AMERICAN PSYCHOLOGICAL ASSOCIATION

Journal of Experimental Psychology:
Learning, Memory, and Cognition

ISSN: 0278-7393

2026, Vol. 52, No. 2, 251–261
https://doi.org/10.1037/xlm0001495

Infants Track Patterns of Emotion Transitions in the Home

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Predicting others' feelings enables efficient social interactions. How do infants learn which emotions precede and follow each other? We propose that infants develop this ability by tuning into the dynamics of their socioemotional environment, in which they observe reliable patterns in how adults shift from one emotion (e.g., anger) to another (e.g., sadness). If infants learn about emotion transitions by observing the adults around them, we expect that the way infants process emotion transitions will reflect both average patterns seen in adults as well as specific patterns of their primary caregiver. We measured 4- to 10-month-old American infants' ($N = 70$) pupillary responses to emotion transitions and surveyed primary caregivers on the frequency of their own emotion transitions. As expected, infants were attuned to average adult patterns of emotion transitions, showing greater pupillary synchrony for more common transitions. Infants also showed sensitivity to their own primary caregiver's specific pattern of emotion transitions, showing similar pupillary responses to other infants in the sample whose caregivers show similar patterns. These findings suggest that infants learn about emotion dynamics by attending to both average and specific statistical patterns in the people around them.

Keywords: emotion development, emotion transitions, statistical learning

The social world is marked by dynamic changes in others' emotions. The ability to predict how others feel from one moment to the next supports efficient social interactions (Koster-Hale & Saxe, 2013; Tamir & Thornton, 2018). Research on emotion dynamics from infancy to adulthood has revealed that emotion transitions follow a fairly consistent pattern across adults (Cunningham et al., 2013; Thornton & Tamir, 2017). Adults leverage these regularities to predict how someone is likely to feel next based on their current state. For example, someone can predict that a person currently feeling sad is more likely to next feel angry than happy (Thornton & Tamir, 2017). Adults make these predictions automatically (Thornton et al., 2019). This ability to accurately predict others' emotions is associated with greater social success (Barrick et al., 2024; Zhao et al., 2022). How do infants develop this detailed knowledge of which emotions are likely to precede and follow each other?

Most adults show similar emotion transitions (Nencheva, Nook, et al., 2024; Prasetio et al., 2020; Thornton & Tamir, 2017). For example, using experience sampling, researchers can track how people experience emotions and emotion transitions throughout the day. By analyzing thousands of such emotion reports, across hundreds of distinct mental states (e.g., sadness and anger, or calmness and excitement), Thornton and Tamir (2017) found remarkable consistency in adults' transition probabilities between states. That is, the same transitions that have a high likelihood for one adult tend to be highly likely in other adults too. Further, there is structure in this transition data. Adults are more likely to experience transitions between emotions that are similar on key dimensions and less likely to transition between emotions that are very different on these dimensions. Most notably, adults are more likely to transition between emotions that are highly similar in *valence* (i.e., how positive or negative the state is) and less likely to transition between emotions that are very different in valence. For example, if someone is feeling a negative emotion, such as anger, they are more likely to experience another negative emotion next, such as sadness, and less likely to experience a positive emotion next, such as happiness. Even infants are more likely to transition between emotions that are similar in valence, according to caregiver reports of infants' emotions. Though infant transitions are more idiosyncratic than adults, they gradually converge to the

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Heather Ferguson served as action editor.

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The data, analysis code, stimuli, and supplementary materials for this study are available at https://osf.io/2xytq/. This work was supported by the National Institutes of Health (Grant R01HD095912) awarded to Casey Lew-Williams, the National Institutes of Health (Grant R01MH114904) awarded to Diana I. Tamir, and the Princeton University (Porter Ogden Jacobus) and Association for Computing Machinery (Special Interest Group on High Performance Computing Fellowships) awarded to Mira L. Nencheva. The authors thank Alexander Todorov for his input on the study design; Luke Walthour, Ella Whitfield, and Kennedy Casey for their help with recording the audiovisual stimuli for the study; and Hannah Van Dusen for her help with the later stages of recruitment and data collection.

Mira L. Nencheva played a lead role in conceptualization, data curation, formal analysis, investigation, methodology, project administration, visualization, writing–original draft, and writing–review and editing. Richard Peng played a supporting role in project administration. Diana I. Tamir played a lead role in funding acquisition and an equal role in conceptualization and writing–review and editing. Casey Lew-Williams played a lead role in funding acquisition and an equal role in conceptualization and writing–review and editing.

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adult-like pattern of valence-driven transitions during the first 5 years of life (Nencheva, Nook, et al., 2024).

Adults have a finely calibrated understanding of how emotions transition from one to another. This allows them to predict which emotions are likely to follow current emotions (Thornton & Tamir, 2017). Adults are remarkably accurate both when estimating how likely a given emotion transition is for the average adult (Thornton & Tamir, 2017), as well as for specific individuals, such as close friends (Zhao et al., 2022). Adults can learn transition probabilities between arbitrary states by observing them unfold over time (Thornton et al., 2023). However, it is unknown how adults accrue their fine-tuned knowledge of real-world emotion transitions. We propose that people learn about emotion dynamics over development, most likely by observing and then approximating the emotion dynamics of their local community, starting in early infancy.

Infants are known to track statistical patterns in perceptual, linguistic, and social events as they unfold over time (Lew-Williams et al., 2011, 2019; Monroy et al., 2017, 2019; Saffran & Kirkham, 2018). Given that emotion transitions follow a fairly consistent statistical pattern, it is plausible that infants extract patterns of emotion dynamics in their environment through statistical learning. Infants reliably differentiate positive versus negative emotion displays by 4–7 months (Dela Cruz et al., 2023; Kotsoni et al., 2001; LaBarbera et al., 1976; Nelson & Dolgin, 1985; Prunty et al., 2022; Safar & Moulson, 2020). They also track their patterns: 15-month-old infants track individuals' "emotional history" (Repacholi, Meltzoff, Hennings, & Ruba, 2016; Repacholi, Meltzoff, Toub, & Ruba, 2016). For example, they expect someone who responds with anger in one situation to continue to do so in other situations. Further, Mermier et al. (2022) showed that infants can discriminate between more versus less likely sequences of emotional facial expressions in lab-based manipulations (e.g., happy facial expressions that are followed 100% of the time by angry expressions, vs. angry expressions that are followed 50% of the time by surprised expressions). In each of these experiments, infants had a training phase in which they learned about the emotions of a specific actor. Although infants were successful in learning the associations between emotion displays, little is known about how infants process these transition displays in light of their experiences with real-world patterns of transitions. Does infant emotion processing reflect their ability to track the patterns of their community's naturally occurring emotion dynamics?

Current Investigation

We propose that infants learn how likely different emotion transitions are from observing the emotions displayed by people in their lives. If this is the case, we predict that infants track which transitions are more versus less likely for people in general (according to existing norms; Thornton & Tamir, 2017), *and* they track the dynamics of the person they spend the most time with: their primary caregiver. That is, as infants gather observations of emotion transitions, particularly from their primary caregiver, we propose that they fine-tune their predictions about emotion transitions to match these experiences.

If infants track the patterns of real-world emotion over time, then we would expect to see two kinds of evidence. First, infants should differentiate between displays of emotion transitions that adults tend to experience frequently versus infrequently (see Thornton & Tamir, 2017). Second, infants should process emotion transitions in a way that reflects the idiosyncrasies of their primary caregiver, such that two infants with similar inputs (i.e., with caregiver who experience similar emotion transition patterns) should show fairly similar ways of processing