range of a word's uses (Slone et al., 2019). Yet *stable*, routine-based contexts (e.g., room in the house, time of day, or surrounding words) may support learning by facilitating the right amount of predictability (Roy et al., 2015). Affect – and its stability or variability across word instances – may operate as a salient contextual cue that shapes children's learning across time. Although researchers have theorized that affect is a part of word-learning contexts (Andrews et al., 2009), prior work has not examined its dynamics over time, which may be important for how we define 'context' from the child's perspective.

Current Study

The current investigation aims to understand the dynamic links between young children's affect, communication, and word learning. Over two days, we measured caregivers' perceptions of their own and their child's affect via text-based surveys every 45 minutes and collected

day-long recordings of household language. In addition, we collected child vocabulary reports from caregivers. First, we aimed to characterize caregivers' and children's affect (as perceived by caregivers) over the course of each day. Next, in a preregistered analysis, we predicted that there would be denser communication in moments of high arousal or positive valence (i.e., more caregiver speech, child vocalizations, and turn-taking). Further, we predicted that children would be more likely to know words used in those contexts. Finally, in an exploratory analysis, we examined whether children would be more likely to know words heard in consistent (vs. variable) affective contexts. Together, these three analyses elucidate how the dynamics of affect can impact children's learning by shaping caregiver-child communication.

Methods

Resource availability

Data and code availability. All code and deidentified survey, vocabulary, and communication measures are available here: https://osf.io/fpqgd/?view_only=c294d2a573304e2484564703a90999ea

Raw audio recordings and transcriptions are not available due to identifiable information.

Exploratory and preregistered analyses. We preregistered the hypothesis that caregiver-affect fluctuations will track communication density throughout the day, with planned exploratory analyses on the effects of caregiver-child emotion dynamics on communication more broadly. In addition to these preregistered analyses, we carried out exploratory analyses relating child affect and word knowledge. The preregistration can be found here: https://aspredicted.org/7LW_2RZ

Method details

Ethics. All research procedures were approved by the Institutional Review Board at Princeton University, and parents provided informed consent before participating.

Participants. We collected data from 25 families with toddlers between 24 and 30 months. Most of the primary caregivers were mothers (N=24). Of this sample, 16% were Asian, 8% Black, 4% Hispanic, 64% white, 4% other, and demographic information was missing for one of the families (4%). This was a highly educated sample, with 56% reporting that the child's mother had earned an advanced degree, and an additional 36% reporting a college degree. Maternal education information was missing for two of the participants (8%).

The sample size was preregistered based on a power analysis on a separate pilot sample to detect the relation between parent valence and adult word count with power greater than 80%. This sample size also matched recent day-long audio-recording studies exploring toddler affect and communication (Fields-Olivieri et al., 2019; 2022).

We preregistered that participants would be excluded if they filled out or reported being near their child on fewer than five surveys (out of 26 total) or did not comply with the instructions of the study. None of the participants met these criteria, in fact, the average response rate was 97%. However, since our analyses examine the role of within-person variability in affect throughout the day, we excluded one participant (not counted in the final sample of 25 participants) because they reported the exact same maximum value (100/100) on 100% of survey questions.

Context of data collection. Participants were recruited within Central New Jersey through the Princeton Baby Lab participant pool during the COVID-19 pandemic. Families chose days when the caregiver would spend most of the day with the child.

Procedure. Before the start of the study, the primary caregiver filled out the MacArthur-Bates Communicative Development Inventory (MCDI; Fenson, 2007) vocabulary questionnaire. We then collected back-to-back day-long recordings on two sequential days using the Language Environment Assessment (LENA) system (LENA Foundation, 2009), as described below. One participating family could only complete one of the two days due to a family emergency; however, they met the inclusion criteria of more than five completed surveys. LENA recorders worn by the child in a front-facing pocket captured caregiver speech throughout each day. Families received a text message at 8:00 a.m. each day of the study, instructing them to turn on the recorder and place it in a front-facing pocket of the provided specialized LENA t-shirt. They were asked to keep the recorder on until at least the last text message of the day (at 6:30 p.m.), covering approximately 10.5 hours. Families could take off the recorder t-shirt for naps and bath time, but were asked to leave the recorder nearby. Over the course of each day, parents were automatically sent text-message reminders every 45 minutes from 9:00 a.m. to 6:00 p.m. to fill out the same 1-minute-long survey (13 survey reminders total). In each survey, caregivers reported how they were feeling and how they thought their child was feeling (see below for more information). Parents were instructed to skip the survey if their child was asleep or if they were not with their child in the preceding 15 minutes. We collected 625 affect surveys, an average of 25.4 surveys per participant. Of those, 75% (481) were collected when the child was awake and with the parent and, therefore, were included in the data analysis.

Caregiver and child communication. We collected two day-long audio recordings (10-16 hours) using the LENA recording system to assess how caregiver and child communication relates to affect measures. Children wore a small audio-recording device in a specialized t-shirt front pocket. The LENA system has software that automatically extracts

estimates of *adult word count* (AWC; the number of words spoken by the adult in the child's proximity), *child vocalization count* (CVC; the number of speech-like vocalizations produced by the child), and *conversational turn count* (CTC; the number of times the caregiver and the child changed speech turns within five seconds) in 5-minute segments.

To assess the links between these three communication measures and caregiver reports of affect, we averaged the estimates for communicative acts in the 15 minutes before and after each affect report. All communication measures were standardized (z-scored) within participants, with 0 indicating the average count for the dyad.

Caregiver and child affect. Affect was quantified using caregiver survey responses throughout the day. Caregivers reported their perceptions of their own affective experiences and their child's displayed affect. We refer to these two measures as 'caregiver affect' and 'child affect' for conciseness. Given that toddlers could not report on their own internal states, we do not have a direct measure of the child's experienced affect, although we did validate parent-report with vocalization-based signals of child affect (see below). It should be noted that although researchers have successfully used some physiological markers of arousal, physiological measures generally fail to differentiate valence and arousal at the same time (for a review, see Sacrey et al., 2021). Similarly, there are no validated automated behavioral measures of displayed valence and arousal in infants, as most of these measures have been trained on adults. In the current investigation, we measured caregivers' perceptions of two affect dimensions: valence and arousal.

Valence measured how "positively or negatively" the caregiver's or child's affect was at a given moment. Caregivers indicated their responses to the question (parent valence: *How positively or negatively are you feeling in this moment?*; child valence: *How positively or*

negatively is your child feeling in this moment?) using a slider with values between 0 (extremely negative) and 100 (extremely positive). This value was centered at 50, resulting in a scale of -50 to +50, with negative numbers indicating negative valence.

Arousal measured how "high or low energy" the caregiver's or the child's affect was at a given moment (parent arousal: *How high or low energy are you feeling in this moment?*; child arousal: *How high or low energy is your child feeling in this moment?*). Like valence, arousal was measured on a slider with values between 0 (indicating extremely low energy) and 100 (indicating extremely high energy). This value was also centered at 50, resulting in a scale of -50 to +50, with positive numbers indicating high activation.

Standardizing measures across participants. All affective measures were standardized (z-scored) within participants, with 0 indicating the average valence or arousal for the caregiver or the child in the dyad.

Classification into four quadrants. We classified each data point into one of four quadrants based on whether the child's valence and arousal values were above or below the average values for the given child: *low valence and low arousal* (V-A-), *low valence and high arousal* (V-A+), *high valence and low arousal* (V+A-), *high valence and high arousal* (V+A+).

Validating caregiver reports of child affect. In order to validate whether caregiver reports of child affect tracked objective measures of child affective displays, we correlated caregiver ratings with the LENA system's automated measures of child crying (averaged over the 15 minutes before and after each survey). A mixed-effects logistic regression with intercepts by dyad showed that caregivers' ratings of children's valence were negatively correlated with children's crying (β = -0.12, t(452.84) =-2.51, p = 0.01), suggesting that our metric of caregiver reports of affect corresponded with the dynamics of affect-related behavior.

Affective context and production of words. In order to link the affective contexts in which children hear words and their production of these words, trained research assistants transcribed caregiver speech in the 5 minutes preceding and following each of the 625 completed affect surveys. Then, for each word on the MCDI questionnaire, we marked all time points where caregivers used that word in the 5-minute interval surrounding a survey. For example, we would mark any time the parent used the word "dog" within 5 minutes of completing an affect survey. We computed the proportion of instances of each word that occurred in each of the four affective quadrants and averaged the standard deviation of valence and arousal across all instances of the word for each dyad as a measure of variability in affective context. Additionally, we marked whether the child produced the word based on caregiver responses to the MCDI questionnaire.

Quantification and statistical analysis

Model selection. For all analyses linking affect and communicative behavior, we used the preregistered mixed-effect model: *communicative behavior measure ~ affect measure at the current time point + affect measure at the previous time point,* with random intercepts by participant. As preregistered, we first ran this model with random intercepts and slopes by participant. If the model failed to converge (which was the case for all analyses we ran), we opted for a simpler model with random intercepts only. We used FDR correction for multiple comparisons and reported standardized regression coefficients.

For the exploratory analyses linking the affective contexts of words to the child's word knowledge, we used a mixed-effects logistic regression with random intercepts by word, controlling for the overall frequency of the word (the number of times the child heard the word over the two days of the study). We constructed separate regressions for each of the four quadrants, with the proportion of time children heard each word in the quadrant as the predictor

of interest. We did not use a more random model, including slopes and intercepts by word, because it resulted in a singular fit error.

Results

Caregiver and child affect fluctuate over the course of a day

First, we characterized the dynamics of child and caregiver affect throughout the day along two dimensions: (1) valence, from negative to positive, and (2) arousal, from low energy to high energy. Similarly to prior EMA studies on child (Nencheva et al., Preprint) and adult (Thornton & Tamir, 2017) emotion dynamics, we found that caregivers reported fluctuations in affect over the course of the day for themselves and their child. We then categorized each report of child affect into one of four quadrants, based on whether it was higher or lower than the average valence and arousal for the participant. The greatest proportion of child affect timepoints fell in the high valence and high arousal quadrant (V+A+; 43%), followed by low valence and low arousal (V-A- ; 28%), high valence and low arousal (V+A-; 17%), and low valence and high arousal (V-A+; 12%). This indicates that most of the time, caregivers perceived their child to be experiencing high arousal and high valence. From the 100-point scale, child affect showed an average 40-point range in valence and a 31-point range on arousal between the highest and lowest value for valence and arousal, respectively, on a given day. Adults self-reported an average 41-point range in valence and 35-point range in arousal.

Although there was high variability within a given day, variability in caregiver and child valence and arousal (measured as standard deviation) showed some stability over the two days of the study. There were significant cross-day correlations for caregiver valence ($r(23) = 0.53$, $p = 0.007$) and child arousal ($r(23) = 0.50$, $p = 0.01$) and smaller correlations for child valence ($r(23) = 0.27$, $p = 0.19$) and caregiver arousal ($r(23) = 0.37$, $p = 0.06$) that did not reach significance.

Further, ratings of caregiver and child affect were moderately correlated. In a linear mixed-effects regression with random intercepts by participant, we found significant relations between child and caregiver valence ($\beta = 0.43$, $t(457) = 10.22$, $p = 3.11 \times 10^{-22}$) and arousal ($\beta = 0.24$, $t(456) = 5.39$, $p = 1.13 \times 10^{-7}$). Together, these descriptive results show that on an average day, (1) caregivers perceived fluctuations in their child's affect, (2) the degree of affect fluctuation remained relatively stable over back-to-back days, and (3) caregivers perceived their own and their child's affect to be a coupled system.



Figure 1. Caregiver and child valence varied over days and across the 25 dyads. This descriptive plot illustrates how affect changed over the course of the day for each dyad (x-axis), as well as how the dynamics of affect differed between dyads (y-axis). Each colored rectangle on the plot represents the affect quadrant for a given child (left panels) or caregiver (right panels) at each hour (x-axis) on the first (top panels) or second (bottom panels) day of the study. The rows on the y-axis represent the affect of a given dyad.

Valence and arousal are associated with caregiver-child communication

Next, we investigated whether these fluctuations in reported affect throughout the day relate to caregiver-child communication. Specifically, we examined whether caregiver and child affect predicted communicative behaviors in the 15 minutes before and after each survey. In a mixed-effects linear model with random intercepts by participant, controlling for affect at the previous time point, we found that child arousal was positively associated with higher adult word count ($\beta = 0.17$, $t(344) = 3.79$, $p_{FDR} = 0.0007$), child vocalization count ($\beta = 0.29$, $t(344) = 6.91$, $p_{FDR} = 9.08\times10^{-11}$), and conversational turn count ($\beta = 0.25$, $t(344) = 5.6$, $p_{FDR} = 1.73\times10^{-7}$). Caregiver arousal was weakly associated with adult word count ($\beta = 0.13$, $t(347) = 2.92$, $p_{FDR} = 0.007$) and marginally associated with child vocalization count ($\beta = 0.08$, $t(347) = 1.84$, $p_{FDR} = 0.08$), but not significantly associated with conversational turn count ($\beta = 0.06$, $t(347) = 1.48$, $p_{FDR} = 0.15$).

Child valence was also positively associated with child vocalization count ($\beta = 0.1$, $t(346) = 2.34$, $p_{FDR} = 0.04$) and marginally associated with adult word count ($\beta = 0.07$, $t(346) = 1.66$, $p_{FDR} = 0.09$), but not significantly associated with conversational turn count ($\beta = 0.08$, $t(346) = 1.8$, $p_{FDR} = 0.14$). Caregiver valence was significantly associated with adult word count ($\beta = 0.1$, $t(346) = 2.17$, $p_{FDR} = 0.04$) and marginally with child vocalization count ($\beta = 0.07$, $t(346) = 1.69$, $p_{FDR} = 0.09$), but did not significantly predict conversational turn count ($\beta = 0.06$, $t(346) = 1.44$, $p_{FDR} = 0.15$).

While not every effect was statistically significant, these results collectively suggest that moments of either high valence or high arousal were associated with richer communication, which may support word learning. In contrast, moments with negative valence and low arousal

contained less speech and less turn-taking. Caregivers' perceptions of child arousal most strongly drove this relation.

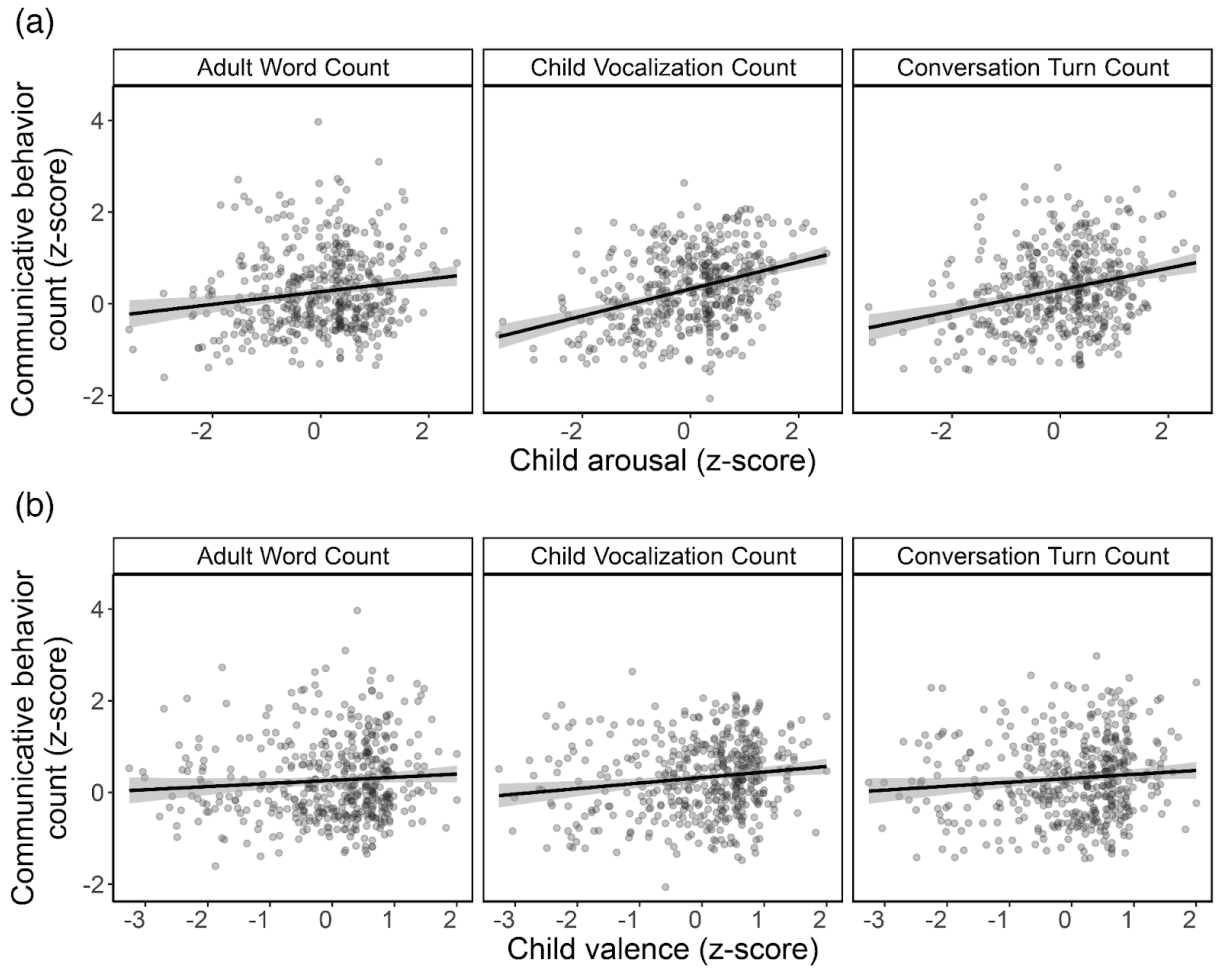

Figure 2. High arousal and high valence were associated with more adult speech, child vocalizations, and turn-taking. Each point represents affect at a given time. The top three panels display child arousal on the x-axis, and the bottom three panels show child valence on the x-axis. The y-axis shows the standardized score of the communicative behavior listed at the top of each panel (adult word count on the left, child vocalization count in the middle, conversational turn count on the right). The regression line is plotted in black, with a shaded 95% confidence interval. Communicative behaviors were highest in moments with either higher valence or higher arousal.

Children know words that they hear in high-valence and/or high-arousal contexts.

Given the observed differences in communication surrounding different affective contexts, we investigated in an exploratory analysis whether individual differences between participants in the affective contexts in which children hear words relate to children's knowledge of those words.

We tested the extent to which the proportion of time children heard a given word within each of the four valence-arousal quadrants of child affect (V+A+, V+A-, V-A+, and V-A-) predicts whether they produce the word. We analyzed this using a mixed-effects logistic regression with random intercepts and slopes by word, controlling for the overall frequency of the word (i.e., the number of times the child heard the word over the two days of the study). We found that children were more likely to know words that they heard more often in the V+A+ (β = 0.12, z = 2.75, p = 0.006), V-A+ (β = 0.09, z = 1.97, p = 0.048), and V+A- (β = 0.1, z = 2.31, p = 0.02) quadrants (Figure 3a,c). Conversely, they were *less* likely to know words they heard more often in the V-A- quadrant (β = -0.23, z = -5.57, $p = 2.54\times10^{-8}$; Figure 3a,c). These findings suggest that children are more likely to know words that they hear more often in high arousal and/or high valence contexts in their everyday lives.

In a mediation analysis, we probed whether this association exists because children experience more dense and rich communication in higher-arousal or higher-valence contexts. When we added to the model the average conversational turn count for all instances of the word, the association between the child's knowledge of the word and the proportion of word instances in a given quadrant was no longer significant for three of the quadrants (V+A+: β = 0.05, z =1.35, p = 0.18, 30% mediated; V-A+: β = 0.03, z = 0.77, p = 0.43, 38% mediated; V+A-: β = 0.03, z = 0.62, p = 0.53, 66% mediated). There was still a significant association for V-A- after including conversational turn count (β = -0.22, z = -5.28, $p = 1.28\times10^{-7}$, 3.7% mediated). This

suggests that moments of higher valence and/or higher arousal may support word learning in part by engendering richer communication (operationalized as more turn counts). However, reduced communication during moments of lower valence and lower arousal may not explain why children do not know words that are usually used within them. This raises the question of what other contributors there may be to children's lower likelihood of knowing words used in low-valence and low-arousal contexts.

In sum, children were more likely to know words that they heard most often in higher-valence and/or higher-arousal contexts and less likely to know words they heard in lower-arousal and lower-valence contexts. The relation between affect and word production was, in part, explained by the denser communication associated with high arousal and high valence.

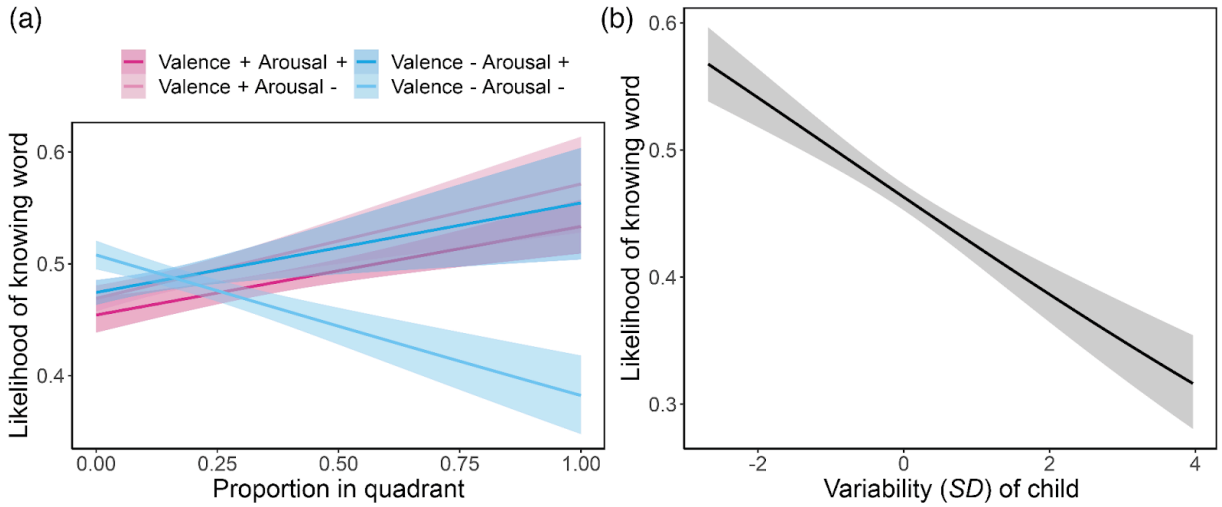

Figure 3. Child affect relates to word knowledge. Panel (a) shows the likelihood of a child producing a given word on the y-axis and the proportion of word instances that appeared in the interval surrounding an affective survey within each of the four quadrants on the x-axis (pink: higher valence; blue: lower valence; and more saturated colors represent higher arousal and less saturated colors represent lower arousal). Each logistic regression line (with shaded 95% CI) corresponds to each of the quadrants, respectively. Children were more likely to know a word if they heard it a greater proportion of time with higher-valence or higher-arousal contexts and less likely to know it if they heard it a greater proportion of time with lower-valence and lower-arousal contexts. Panel (b) plots the likelihood of the child knowing a given word on the y-axis and the variability in child affect across all instances of the word on the x-axis. Children were more likely to know words heard in more stable affective contexts.

Children know words that they hear in more stable affective contexts.

In addition to exploring which affective moments were most strongly associated with children's word knowledge, we also examined whether hearing words with stable vs. variable affect over two days was more strongly associated with word knowledge. We found that children were *less* likely to know words that they heard with greater variability (standard deviation of valence and arousal across all instances of the word for a given child) in a mixed logistic regression with intercepts by word (β = -0.14, z = -2.95, p = 0.003; Figure 3b). This suggests that children were more likely to know words that they heard in moments with more similar affect across time.

Discussion

Many aspects of children's home environments matter for word learning, such as patterns in the time of day or room in the home in which children hear a word (Roy et al., 2015). The current investigation expands our understanding of communicative contexts by considering the dynamic interplay between U.S. caregivers' and children's affect and communication in everyday life. The two key findings were that caregivers and toddlers vocalized and exchanged conversational turns more in moments of higher arousal or valence, and children were more likely to know words heard in these moments.These findings highlight the important role of affect in the early word learning environment.

Higher valence and arousal were both associated with denser communication, specifically more vocalizations and turn-taking. One interpretation of this relation is that affect shapes communication – an idea that converges with research linking higher physiological arousal with more infant and caregiver vocalizations (Wass et al., 2022) and negative affect with fewer vocalizations in infants (Fields-Olivieri et al., 2020) and decreased communication in adults

(daSilva et al., 2021; Ellwood-Lowe et al., 2022; Roby & Scott, 2022). But an alternative interpretation is that communication shapes affect. For example, social interactions are associated with more smiling in infants (Ellsworth et al., 1993) and greater well-being in adults (Sun et al., 2020). Regardless of directionality, the tight coupling between affect and communication suggests that these two components of experience should be considered simultaneously to understand how children learn in early communicative interactions.

Children were also more likely to know words that they heard in moments of higher valence or arousal. A likely interpretation is that experiences of higher valence and arousal support word learning via attention and memory processes (Guo et al., 2018; Miller et al., 2018; Outters et al., 2023). Relatedly, the greater turn-taking observed in these moments may help explain children's learning (Donnelly & Kidd, 2021; Feurstein et al., 2023), as turn-taking partially mediated the link between the affective context and children's knowledge of a word. That is, turn-taking – an established index of the quality of caregiver-child communication – may, alongside other factors, explain why children are more likely to know words heard in high-valence or high-arousal contexts. Another possibility is that certain modes of conversation (e.g., discussing favorite toys or topics) may bring about more positive or high-arousal feelings. Although we cannot disentangle these possibilities, we found that children were more likely to know words heard in stable affective contexts over time, across the continuum of valence and arousal. This suggests that, in addition to shaping communication and learning, affect can serve as a context that helps children link experiences hearing particular words across time. These findings highlight the importance of understanding the rich connections between the dynamics of word learning and affect throughout the day to gain a complete picture of early learning.

Although our study design enabled us to measure the real-world dynamics of affect and speech, there were several key limitations. First, relying on caregivers' perceptions of children's affect constrains our ability to capture children's affective experiences and displays. Although caregivers' perceptions of child affect are interesting as a window into caregivers' responses to the behaviors they perceive, they do not perfectly reflect the child's experiences. We chose this approach for several reasons: (1) alternative measures of affect (such as physiology) are limited in capturing both valence *and* arousal (e.g., distress and excitement have overlapping physiological fingerprints; Sacrey et al., 2021); (2) self-report is not possible with children this young; (3) caregiver report is widely used to assess the development of young children (Bricker et al., 1999; Parade & Leerkes, 2008); and (4) caregiver report of child emotion is moderately correlated with child self-report in slightly older children (Nauta et al., 2004). Indeed, our data showed a correlation between caregivers' reports of child valence and the frequency of children's crying. Future research could combine caregiver reports with child physiology and behavior in order to measure these different components of affect more robustly.

A second limitation is the observational design. Although this served the crucial purpose of allowing us to characterize natural fluctuations in affect and communication, it limited our ability to infer causal links. Future research could use mood inductions (e.g., watching a sad video clip; Devilly & O'Donohue, 2021) or communicative interventions (e.g., reminders to engage with the child; Roberts & Kaiser, 2011) while retaining the naturalistic design of the study. Combined with time-lagged analyses, this approach would allow researchers to disentangle the effects of affect on communication and vice-versa.

Constraints on generality

A final limitation of the current investigation is its relatively homogeneous sample. The participating families were U.S.-based, highly educated, and 64% white. Our findings, therefore, should be interpreted with this context in mind, and we hope they spark efforts to understand how affect and communication interact in other communities. There are known cultural differences in how affect is expressed and valued (Mesquita & Frijda, 1992; Safdar et al., 2009; Tsai et al., 2006). Therefore, it is likely that valence and arousal may have different effects on communication across different cultural contexts. Future research should examine how infants tune in to their local community's affective and speech context.

Conclusion

This investigation combined day-long audio recording and ecological momentary assessment to understand how the dynamics of affect in the home relate to children's early communicative experiences and word knowledge. Higher arousal and valence were positively associated with turn-taking, and children were more likely to know words that they heard in these contexts. This research broadens current definitions of learning contexts to include affective experiences and displays from caregivers and children. Together, the findings indicate that affect and communication are interdependent systems that should be studied in tandem in order to understand children's learning.

Chapter IV: Caregiver speech predicts the emergence of children's emotion vocabulary[3]

From infancy through adulthood, humans experience and communicate rich and dynamic mental experiences. Words can capture these experiences, allowing us to peer into others' minds and share our own internal experiences with others. Children's ability to verbally label their emotions is an important force in their socio-emotional development (Hoemann et al., 2019). Children who can label their emotions have more effective emotion regulation, more peer integration in kindergarten, and greater socio-emotional school readiness (Cole et al., 2010; Eisenberg et al., 2005; Fabes et al., 2001; Roben et al., 2013; Trentacosta & Izard, 2007). How do children learn these important labels?

Children's earliest social interactions include information about emotion experiences and emotion language simultaneously. For example, as a child observes a facial expression associated with happiness – a smile, or a positive disposition – they may hear *emotion labels*, such as "happy", which directly name an internal emotional state. These labels may occur alongside *valenced words*, i.e., positive, or negative words such as "smile" and "good," which contain emotional information but do not explicitly name the experienced internal state. That is, a natural conceptual structure emerges over time because emotion experiences co-occur with valenced words and emotion labels.

Young children have a propensity to track the statistics of their input, allowing them to group co-occurring inputs together into emotion concepts. Caregivers may help scaffold children's learning about emotion and language simultaneously. In the current investigation, we

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explored how children develop emotion labels, and how this relates to caregivers' dynamic use of valenced language.

Emotion labels in context

Emotion labels are a subset of valenced words that refer to a highly positive or negative internal mental state, such as "happy" or "sad". Cabanac (2002) defines emotions as "any mental experience with high intensity and high hedonic content (pleasure/displeasure)." They are on average less concrete than early-learned neutral words (e.g., "truck"; Vigliocco et al., 2014), meaning that it is hard to highlight a concrete object, action, or sensation in the physical environment of the child as the referent of the emotion label. One cannot point to, look at, or hand "happiness" or "sadness" to a child. In order to learn emotion labels, speakers have to abstract across variable physical contexts (Barrett et al., 2011; Hoemann et al., 2019, 2020). For example, a person may experience joy when their favorite soccer player scores a goal or when the villain in a cartoon slips on a banana peel. Speakers also need to learn that multiple emotion labels can apply to the same physical context. For example, tears can signal joy or grief. Or, the arrival of a visitor may evoke excitement or dread. Despite this variability, developing abstract concepts is core to human cognition (Borghi, 2022).

The variability surrounding emotion labels poses a challenge for learning this important class of words. Indeed, infants learn words later if they lack a concrete referent (Bergelson & Swingley, 2013). However, when comparing across different words that similarly lack a concrete referent, emotionally charged abstract words, such as emotion labels, are learned earlier than abstract words that are more neutral (e.g., "premise" or "status"; Ponari et al., 2018, 2020). The emotional content of these abstract words, specifically how positive or negative they are, may bootstrap children's learning. Valence – the relative positivity or negativity of an experience – is

the dimension that most strongly organizes adult emotion representations (Russell, 1980; Tamir et al., 2016; Thornton & Tamir, 2020) and is present in young children (Nook et al., 2017). Early childhood may be an especially important time for young children's development of valence-based representations. Valence gradually emerges in the first 5 years of life as a dimension that organizes children's representations of non-linguistic emotion cues and emotional experiences, in tandem with children's expanding vocabularies (Nencheva et al., 2021; Woodard, Zettersten & Pollak, 2021). Children's ability to label emotions with specificity emerges during this same span in early childhood (Widen, 2013; Wu et al., 2022). What allows young children to extract information about the valence of these words?

One important source of information that may support children's learning of emotion labels is the context in which these words occur (Thornton et al., 2020). Emotions are more likely to precede and follow other similarly positive or similarly negative emotions (Thornton & Tamir, 2017). For example, if someone experiences a negative emotion (e.g., sadness), they are more likely to experience another negative emotion next (anger) rather than a positive emotion (happiness). When adults observe sequences of novel emotion labels (Thornton et al., 2020), they later judge emotion labels as more similar if they had consistently preceded or followed each other, suggesting that context offers a useful cue for the learning of concepts. Children's early input likely reflects this valence-consistent context for emotion experiences. This context may serve as a key source of information during learning. When children observe that a new emotion co-occurs with another positive emotion, or within a positive context, this offers key information about the meaning of the new emotion. Infants may likewise track how often emotion words co-occur in order to construct the meaning of a particular emotion concept (Shablack et al., 2020). That is, nearby emotion labels and other related words may cue the

valence of a novel emotion label. In order for young children to learn these relations, they must simultaneously track statistical information across time and form semantic connections between words that occur close to each other in time.

Using statistical information to learn novel labels

There is considerable evidence that young children track the statistics of temporal sequences. How may this domain-general mechanism support children's learning of emotion labels? Infants implicitly track syllables, words, objects, and events in their environment and detect when their statistics are altered (Lew-Williams et al., 2011; Saffran et al., 1996; Saffran & Kirkham, 2018). Infants are sensitive to how stimuli in their environment are distributed across time, a skill necessary for learning the semantic relations between words, and more specifically, for linking emotion labels with their valenced contexts. Research has already shown that infants do this for non-valenced terms. For example, young children can infer what a label refers to based on information in surrounding sentences (Horowitz & Frank, 2015; Schwab & Lew-Williams, 2020). By two years of age, toddlers reliably infer that two words are similar if both co-occur with the same related words (Lany & Saffran, 2010; Wojcik & Saffran, 2015). When semantically related words precede a label, they guide young learners' attention and facilitate processing of the label (Peters et al., 2021). These findings offer further evidence that toddlers should be able to extract the valence of a novel emotion label from the valence of its context.

Research on children's semantic networks shows that children's vocabulary composition is associated with their ability to use semantic context to learn new words. That is, children are more likely to learn novel labels that are (vs. are not) semantically related to words they already know (Hills et al., 2009). Young children are also faster to recognize a novel label that belongs to

a category that is well (vs. poorly) represented in their vocabulary (Borovsky et al., 2016). These findings provide further reason to believe that children may be more able to capitalize on valence cues in the context of a novel emotion label if they already know many positive or negative words. This valenced knowledge should bootstrap a child's emotion label learning, compared to children who mostly know neutral words.

There is evidence that caregivers may adapt their speech in ways that scaffold young children's ability to track the co-occurrences of related words. When addressing young children, caregivers immediately precede and follow a given word with related words more so than when they are addressing adults (Hills, 2013). This adaptation may support learning, as children learn novel labels better when they are surrounded by related rather than unrelated discourse (Fernald et al., 2009; Schwab & Lew-Williams, 2017, 2020). In the domain of emotion words, this suggests that caregivers could likewise provide context for emotion labels that support children's learning of these important words. Caregivers may curate similarly valenced words around the introduction of unfamiliar emotion labels. For example, when introducing the label "happy", a caregiver can provide information about the situation or actions surrounding the emotion (e.g., "Rosa got a wonderful present for her birthday! She was so happy!"). By introducing other positive words concurrently, such as "wonderful", "present", and "birthday", caregivers can cue children to cluster these concepts together, and to think about them separately from concepts that rarely show up concurrently, like "yucky", or "sad". The emotion labels can then take on meaning, as young children cue into the valence (i.e., the positivity vs. negativity) of the cluster, and thus the valence of the emotion label "happy". Therefore, caregiver cues to the valence of an emotion label in the discourse surrounding the labeling event may support learning both in the moment (by helping children infer the meaning of the novel emotion label) as well as over the

course of development (by building up a network of semantic similarity between the emotion label and other valenced words).

Current investigation

In the current investigation, we explore (1) the emergence of valenced words in children's production, and (2) how caregiver discourse may support young children's learning of emotion labels.

In Study 1, we characterize the development of 1- to 2-year-old children's semantic network of valenced words and examine the rate at which young children learn emotional and neutral words. We hypothesized that children's early vocabularies will consist primarily of concrete neutral words, and would later expand to include more abstract positive and negative words. We tested this using data from Wordbank, a large database of the productive vocabularies of young children (Fenson, 2007; Frank et al., 2017). As children learn more valenced words, they should be able to use this rich semantic network to bootstrap their understanding of new emotion labels and vice versa. We test this possibility in Study 2, using the same database, hypothesizing that knowing highly emotional words makes it easier for children to learn emotion labels, and vice versa.

Next, we test how children form these semantic connections between emotion labels and other valenced words. Specifically, in Studies 3, 4 and 5, we examined how the structure of caregiver input may leverage the valenced, semantic connections to facilitate emotion label learning. If the co-occurrence of similarly-valenced words bootstraps emotion label learning, then young children should learn emotion labels best when caregivers provide useful context about the valence of the labels. In Study 3, we hypothesized that caregivers use emotion labels within contexts that match in valence. We characterized the temporal dynamics of sentiment in

caregiver speech surrounding emotion labels in English corpora (including North American, British) from the Child Language Data Exchange System (MacWhinney, 2000, 2014; Sanchez et al., 2019). In Studies 4 and 5, we provide correlational evidence that co-occurrence between emotion labels and similarly-valenced words in children's input may support children's production of emotion labels. Study 4 examined whether variability in the extent to which different emotion labels lend themselves to such co-occurrence in child-directed speech predicts earlier or later production. Study 5 then examined the longitudinal hypothesis that children produce emotion labels in more accurate contexts when their caregivers surround emotion labels with similarly valenced words. Together, the five studies provide insight into how young children may use dynamic language input to construct complex meanings.

Analysis code and materials for all studies are available at: https://osf.io/n689q/?view_only=f8cbc3ad7281495da0ff02be935c7e6c

STUDY 1: The development of children's emotion vocabulary

How does the representation of valence in young children's vocabularies develop over time? In Study 1, we characterized the development of young children's semantic networks of emotion-related words. Our exploratory analyses arbitrate between two possibilities. On the one hand, young children may learn new words uniformly across the valence continuum by learning emotional and neutral words simultaneously. Alternatively, young children may learn some parts of this emotional continuum before others.

Our predictions are grounded in findings from three prior studies that we aimed to replicate in our dataset; namely, that children learn abstract words later than concrete words (Bergelson & Swingley, 2013), that valenced words are, on average, less concrete than neutral words (Vigliocco et al., 2014), and that older children learn highly positive or negative abstract

words (e.g., “delight” or “tyranny”) earlier than relatively neutral abstract words (e.g., “scheme” or “premise”; Ponari et al., 2018, 2020)

Based on these findings, we predict that (1) toddlers would first learn ‘neutral’ concrete words and then learn the relatively abstract valenced words. Toddlers should learn neutral abstract words even later (2) this would result in a gradually increasing emotional range in children’s vocabularies over the first few years of life. The present study served to motivate our main research questions addressed in Studies 2-5.

Method

Dataset

We tested these predictions on the vocabularies of 5,520 toddlers between the ages of 16 and 30 months using parent-report data from the MacArthur-Bates Communicative Development Inventory MCDI (Fenson, 2007), Wordbank version 0.3.0 (Frank et al., 2017). This measure asks caregivers to report which of a set of 680 words their child understands and says.

Of the toddlers included in the Wordbank database, 1,989 were female, 2,105 were male; 2202 identified as White, 67 as Asian, 222 as Black, 131 as Hispanic, and 93 as other. Gender information was missing for 1,426 of the participants and ethnicity information was missing for 2,805 of the participants. For the last analysis in Study 1, which computed the emotional range of children’s vocabularies, we excluded 9 participants who did not produce any words.

The dates of data collection were not included in the Wordbank database; however, a list of contributing publications and researchers can be found on the Wordbank website (http://wordbank.stanford.edu/contributors). Papers contributing to the English database range in publication dates between the years 2000 and 2016 and were collected in North America.

Variables

Word emotionality and valence. We performed a sentiment analysis using the *affectr* package (Thornton & Tamir, 2020) to compute the valence of all words in the MCDI form (680 words total). This tool computes the valence of a word based on its similarity to other, previously rated, emotion labels (Tamir et al., 2016; Thornton & Tamir, 2017, 2020). This dimension of valence distinguishes positive from negative words (hereafter referred to as *valence*) and valenced words (i.e., positive and negative) from non-valenced words (i.e., neutral; hereafter referred to as *emotionality,* computed as the absolute value of valence). We verified the valence values extracted via sentiment analysis by comparing them to normed human valence ratings for 492 of the MCDI words (Warriner et al., 2013). We found a robust correlation between sentiment analysis estimates and human ratings ($r = 0.62$, $p = 1.87 \times 10^{-53}$), suggesting that the computational sentiment analysis yielded comparable values to human raters. Therefore, our analyses exclusively used the continuous measures of valence from this sentiment analysis. We also computed the emotionality of each word, giving high values to highly positive *and* highly negative words, and low values to relatively more neutral words (see Figure 1a). The values for valence and emotionality were z-scored in all statistical analyses.

Emotional range. We assessed the emotional range of a child's vocabulary by computing the standard deviation of the valence of all words produced by the child. By definition of this metric, children who produced words spanning a wider range of valenced values (covering positive and negative extremes of the valence continuum) had a wider emotional range than children who produced a narrower range of valenced values (for example, covering primarily the 'neutral' middle of this continuum). This measure was then z-scored for statistical analyses.

Concreteness. We obtained concreteness ratings from Köper & im Walde (2017) for the words in the MCDI (available for 560 of the 680 words).

Word frequency. In order to control for effects of the frequency of words in children's input, we computed the log frequency (number of occurrences of a target word per million words) of each word in CHILDES, a large database of transcribed caregiver-child interactions, using the childes-db R package (Sanchez et al., 2019). For this estimate, we included all corpora of English speech by caregivers (including both mothers and fathers) addressing toddlers between the ages of 15 and 30 months (a total of 49 corpora of 522 children). Frequency in CHILDES could not be estimated for 53 of the words. These words were excluded only when reporting results controlling for frequency. There was a small positive correlation between the emotionality of a word and its frequency in child input ($r = 0.09$, $p = 0.02$), suggesting that if highly emotional words are learned later, this is not because children hear them less often.

Age of acquisition. We computed the age at which at least 50% of children produced the word, also known as age of acquisition (AoA). To extract this number, we used the fit_aoa function in wordbankr (Braginsky et al., 2018; Frank et al., 2017) to fit a logistic curve over the proportion of children producing each word over time. In this analysis, 69 words were excluded because they did not reach a threshold of 50% of children producing the word within the study age range. All analyses of age of acquisition were performed on the remaining 608 words of the MCDI.

A table with the analyzed words and their age of acquisition, valence, concreteness, and frequency can be found on the project osf page.

Data analysis

For all analyses in Study 1, we used linear regression predicting the age of acquisition of the word from its emotionality. Standardized regression coefficients (β) were estimated using the *lm.beta* function (Behrendt, 2014). All analyses were performed in R, version 4.1.3 (R Core Team, 2022).

Results and Discussion

Emotionality shapes toddlers' early word productions

We first explored whether the age at which toddlers produce a word is related to the word's emotionality, and tested our prediction that toddlers would produce valenced words later than neutral words. This regression showed a small but significant positive effect of emotionality on age of acquisition (AoA ~ emotionality; $\beta_{emotionality} = 0.08$, $t(606) = 2.06$, $p = 0.04$), such that the more extremely positive or negative a word was, the later toddlers produced it (see Figure 1b). This effect held when controlling for word frequency (AoA ~ emotionality + frequency; $\beta_{emotionality} \sim 0.1$, $t(560) = 2.37$, $p = 0.02$), and after removing the most influential data points (Supplementary Analysis 1) and the most extremely positive and negative words (Supplementary Analysis 2). We did not find an overall effect of valence (i.e., positive words were learned around the same time as negative words), replicating prior work from Braginsky et al. (2016). The effect of emotionality did not interact with that of valence (Supplementary Analysis 3).

Emotionality and concreteness: A replication of prior findings

To explore why toddlers in this dataset produced valenced words later, we replicated several findings in prior literature showing an interplay of valence and abstractness in children's word learning. First, using concreteness ratings from Köper & im Walde (2017), we replicated a significant negative association between the emotionality and concreteness of words in the

MCDI (concreteness ~ emotionality; $\beta_{emotionality}$ ~ -0.41 $t(558) = -10.6$, $p = 5.02 \times 10^{-24}$), previously shown in Vigliocco et al. (2014). In short: the more emotional a word is, the less concrete it is. Second, we replicated the result from Bergelson and Swingley (2013) that children learn concrete words earlier than abstract words (AoA ~ concreteness; $\beta_{concreteness} = -0.3$, $t(561) = -7.49$, $p = 2.74 \times 10^{-13}$).

Next, we performed exploratory analyses to probe whether concreteness explains the link between emotionality and later AoA. When controlling for concreteness, the effect of emotionality on age of acquisition was no longer significant (AoA ~ emotionality + concreteness; $\beta_{emotionality}$ ~ -0.05, $t(557) = -1.25$, $p = 0.21$). This result – along with the findings that emotionality predicts concreteness and that concreteness predicts AoA – suggests that in this sample, concreteness mediates the effect of emotionality on AoA. That is, toddlers are likely to learn highly emotional words later than neutral words because they are less concrete. However, it is important to note that the current study was not designed to probe the nuanced interplay of emotionality and concreteness. Future investigations that are specifically designed to hold concreteness constant and to vary emotionality (e.g., by creating matched pairs, as in Ponari et al., 2018, 2020) will enable better understanding of these effects in toddlers.

Ponari et al. (2018, 2020) showed that older children learn highly positive and negative abstract words earlier than neutral abstract words. We also replicated this finding in our analyses. As an example, we found that the highly positive word “smile” has an AoA of 27 months, whereas the frequency-matched relatively neutral concrete words “tongue” and “bowl” have an earlier AoA of 23 months. In contrast, abstract neutral words like “pretend” and “think” have a later AoA of 30 months. There was variability in the size of this effect for different words; for example, “bucket”, another frequency-matched relatively neutral word, has an age of acquisition

of 26 months. However, these results suggest that children, on average, (1) hear highly emotional words just as frequently as more neutral words, (2) learn highly valenced abstract words later than concrete neutral words, and (3) learn highly valenced words earlier than neutral abstract words (Supplementary Analysis 5).

The emotional range of children's vocabularies expands over time

Regardless of the specific mechanism that results in toddlers' later production of highly valenced words, we hypothesized that this trend would shape children's growing vocabularies over the first few years of life. We examined how the range of positive and negative words in toddlers' vocabularies changes over time. How do the learning trajectories of differently valenced words affect the overall range of valenced words that children produce? If toddlers learn highly positive and negative abstract words later than relatively neutral concrete words, and if they do not yet produce many neutral abstract words, then the emotional range of their vocabularies should also increase over the first few years of life. In this analysis, we assessed how the emotional range of children's vocabularies changes over time in a linear regression predicting emotional range from age, controlling for vocabulary size. Indeed, emotional range increased with age (valence range ~ age; $\beta_{age} \sim 0.46$, $t(5498) = 37.96$, $p = 2.78 \times 10^{-280}$). For example, at 16 months, toddlers' vocabularies had an average emotion range of 0.15 (valence: mean = 0.04, min = -0.33, max = 0.41; Figure 1c), whereas at 30 months, they had an average range of 0.18 (valence: mean = 0.04, min = -0.64, max = 0.82; Figure 1c). The increase in emotion range remained significant when controlling for vocabulary size (valence range ~ age + vocabulary size $\beta_{age} = 0.14$, $t(5497) = 8.07$, $p = 8.35 \times 10^{-16}$), suggesting that the expansion in emotion range is not merely a byproduct of larger vocabularies in older children, but rather are

the result of specific expansions in toddlers' productions of highly positive and negative words (Supplementary Analysis 5).

Together, these findings support the hypothesis that children's early semantic networks start off relatively sparse in terms of representing highly positive or negative words, and instead are more densely populated by neutral concrete words. Over time, as children learn more valenced words, their semantic networks represent an increasingly wide range of positive and negative words. This developmental change may have important consequences for children's ability to learn and express emotion-related information. In Study 2, we explored how the increasing emotional range of children's semantic networks interacts with their production of specific emotion labels.

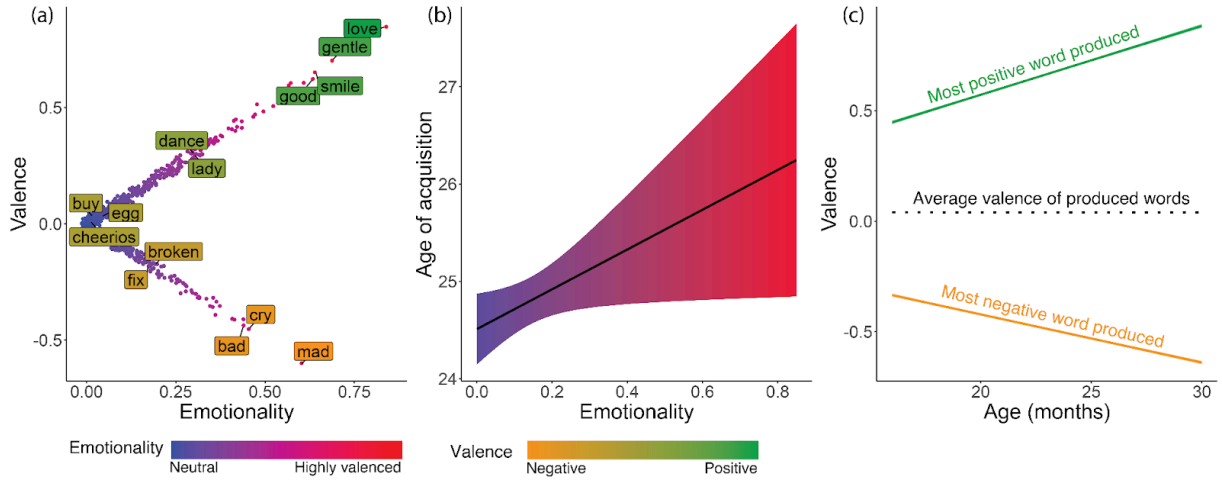

Figure 1. Panel (a) shows the distribution of valence (y-axis) and emotionality (x-axis) across all words in the MCDI. Since emotionality is computed as the absolute value of valence, highly positive and negative words are both high in emotionality. Points were randomly jittered to show the spread of values. A few select words are highlighted to illustrate the kinds of words that are in different parts of the spectrum. The color of the points represents their emotionality (highly positive / negative words in red and neutral words in blue), and the color of the words represents their valence (negative words in yellow and positive words in green). Panel (b) shows the relation between the emotionality of a word (on the x-axis), and the age of acquisition of the word as the age at which 50% of children produce the word based on *wordbankr* (on the y-axis). The shaded area shows a 95% confidence interval of the prediction. Panel (c) shows the link between age and the valence of the most positive (green) and most negative (yellow) word that children at the corresponding age in this sample produced. The dashed line represents the average valence of all words produced by children at a given age.

STUDY 2: The structure of children's emotion vocabulary

In Study 1, we characterized how young children's semantic networks include an increasingly wide emotional range between 16 and 30 months of age. In Study 2, we hypothesized that knowing valenced words makes it easier for children to learn emotion labels and vice versa. For example, knowing the words like "smile" and "nice" might bootstrap learning of labels like "happy"; similarly, knowing an emotion label like "sad" could bootstrap learning of related valenced words like "bad" and "cry". That is, there should be a relation between the network of valenced words that a child produces and the child's production of emotion labels. Here we tested this possibility. We predicted that children would be more likely to produce a specific emotion label if they know other similarly-valenced words. In an exploratory analysis, we examined two forms of similarity between an emotion label and words in the child's vocabulary: one looking at overall emotionality, and another assessing overall positivity vs. negativity (valence).

Method

Dataset

In Study 2, we reanalyzed the vocabularies of 5,520 toddlers between the ages of 16 and 30 months from the MCDI (Fenson, 2007) in Wordbank version 0.3.0 (Frank et al., 2017).

Variables

Emotion label production. In order to assess emotion labels, we noted which (if any) of the eight emotion labels included in the MCDI ("hate", "love", "happy", "hurt", "mad", "sad", "scared", "tired") each child produced. The criterion for counting a word from the MCDI as an emotion label was that it had to refer to an internal mental state or experience that was highly valenced (positive or negative; Cabanac, 2002).

Quantifying semantic connections. We measured connections between each emotion label with all other words produced by the child as the similarity in valence or emotionality between the words. Similarity was computed as the difference in these measures between the emotion label and the word (scaled between 0 and 1), subtracted from 1. As a summary measure, for each emotion label, we computed its *strength centrality*, a measure commonly used to assess how strongly connected a given element of a network is to all other elements of that network (Candeloro et al., 2016). We did so by averaging the weight of the connections between the emotion label and each word produced by the child.

We quantified the strength of the semantic connection between a given emotion label and the remaining words in the child's productive vocabulary in terms of both valence and emotionality (for an example, see Figure 2a). The valence component quantifies similarity between two words based on the relative positivity or negativity of these words. This metric groups positive words with other positive words and negative words with negative words. For example, positive labels (e.g., "happy") have strong connections with other positive words (e.g., "smile") and negative labels (e.g., "sad") have strong connections with other negative words (e.g., "cry"). In contrast, the label would have weak connections with words with oppositely signed valence from the label (e.g., the connection between the negative label "sad" and the positive word "smile").

The emotionality component quantifies similarity between two words based on how extreme the valence of the words is, regardless of whether they are positive or negative. This metric groups both highly positive and negative words together as distinct from neutral words. For example, a positive emotion label (e.g., "happy") would share a strong connection with both

positive and negative words (e.g., “smile” and “cry”), but a weak connection with relatively neutral words (e.g., “spoon”).

For each emotion label and for each child, we computed how strongly the emotion label was connected to other words in the child’s vocabulary for each of these two components, using the method described above (for an example see Figure 2a). Because in some cases the two strength centrality measures (emotionality and valence) were collinear, we included each in a separate model.

Data analysis

In Study 2, we used mixed-effects logistic regressions to predict whether each child produces each of the 8 emotion labels (Bates at al., 2015). For all models, we included random intercepts and effects by participant for the variable of interest (the average connection strengths of the labels, measured as strength centrality as described above). Additionally, we controlled for the child’s vocabulary size and the label frequency. Full model formulae are included in the results section.

Results and Discussion

Semantic connections predict production of specific emotion labels

We tested the prediction that children are more likely to produce a specific emotion label when they already know similarly valenced words. In this analysis, we quantify the connections between a specific label and other words in the child’s vocabulary to predict production of individual labels. In a mixed-effect logistic regression, we predicted whether the child produces the specific emotion label depending on how strongly the label was connected to the rest of the child’s vocabulary (its strength centrality). We controlled for vocabulary size and label frequency, and included random intercepts per child.

As expected, we found that children were more likely to produce emotion labels that were better connected in terms of emotionality (production of label (yes / no) ~ emotionality strength centrality + vocabulary size + label frequency + label concreteness + (1+emotionality strength centrality | participant); $\beta = 0.8$, $z = 21.95$, $p = 9.42\times10^{-107}$). That is, children were more likely to produce an emotion label if they already knew words with a similar degree of emotionality (both highly positive and negative words). Similarly, children were more likely to produce emotion labels with strong connections in terms of valence (production of label (yes / no) ~ valence strength centrality + vocabulary size + label frequency + label concreteness + (1+valence strength centrality | participant); $\beta = 1.07$, $z = 29.84$, $p = 1.34\times10^{-195}$). That is, children were more likely to produce an emotion label if they already produced words that were similarly positive or negative (see Figure 2b). This analysis leaves open the possibility of a mutually reinforcing link between the production of emotion labels and other valenced words.

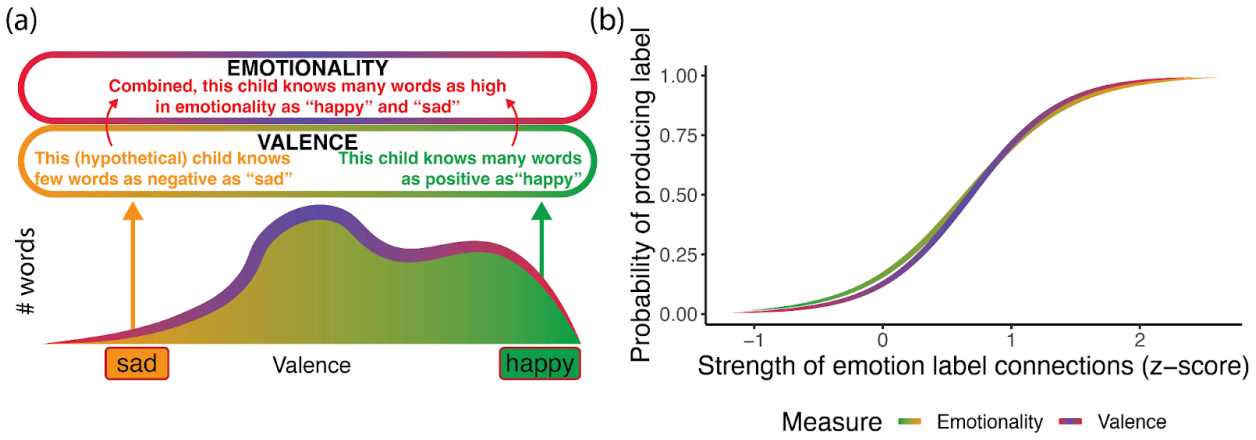

Figure 2. Panel (a) shows an example of how two labels can be similar or different in how well-connected they are to other words in the child's vocabulary. The mock density plot represents how many words the child knows in different parts of the valence continuum. Yellow represents negative words and green - positive ones. Red represents words that are highly positive or negative, and blue - relatively neutral words. For example, this child knows quite a few positive and neutral words, but relatively few negative labels. This means that the label "happy" is strongly connected both in terms of valence (as the child knows many other positive words) as well as emotionality (as there are many highly positive or highly negative words in the child's vocabulary). The label "sad" is similarly strongly connected in terms of emotionality, but less so in terms of valence (as the child doesn't know many negative words). Panel (b) shows the probability of a child producing an emotion label (y-axis) as a function of how strongly the emotion label is connected to other words the child knows (x-axis) based on the predictions of a logistic regression fitted to the data. The green-yellow gradient line represents connection strength in terms of valence, and the red-blue gradient line represents connection strength in terms of emotionality.

STUDY 3: Caregiver cues to networks of emotion words

In Study 2, we observed that children are more likely to produce an emotion label when it is embedded in a rich network of known valenced words. How do children learn these important semantic connections between emotion labels and other valenced words? In Study 3, we hypothesized that caregivers may build these connections for their children through their language input. Specifically, we expected that when caregivers produced an emotion label, they would embed it within sentences that include other similarly valenced words, such that emotion labels and valenced words co-occur in time. We probed this question in a preliminary exploratory analysis of the 8 emotion labels used in Study 2, and a preregistered analysis of 94 mental state labels.

Method

Dataset

Our goal was to measure how parents contextualize emotion labels in real parent-child interactions. We thus examined a dataset that includes transcripts of parent-child conversations. We analyzed caregiver-child interactions from 2,936 CHILDES transcripts in English (including North American English, British English), containing over one million caregiver utterances. The dates of data collection were only available for ~60% of transcribed interactions. Dated transcribed interactions were collected between 1962 and 2009.

The transcripts contained speech from the caregivers of 587 children between the ages of 16 and 30 months, of which 292 were female, 261 male. Gender information was missing for 54 of the children, and the dataset did not include ethnicity information for any of the participants. Analyses were conducted using the childes-db R package (Sanchez et al., 2019).

Only a subset of the transcribed interactions contained the mental state labels of interest. For the preliminary analysis of 8 emotion labels, there were 1,522 transcribed interactions of caregivers addressing 266 children. This resulted in 7,972 utterances containing emotion labels and 156,678 surrounding utterances. For the preregistered analysis of 94 additional mental state labels, there were 1,675 transcripts of caregivers addressing 366 children. This included 8,834 utterances containing this set of emotion labels and 174,094 surrounding utterances.

Emotion labels

In a preliminary analysis, we identified parent (both mothers' and fathers') utterances containing any of the eight emotion labels used in Study 2 ("hate", "love", "happy", "hurt", "mad", "sad", "scared", "tired"). Utterances containing negation (272 utterances) or multiple

types of emotion labels (e.g., both a positive and a negative label; 59 utterances) were excluded. In a second preregistered analysis, we analyzed caregivers' labeling of 94 mental states. These states followed a broader definition of any word labeling an internal mental experience, and were selected from a list of 166 validated mental states from Tamir et al. (2016). We excluded any states that did not occur in caregiver speech or that were only used in a different sense that did not label a mental state (e.g., "warm" and "gloomy" can be used to refer to temperature or weather). Because these labels were not specifically selected to reflect the words present in toddlers' early communicative interactions, they were less frequent than the labels in the first analysis. For this study, we preregistered a primary analysis for the mental states that were rated the highest on emotion (normed rating of at least 0.75 out of 1, $N = 47$ labels) from Tamir et al. (2016), as well as an exploratory analysis for the full set of 94 labels. The results between the two sets of states were similar, but stronger for the larger set of 94 labels. The preregistration can be found here: https://aspredicted.org/Y7J_MT4, and the list of states can be found on the project osf page.

Variables

We quantified the valence of caregivers' words surrounding an emotion label in two ways.

Valenced context of preceding and following utterances. First, we analyzed the utterances surrounding an utterance with an emotion label. For each labeling instance, we computed the valenced sentiment of the 10 preceding and 10 following utterances, using the affectr package (Thornton & Tamir, 2020). If an utterance was fewer than 10 utterances away from more than one emotion label, we counted the distance to the closest label only.

Sentence valenced context. Second, we assessed the narrow context of the immediate sentence in which the emotion label was embedded. We computed the valenced sentiment of the sentence frame, excluding the label itself, using the affectr package (Thornton & Tamir, 2020).

Data analysis

All analyses in Study 3 were carried out as mixed-effect linear regressions (Bates et al., 2015). For all models, we started with random intercepts and effects by speaker. However, for the analysis of the valenced context of surrounding utterances, this model did not converge for all except one of the four regressions. Therefore, for this analysis, we only included random intercepts, but not effects by speaker. In the analysis examining valenced context in the labeling sentence, the model with random intercepts and effects by speaker converged. Model formulae are included in the results section below.

Results and Discussion

Caregivers precede and follow emotion labels with valenced utterances

We first characterized the extent to which caregivers provide appropriately valenced context for emotion labels. To do so, we assessed how the valence of caregiver speech changed over the 10 utterances preceding and following their use of an emotion label. A mixed-effect regression predicted the valence of each utterance from its distance to the closest emotion label. The model included random intercepts by speaker. We constructed two separate models: one for positive emotion labels, one for negative emotion labels.

In the preliminary analysis of 8 emotion labels, we found that caregivers used more positive words as utterances got closer to a positive emotion label (valence of utterance ~

distance of utterance from label + label concreteness + (1 | speaker); $\beta_{distance}$ = -0.1, t(65,008.5) = -21.28, $p = 3.99\times10^{-100}$), and similarly, that caregivers used more negative words as utterances got closer to a negative emotion label (valence of utterance ~ distance of utterance from label + label concreteness + (1 | speaker); $\beta_{distance}$ = 0.07, t(87,835.01) = 17.4, $p = 9.33\times10^{-68}$; see the top panel of Figure 3a).

These results were replicated in our preregistered analysis of 94 mental state labels (see the bottom panel of Figure 3a). That is, more positive caregivers' utterances appeared more closely to positive mental state labels (valence of utterance ~ distance of utterance from label + label concreteness +(1 | speaker); $\beta_{distance}$ = -0.01, t(112,403.1) = -3.55, p = 0.0004), and similarly, more negative caregivers' utterances appeared more closely to negative mental state labels (valence of utterance ~ distance of utterance from label + label concreteness + (1 | speaker); β = 0.05, t(58,092.69) = 9.5, $p = 2.10\times10^{-21}$). The results were similar for the smaller preregistered subset of highly emotional mental states (rated over 0.75 out of 1 on emotion), both for positive labels (β = -0.03, t(24,803.19) = -3.61, p = 0.0003), and negative labels (β = 0.06, t(17,979.91) = 7.35, $p = 2.03\times10^{-13}$).

This increase in valenced context surrounding mental state labels was strongest in the utterances closest to the label (Supplementary Figure 3). For example, ten utterances away from an emotion label (e.g., "happy" or "sad"), parents' utterances were relatively neutral (e.g., "He's coming to get Carl" or "What's he doing?"). But the utterances closer to a positive emotion label became increasingly positive (e.g., "Well the Hokey Cokey that's your favorite isn't it?" [5 utterances away], "Because I wanna get him dancing ya know!" [3 utterances away], "Can I have a big kiss?" [1 utterance away]). Similarly, the utterances closer to a negative emotion label became increasingly negative (e.g., "What did you hurt?" [5 utterances away], "Don't do what

you're doing" [3 utterances away], "You're gonna break it" [1 utterance away]). These converging results suggest that caregivers provide valenced context in the utterances preceding and following the production of emotion labels or of mental state labels more broadly.

Caregivers embed emotion labels within valenced sentences

Next, we probed whether caregivers provide similarly valenced words in the same sentence as emotion labels. Specifically, we tested whether the valence of the emotion label predicted the sentiment of the sentence in which the label was embedded. We evaluated this prediction in a mixed-effect regression with a fixed effect of the valence of the label and random intercepts by transcript. As expected, the valence of the emotion label predicted the sentiment of the sentence in which the label was embedded both in the 8-label preliminary analysis (valence of sentence ~ valence of label + label concreteness + (1 + valence of label | speaker); $\beta = 0.23$, $t(193.08 = 5.97$, $p = 1.1\times10^{-8}$; see Figure 3b top panel) and the 94-state preregistered analysis (valence of sentence ~ valence of label + label concreteness + (1 + valence of label | speaker); $\beta = 0.21$, $t(163.17) = 9.34$, $p = 7.1\times10^{-17}$; see Figure 3 bottom panel). Caregivers introduced negative emotion labels like "mad", "scared", and "sad" within sentences that contained other negative words like "mess", "monster", and "crying" (e.g., "Hey don't make a mess because you're mad", "I think they're scared of the monster", "What are you sad too, are you crying?"). Similarly, caregivers labeled positive emotions, like "happy", within sentences containing other positive words, like "kiss" and "smiling" (e.g., "Somebody must have given him a kiss there because he's happy now" and "These look like happy pins - that guy's laughing, that guy's smiling").

Together, these analyses highlight that caregivers surround emotion labels with similarly valenced words, both within the utterance containing the label as well as in the surrounding

sentences. The temporal proximity of similarly valenced words may provide opportunities for children to link emotion labels and related words. By providing valenced contexts, caregivers may support the integration of emotion labels into a network of related words and concepts, which in turn may facilitate children's learning. In Studies 4 and 5 we explore correlational links between caregiver input and child production.

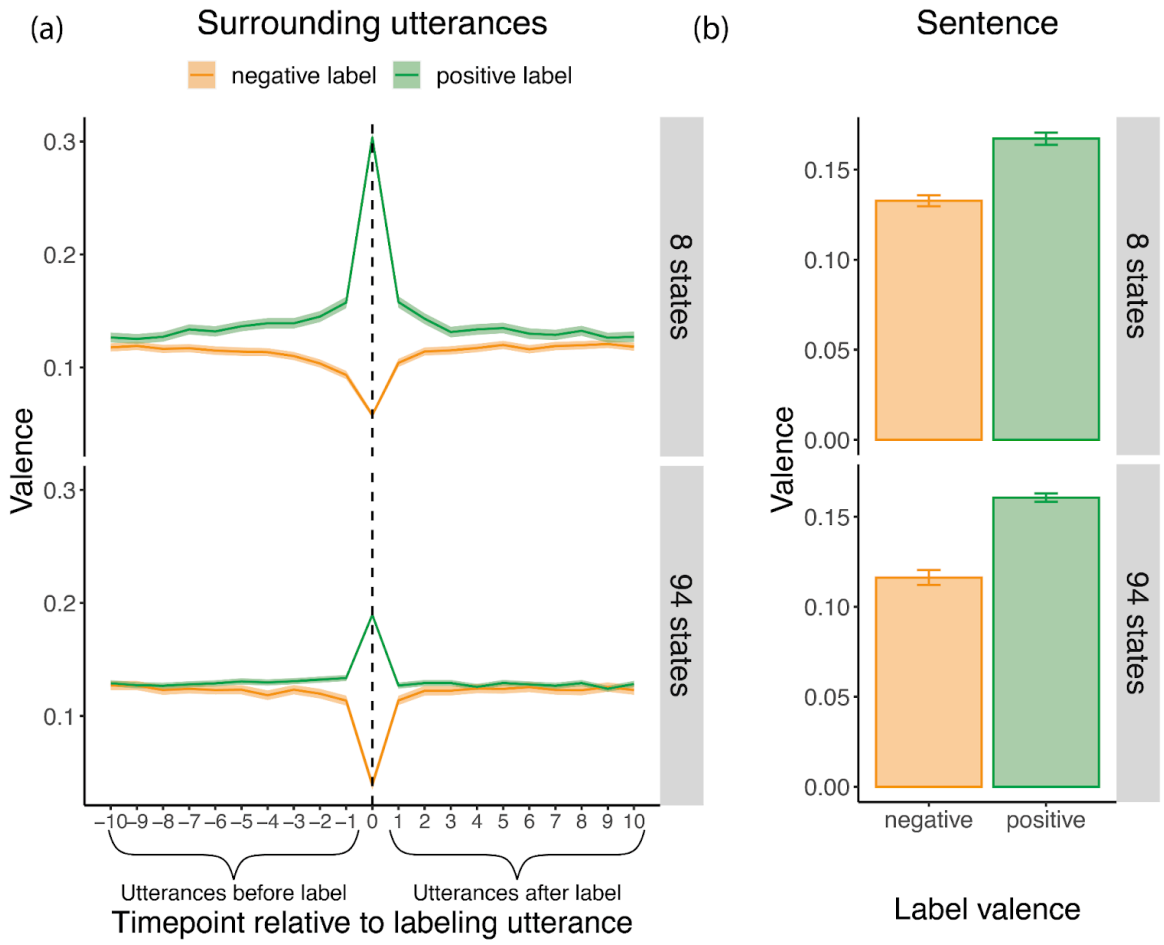

Figure 3: Panel (a) shows the sentiment of the utterances preceding and following an emotion label for the preliminary analysis with 8 emotion labels (top) and the preregistered analysis with 94 mental state labels (bottom). The lines represent the average sentiment at each time point relative to the labeling utterance for positive (green) and negative (yellow) labels respectively, with the shaded area representing a 95% confidence interval. Panel (b) shows the sentiment of the sentence (excluding the emotion label) in labeled utterances for the 8-emotion-label analysis (top) and the 94-mental-state-label

analysis (bottom). Panel (b) shows the average sentence valence for positive and negative labels (in green and yellow respectively), with 95% confidence interval error bars. Note that the average valence of all utterances is positive (above 0). This reflects the generally positive sentiment of child-directed speech. However, there is still an overall difference in valence such that the utterances preceding negative emotion labels become less positive.

STUDY 4: Learning contextualized emotion labels

In Study 3, we observed that caregivers position emotion labels in contexts that are matched in valence. This temporal proximity between emotion labels and other similarly valenced words may provide opportunities for children to form semantic connections between them. If true, this could explain why children learn to produce emotion labels and similarly valenced words in tandem. However, not all emotion labels are contextualized to the same degree. Some emotion labels may more consistently appear in well-matched contexts, whereas others may not consistently appear in matched contexts. In Study 4, we examined how variability in the contexts surrounding different labels relates to the age when children produce them. An exploratory analysis examined whether emotion labels that consistently occur in valenced contexts in caregiver speech show an earlier age of acquisition.

Method

Dataset

Study 4 analyzed the same set of caregiver utterances containing emotion labels from CHILDES as in Study 3, along with the utterances preceding and following the emotion label. Age of acquisition was assessed using the same data as in Studies 1 and 2.

Measures

Valenced context. We quantified the valence of the utterances preceding and following each emotion label. Using the same method as Study 3, the valenced context of the surrounding utterances was quantified as the regression coefficient in a model estimating the utterance valence based on its proximity to an emotion label. We constructed a separate model to estimate

the valenced context for each of the eight emotion labels used in Studies 2 and 3. We added a random intercept by speaker in the model estimating valenced context to ensure that the estimated context would not be driven by few outlier subjects. This valenced context estimate aggregated over all instances of the emotion label in the available data in CHILDES for caregivers addressing 16-30-month-old children.

Age of acquisition. We used the method outlined in Study 1 to estimate the age of acquisition for each emotion label based on child vocabularies in Wordbank (Braginsky et al., 2018; Frank et al., 2017). The emotion label "hate" was excluded from this analysis, because fewer than 50% of children produced it within the 16–30-month age range.

Data Analysis

All analyses in Study 4 were linear regressions, predicting AoA. Model formulae are included in the results section.

Results and Discussion

We tested whether emotion labels that consistently occur in valenced contexts have an earlier age of acquisition. In a linear regression, we found that emotion labels that were consistently surrounded by valenced context in caregiver input in CHILDES had an earlier age of acquisition in Wordbank (AoA ~ valenced context; $\beta_{valenced\ context}$ = -0.80, $t(5)$ = -3.01, p = 0.03; see Figure 4). This effect remained marginally significant when controlling for the label frequency and concreteness (AoA ~ valenced context + frequency + label concreteness; $\beta_{valenced\ context}$ = -0.98, $t(3)$ = -3.25, p = 0.048). This result is consistent with a possible bidirectional link, such that related words surrounding an emotion label may support children in constructing the label's complex meaning, and that early production of an emotion label may provide opportunities for introducing related valenced words in close proximity. However, because of the

small number of emotion labels tested, it is difficult to disentangle this possibility from other confounding factors, such as the valence of the label itself (see Supplementary Analysis 9).

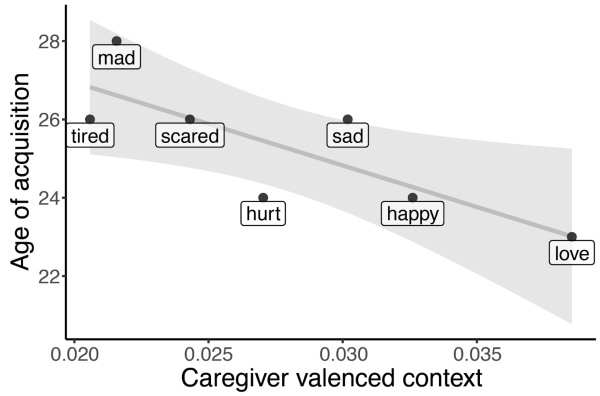

Figure 4: The x-axis shows the average valenced contexts of all instances for each emotion label in caregiver speech for children between 16 and 30 months. The y-axis shows the age of acquisition of each emotion label (measured as the age at which half of children produce the label in a normative sample from Wordbank).

STUDY 5: Longitudinal effect of caregivers' valenced context on children's emotion label production

Study 5 probed links between caregivers' input and their child's development of emotion labels. In this longitudinal analysis, we tested whether caregivers who surround emotion labels with more valenced contexts have children who later produce emotion labels with higher accuracy in appropriately valenced contexts. We examined this prediction in an exploratory analysis using the same 8 emotion labels that were used in previous studies, as well as a preregistered analysis of 87 mental state labels. By measuring speech within the same dyad, we can assess how caregivers' input shapes children's production of specific emotion labels over time.

Method

Dataset

For this longitudinal analysis, we used a subset of corpora from CHILDES that included only parent-child dyads with multiple recorded interactions spanning at least two months of the child's development. For each dyad, we defined two age ranges: one for evaluating initial

caregiver input and another for evaluating later child production. Because recordings for each dyad spanned different ages and amounts of time (see Figure 5a), we split the total number of recorded interactions in two, based on the median age range across all transcripts for that dyad (Time 1 and Time 2).

We quantified caregiver input in the first part of the dyad's data (T1) as the valenced context surrounding emotion labels. We quantified the child's production in the second part of the dyad's data (T2) as an estimate of the child's appropriate production of emotion labels, defined specifically as the valenced context in which the child produced emotion labels. For example, if the dataset included 10 transcribed interactions for a given dyad at different ages, the first 5 interactions would be included in the parent input data, and the second 5 interactions would be included in the child production data. Interactions recorded at the median age for the dyad were included in the parent input estimate. In some cases, this process resulted in a slightly uneven split between the two parts of the dyad's data, as some dyads had multiple recorded interactions at the median age, and some recorded interactions did not include emotion labels. We excluded dyads if the caregiver did not produce emotion labels in the first part, or if the child did not produce emotion labels in the second part of the dyad's data.

For the preliminary analysis of 8 emotion labels, this resulted in a final sample of 35 children (19 female, 16 male, unknown ethnicity), with 2,199 parent and 1,212 child instances of these labels during T1 and T2, respectively. Because some of the 87 labels included in the preregistered analysis were not produced by young children (and did not appear on the MCDI), only 26 dyads had both parent and child productions of even one of these words. Thus, our analysis included 2,483 parent and 583 child instances of these labels during T1 and T2, respectively.

Measures

Valenced context. As in Study 3, we characterized the valenced context in which caregivers and children used emotion labels in two ways: first, as the broad context of the 10 utterances preceding and following an emotion label, and second, as the narrow context of the sentence within which the label was embedded. For each dyad, we computed these two indices both in caregiver input and in child production.

To quantify the broad context of the preceding and following utterances, as in Study 3, we measured caregiver valenced context in the utterances preceding and following an emotion label. This measure was quantified as the regression coefficient in a model estimating the utterance valence based on its proximity to an emotion label. In Study 3, valenced context was similar for positive and negative labels, therefore we computed a single index for each speaker by averaging the valence coefficients across all positive and negative emotion labels.

As in Study 3, we quantified the narrow context of the sentence within which an emotion label was embedded. The resulting coefficient served as a valenced context index of how well the valence of the sentence matched the valence of the label within it.

Data analysis

In Study 5, we used linear regression to predict the valenced context surrounding children's mental state labels during T2 based on the valenced context of caregivers' productions during T1. In Supplementary Analysis 8, we additionally report concurrent links between caregiver input and child production within T1 and within T2. Model formulae are included in the results section below. The preregistration can be found here: https://aspredicted.org/G38_LRH, and the list of mental state labels can be found on the project osf page.

We controlled for the child's median age, as well as two measures of the child's language development during T2: the mean length of the child's utterances (MLU; Miller & Chapman, 1981), and the child's lexical diversity, measured as the average type-token ratio (TTR; Templin, 1957). We did so to isolate broader effects of language development, because children who produce many different words and longer utterances during T1 may be more likely to produce emotion labels and mental state labels in appropriate contexts during T2.

In addition, we controlled for the mean emotionality (i.e., absolute valence of emotion words, whether positive or negative) of caregiver utterances during T1 in order to distinguish between the effects of caregivers' overall use of valenced language from caregivers' use of appropriately valenced words in context (i.e., speech surrounding emotion labels). Similarly, we controlled for the number of instances of mental state labels in caregiver speech during T1. Additionally, we controlled for the average concreteness of the emotion and mental state labels used by the caregiver and the child in T1 and T2 respectively. Thus, all regression results reported below include the following control variables: median child age, the two measures of child language development (MLU and TTR at T2), caregivers' overall use of valenced language during T1, and the number of caregiver mental state label instances during T1, and concreteness. For simplicity, when reporting model formulae, these variables are referred to collectively as control variables.

Results and Discussion

Valence in caregiver input predicts child emotion label production

First, we examined if the valenced context caregivers provided in the utterances surrounding emotion labels and mental state labels would predict the contexts in which their child later produced emotion labels and mental state labels. That is, do patterns of child

production follow patterns of caregiver input? After controlling for the dimensions of speech outlined above, caregiver input during T1 predicted the child's production of emotion and mental state labels during T2, both in the preliminary analysis of 8 emotion labels (child surrounding context (T2) ~ caregiver surrounding context (T1) + control variables ~ $\beta_{caregiver\ context\ (T1)} = 0.35$, $t(31) = 2.18$, $p = 0.037$; see Figure 5b top panel) and in the preregistered analysis of 87 mental state labels (child surrounding context (T2) ~ caregiver surrounding context (T1) + control variables ~ $\beta_{caregiver\ context\ (T1)} = 0.4$, $t(24) = 2.36$, $p = 0.027$; see Figure 5b bottom panel).

This directionality of the effect was specific to parent input later predicting child output (Supplementary Analysis 8). Child production during T1 did not predict later caregiver valenced context during T2. Similarly, we did not observe concurrent links within T1 or within T2 between caregiver and child valenced context (Supplementary Analysis 8). Together, these results are consistent with the idea that the broad, multi-utterance valenced context in caregivers' input may support children's ability to integrate emotion labels into a similarly complex and dynamic context. Further, we provide some evidence that caregiver valenced context may support child production over time, possibly by allowing children to accumulate aggregate co-occurrence statistics of mental state labels and related valenced words.

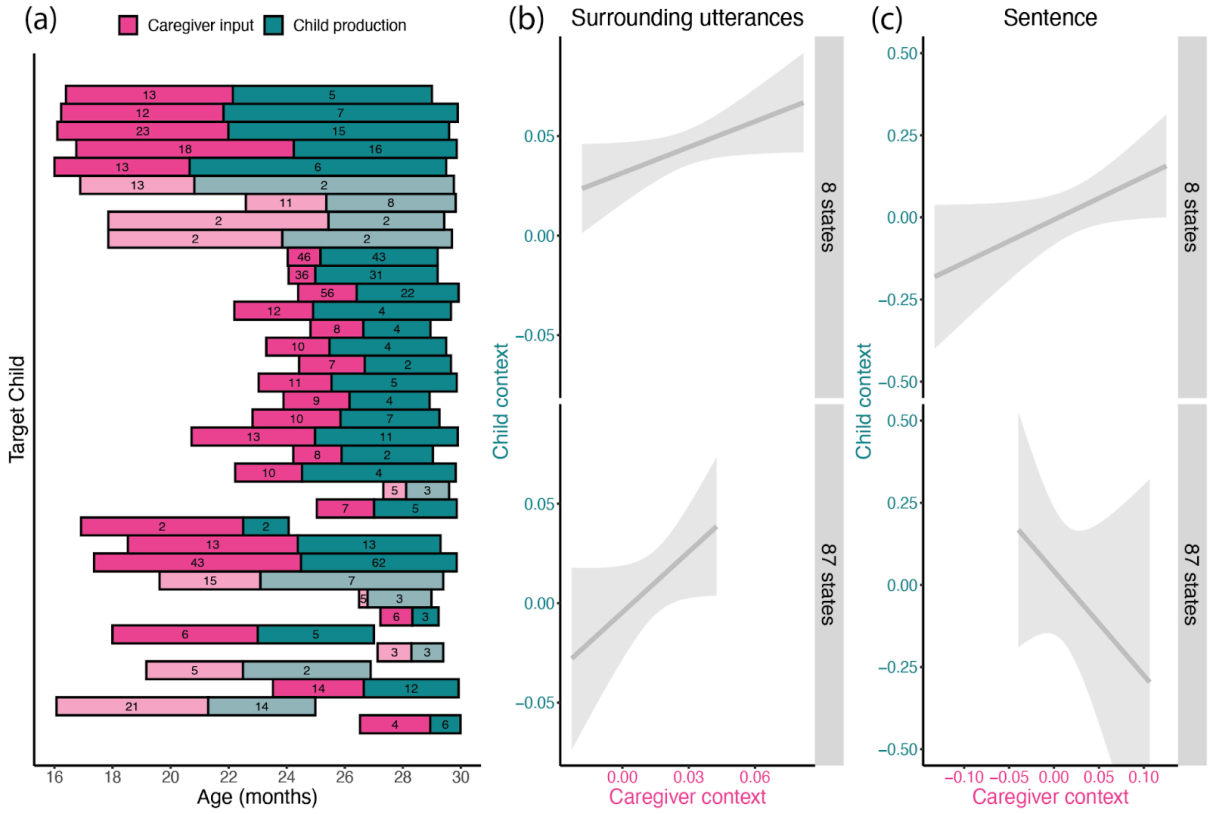

Figure 5: Panel (a) is a descriptive plot of the age range for each dyad (x axis). Each row represents one dyad, with the darkened part of the age range marking the earlier section used to assess caregiver input. The lighter section shows the part of the age range used to assess child production. The numbers in each rectangle show the number of transcripts included in that portion of the dyad's age range. Panels (b) and (c) show how caregiver valenced context in the earlier portion of the age range (x-axis) relates to the child's valenced context in the later part of the age range (y-axis). Panel (b) shows the valenced context of the utterances surrounding an emotion or mental state label, whereas panel (c) shows the valenced context of the sentence in which the emotion or mental state label was embedded. The top panels in (b) and (c) show the results from the preliminary analysis of 8 emotion labels, and the bottom panels show the preregistered analysis of 87 mental state labels.

Second, we tested whether the valence of the sentences in which caregivers embed emotion labels predicts children's appropriate production of emotion labels. In the preliminary analysis of 8 emotion labels, after controlling for the dimensions of speech outlined above, the valenced context of sentences surrounding an emotion label in caregiver input during T1 was marginally predictive of the valenced context of sentences surrounding the child's production of emotion labels during T2 (child sentence context (T2) ~ caregiver sentence context (T1) +

control variables ~ $\beta_{caregiver\ context\ (T1)}$ = = 0.37, $t(26) = 2$, $p \sim 0.056$; see Figure 5c top panel). However, we did not find evidence for this in the preregistered analysis of 87 mental state labels (child sentence context (T2) ~ caregiver sentence context (T1) + control variables ~ $\beta_{caregiver\ context\ (T1)}$ = -0.27, $t(17) = -1.01$, $p \sim 0.33$; see Figure 5c bottom panel). These findings suggest only weak evidence for effects of caregiver valenced context on child valenced context within the labeling sentence, potentially resulting from the fact that child utterances at this age are still quite short.

General Discussion

Children's ability to communicate about their emotions is a key determinant of their socio-emotional development (Hoemann et al., 2019). In this investigation, we describe the emergence of a network of emotion labels and mental state labels in toddlerhood, as well as the contextual cues in caregiver input that may give rise to the development of children's emotion vocabulary. Overall, we showed that children's production of emotion labels is embedded in a developing network of related positive and negative words. We propose that caregivers may support children's ability to draw these connections by surrounding emotion labels with other words matched in valence. Indeed, we found correlational evidence that individual differences across caregivers predicted children's later production of emotion labels in appropriate contexts.

In Studies 1 and 2, we situated children's production of emotion labels within the developmental trajectory of toddler's expanding network of valenced words. Study 1 revealed that toddlers start off by learning predominantly concrete neutral words, and over time, expand the emotional range of their semantic network by incorporating highly positive and highly negative abstract words. This is the case even though valenced words are just as frequent as concrete neutral words. What might explain this learning trajectory, if not frequency? The words

included in the MCDI, which we used for the analyses in Studies 1 and 2, were selected to represent children's first words. Since infants learn abstract words later (Bergelson & Swingley, 2013), this set is skewed toward words with concrete referents. Because highly emotional words, like "good" or "bad", are, on average, less concrete than relatively neutral words, like "spoon" or "shake" (Vigliocco et al., 2014), the valenced words in a toddler's vocabulary may be some of the most abstract words they produce. Relatedly, valenced words may be some of the *first* abstract words that young children learn. Supplementary Figure 2 qualitatively shows that the earliest acquired abstract words are higher in emotionality, whereas the later acquired abstract words were relatively more neutral. This is consistent with the findings from Ponari et al. (2018, 2020), which suggest that older children learn highly positive or negative abstract words earlier than neutral abstract words. Future research across a wider age range from infancy to childhood to adolescence will be needed to understand how abstractness and emotionality may shape children's vocabularies in different ways and at different ages, and how these changes interact with other developing cognitive systems and abilities.

Toddlers' early vocabularies only sparsely include highly positive and negative words and concepts, which shapes the early semantic connections that they can access. Simulation-based and empirical work both suggest that words that are connected to many other words in the child's vocabulary are learned better (Borovsky et al., 2016; Hills et al., 2009). Similarly, in Study 2, we found that children were more likely to produce a given emotion label when they knew other words with similar valence or emotionality. That is, our results suggest that children do not learn emotion labels in isolation, but rather emotion labels are integrated into a network of valenced concepts. There are several possible explanations for this relation. For example, before they learn emotion labels, children may need to learn related valenced words

that can then scaffold their learning of emotion labels. As children learn more valenced words, it may be easier for novel emotion labels to become integrated into a pre-existing rich semantic network that contains a full continuum of positive and negative concepts. It is also possible that learned emotion labels serve as 'hubs' that link new, similarly valenced supporting words. The most likely explanation is that there is a bi-directional link, such that knowing more valenced words supports learning new emotion labels and vice-versa. That is, emotion labels, mental state labels, and valenced words may be part of an inseparable interconnected network that is learned as part of a shared semantic space. However, additional research is needed to understand and disentangle the mechanisms that support children's learning of highly positive and negative words, whether those label specific emotions, mental states or neither. The current investigation suggests that children's learning of emotion labels may be best explored in the context of children's full vocabulary network (Wojcik, 2018), rather than in isolation.

What kind of input supports children in forming these semantic connections? In Studies 3, 4 and 5, we found that caregiver input includes consistent links between emotion labels and similarly-valenced words, which may facilitate children's learning over time, although this would need to be investigated in a study that can appropriately pinpoint causal links. Nonetheless, our data suggest that caregivers' contextual scaffolding may support children's learning at two timescales. In the moment, it may activate the appropriate valenced semantic space before and after an emotion label is introduced. Such extended activation can facilitate the consolidation of emotion labels by creating an 'optimal moment' for learning, similar to the contextual effects on memory observed for other words (Borovsky et al., 2010; Coutanche & Thompson-Schill, 2014). Additionally, over the course of many instances of an emotion label in caregiver speech, the surrounding valenced context may increase the co-occurrence probabilities

between the emotion label and related valenced words, which may help children to infer similarity between the emotion label and other similarly valenced words. There is evidence that toddlers perceive words with similar occurrence statistics as more similar to each other in meaning (Lany & Saffran, 2010; Wojcik & Saffran, 2015), and that adults perceive novel emotion labels as more similar when they follow each other closely in time (Thornton et al., 2020). Evidence from adult neuroscience suggests that when events consistently follow each other closely in time, they form overlapping neural representations (Raymond et al., 1992; Thornton et al., 2019). This allows the brain to link representations together that are more similar, as well as to co-activate related concepts in the future. Over time, these statistical associations may allow children to construct dimensions, such as valence, that are important for understanding emotion labels with specificity. Importantly, semantic associations are one of many kinds of statistical regularities that accompany emotional experiences.

In Study 4, we found that children learn emotion labels earlier if those labels are consistently surrounded by informative valenced contexts. Study 4 first demonstrated a relation between an aggregate summary of the valenced context of each emotion label and children's average production of the label. Study 5 then revealed links between each child's input across time and their later production. This longitudinal analysis showed that children whose caregivers surrounded emotion labels with matching valenced contexts in their input went on to also produce emotion labels that matched the sentiment of the surrounding context. Thus, we could trace links between emotion-related context in both caregiver and child speech. These links were robust even when controlling for the child's age, markers of the child's overall language development, specifically, the length of the child's utterances and the complexity of children's overall language use, caregivers' use of valenced language and frequency of labeling emotions

and mental states. That said, it is still uncertain whether there is a direct causal link between caregiver input and child production, particularly in the extent to which sentence-level valenced context in caregivers' speech predicts that in young children's speech. We posit that caregivers who use more valenced language surrounding emotion labels provide opportunities for the child to create stronger semantic connections between the label and related words, and therefore enable more successful use of the label in appropriate contexts later on. At the same time, caregivers provide these valenced contexts in a highly interactive setting. It is possible that children who have a better understanding of emotion labels may elicit more contextual elaboration from their caregivers. In fact, there is likely to be bidirectional reinforcement between caregiver and child valenced speech, such that caregivers and children co-create learning moments that activate and expand a broader network of valenced concepts surrounding emotion labels.

Limitations and future directions

The current study relies strongly on descriptive methods based on large pre-existing databases. This approach comes with key strengths: it offers many datapoints per child and in aggregate, and provides insights into naturally occurring behaviors in caregiver-child interactions. However, it comes with key limitations too.

One major limitation in this investigation is that we were limited by the words included in the MCDI, which includes very few emotion labels and was not designed to include control words that span the full spectrum of positive and negative as well as neutral concepts – particularly words that are matched for frequency and concreteness. Additionally, this questionnaire was specifically designed for infants and toddlers. Future research across a wider age range – from infancy to childhood to adolescence – will be needed to understand how

abstractness and emotionality may shape children's vocabulary growth in similar or different ways both within and across ages, and how any potential changes interact with other developing cognitive systems and abilities. Moreover, parent-report measures of children's productive vocabulary pale in comparison to robust, child-driven measures of production and comprehension.

Importantly, our descriptive approach limits our ability to make causal inferences about potential links between caregiver input and child learning. Our measures of caregiver input (quantified using data from the CHILDES database) are disconnected from standardized measures of production (quantified using Wordbank), which makes it impossible to link an individual child's input and their parent-reported ability to produce a given word. Further, all standardized measures of children's production of emotion labels (in Studies 1, 2 and 4) relied on cross-sectional data, due to the deidentified nature of data in WordBank. A combination of densely sampled caregiver input across time and robust measures of production and comprehension would enable firmer conclusions about causal links between valenced context and emotion word learning, especially alongside carefully controlled experimental work. Additionally, going forward, it will be important to examine relations between caregiver input and child production on a shorter timescale, as we do not know how children learn emotion labels or abstract words during real-time interaction with caregivers. It is likely that children play an important role in ramping up emotion during everyday conversations, and therefore play an important (and under-studied) role in shaping their own emotion-related input. Additional research is needed to elucidate how the dynamics of caregiver-child interactions that surround emotion labels give rise to children's context-appropriate production of new emotion words.

In this investigation we characterize the context of emotion labels in terms of the valenced words that surround them. However, in reality, this context is much broader as it is intertwined with the child's personal emotional experiences, as well as their perception of emotion displays from caregivers. For example, Wu et al. (2022) showed that children relied on observed facial configurations and body postures in labeling emotions. This makes emotion labels very different from other types of abstract words in that they accompany internal sensations and external percepts. It is important to expand what exactly constitutes valenced context by including measures of affect-related internal physical sensations, social touch, vocal prosody, and facial and body movements. Further, the dynamics of emotion in speech and caregivers' use of valenced words is likely to vary substantially across cultures, communities and languages. Even though the Wordbank and CHILDES databases allow us to access a much larger English-speaking participant pool than would be possible with individual lab studies, these datasets oversample White, high socio-economic status participants in a limited number of Western countries. Exploring the role of a variety of emotion-related cues across different communities would position the field to uncover a richer complexity of emotion contexts and their impact on learning.

Conclusion

This investigation introduces new ways to harness the complex statistics of caregivers' language input and children's word learning. Here we used an approach that specifically analyzes abstract, valenced words, but the applicability of this approach extends beyond just this domain. Much of the research on how children learn novel labels has focused on how infants learn statistical co-occurrences between labels and the physical objects they refer to (Frank et al., 2009; Trueswell et al., 2013; Yu & Smith, 2007). But, how do young children learn novel labels

whose referent or meaning is less concrete? Understanding context, broadly defined, offers a crucial path forward (Wojcik, 2018). Our findings have implications for understanding children's word learning beyond emotion labels and related valenced words, and future work can use our approaches to examine the roles of different contextual caregiver cues in shaping children's learning of different types of words. That is, this investigation provides techniques for characterizing the 'quality' of infant-directed speech in a way that is grounded, inclusive, and nuanced. We showed that patterns of words and contexts converged to support the emergence of emotion labels and similarly-valenced words in children's productions, and our approach will enable other researchers to quantify how caregivers dynamically use words that support children's learning of words with complex, abstract meanings.

Chapter V: Conclusions

The studies in this dissertation demonstrate that emotion and language are dynamically coupled across multiple timescales. In Chapter II, developmental changes in emotion transitions were shown to relate to general and specific emotion vocabulary during the first five years of life. Chapter III uncovered dynamic links between affect, communication, and word learning in children's home environments. Finally, in Chapter IV, the local timing of positive and negative words surrounding emotion labels related to how children used emotion labels in context. These findings underscore three dynamic ways in which emotion and language interact in development.

First, changes in language support emotion development, and vice versa. In Chapter II, children's vocabulary size and knowledge of emotion labels correlated with more mature and organized emotion transitions. One possible interpretation of these findings is that children's language abilities allow them to break into the statistics of emotion in a way that helps them match the adult pattern of emotion transitions, with greater likelihood between emotions that are more (vs. less) similar in valence. For instance, attaching verbal labels to abstract emotional experiences may help children track which emotions precede and follow each other. As shown in prior work, language can also scaffold related abilities like statistical learning, the ability to track patterns in how events unfold over time (Misyak & Christiansen, 2012), or help children regulate their emotional experiences (Cole et al., 2010). Similarly, predictable adult-like emotion dynamics may create opportunities for high-quality language input that support vocabulary growth. Although there is no research testing this possibility, if a caregiver can more effectively predict their child's emotional state, they may time their language input more effectively to

support their child's learning (e.g., by clustering their language input around moments when the child is more receptive to it, as we saw in Chapter IV). Further, if caregivers use emotional language to talk about a child's emotional state, smoother transitions between similarly valenced emotional states can provide discourse continuity with longer clusters of positive or negative talk (as seen in Chapter III). It is also possible that links between language and emotion can occur through third variables, including aspects of conceptual development such as the ability to extract abstract categories, which may support (and be supported by) both language and emotion development (Arunachalam & Waxman, 2010; Hoemann et al., 2019; Lindquist et al., 2015; Ogren & Johnson, 2021; Shablack et al., 2020). In order to disentangle these different influences on development, future research can use longitudinal designs that densely sample the development of children's emotion dynamics and language. Sampling at the timescale of days or weeks can allow scientists to identify the moments when children make incremental steps in their language or emotion abilities (e.g., the moment when they learn emotion labels like "happy" or "sad"), and examine the developmental changes that immediately preceded or followed it. For example, do changes in a child's transitions between happiness and other emotions precede or follow their production of the word "happy"?

Second, language and emotion change how children interact with people in the moment. In Chapter III, we found that when children experienced more positive valence or higher arousal throughout the day, caregivers and children vocalized more and took more conversational turns. Children were also more likely to know the words used in these contexts. One possible interpretation of these findings is that positive or high arousal affective states make children more likely to engage and communicate with others, or that negative or lower arousal states dampen communication, in a way that shapes their uptake of words used by caregivers.

Conversely, it is possible that engaging in rich and high-quality communicative interactions with caregivers or discussing familiar topics results in more positive valence and higher arousal. A combination of much denser sampling of emotion and speech – along with experimental manipulations of each – could allow researchers to understand causal links within short timescales.

Finally, children may aggregate local patterns in language and emotion to infer word meanings. In Chapter IV, we saw that when caregivers used many related positive or negative words in the utterances surrounding an emotion label, children were better at using emotion labels in the appropriate context. This is consistent with the possibility that children use statistical regularities in language to infer emotion categories (Hoemann et al., 2019; Ogren & Sandhofer, 2022; Ruba et al., 2020; Woodard et al., 2021). Similarly, in Chapter III, children were more likely to know words used in more consistent affective contexts. It is possible that, from children's vantage point, emotional experiences are an integral part of the context of early word learning. Words that appear in distinctive and consistent temporal (e.g., time of day) and spatial (e.g., room of the house) contexts tend to be learned earlier (Roy et al., 2015). Although these different aspects of the context in which children learn about language and emotion are traditionally studied in different fields, infants experience them together and may process them as parts of a contextual whole.

The work described in this dissertation sets the stage for a number of open questions about the interaction of language and emotion in early development. What specific language and emotion cues do children access in their home environments? Caregivers' vocal tone, words, and facial movements communicate affective information, and their pitch contours, speech rate, use of specific words, and discourse topics shape children's attention and learning. With the rise in

automated tools for coding human behavior from large at-home video corpora, future research could uncover more fine-grained micro-interactions between emotion and speech within each communicative interaction (Kosie & Lew-Williams, 2023; Kosie et al., in prep). This descriptive approach can yield targets for experimental studies that investigate how children use multimodal affective information to uncover categories of emotional experiences or to learn words.

In addition to understanding how the different facets of emotion and language input unfold over time, future work using neuro-physiological measures can advance our understanding of children's internal experiences. These measures can uncover physiological mechanisms that impact learning and individual differences in how children are affected by their environment. Physiology can provide another link between cognitive and affective processes. For example, in adults, cortisol has been shown to impact memory (Newcomer et al., 1999), and in adults and children, moderate physiological arousal is related to better semantic memory (Guo et al., 2018; Miller et al., 2018; Outters et al., 2023).

Examining cross-cultural and individual differences across children's learning environments can also refine our theories about the interaction of emotion and language in development. The study of individual differences in early learning environments (such as the cultural and social context in which children learn) focuses almost exclusively on cumulative caregiver input or treats emotion and language as separate. However, traits like socioeconomic status and culture, which shape children's learning environments, are, in fact, highly diverse phenomena, and are tightly intertwined with both emotions and language. How do display rules across cultures (Safdar et al., 2009) change what information children use to learn which emotion precede and follow each other? Across different communities, children interact with very different sets of caregivers and peers (Okocha, Burke, et al., under review; Kana'Iaupuni et al.,

2005). How does interacting with a larger network, such as in extended kin households (Okocha & Burke et al., under review) or with a greater number of peers (e.g., in preschool or daycare), shape how children learn about the dynamics of emotion and language? Investigating this type of variability in children's learning environments can reveal how children tune into the affective and linguistic features that matter in their local environment.

Further, how do atypical language or emotion input or abilities shape child well-being? Various factors including socio-economic status (Ellwood-Lowe et al., 2022), caregiver psychopathology (Trull et al., 2015; Wichers et al., 2015), and child maltreatment (Pollak, 2008; Pollak et al., 2000) are associated with atypical dynamics of emotion in the home. If affective dynamics relate to children's language development, do atypical affective dynamics in the home change the trajectory of infants' language development? Alternatively, do they lead to alternative paths to language development, in which affect plays a different role? Given that approximately one-third of mothers meet the diagnostic criteria for depression during the first three years of a child's life (Wang et al., 2011), it is increasingly important to understand how variability in affect across households shapes children's language development. Depression is associated with atypical emotion dynamics (Lydon-Staley et al., 2019; Nelson et al., 2020; Pe et al., 2015; Shin et al., 2022) and caregiver communicative behaviors (Field, 2010; Humphreys et al., 2018). In particular, depressed mothers exhibit lower affective synchrony with their infant (Feldman, 2003; Reck et al., 2011), and use fewer affective cues in communicating (Herrera et al., 2004). What effects do these differences have on how infants in homes with a depressed caregiver use affective cues to support their language development? In addition to exploring the role of emotion and language input on child development and well-being, we can examine how atypical development in each of those domains shapes children's development in the other. Does atypical

language development change how children learn about emotion? Relatedly, does atypical emotion development change how children break into the structure of language? Although there is evidence that atypical language development is associated with emotion difficulties in children and adolescents (e.g., Forrest et al., 2020; Fujiki et al., 2002; van den Bedem et al., 2018), less work has been dedicated to the role of atypical emotion development on language. Further, the dynamic mechanisms that link these processes are unknown.

Delving into the intricate interplay between emotion and language during early childhood may unlock essential insights into the foundations of communication. How do the multifaceted moments of children's communicative experiences accumulate over many years of development to create expert communicators who easily navigate complex interpersonal situations? Pointing a lens on how real-world communication unfolds over time provides a vantage point for uncovering novel factors contributing to overall child well-being.

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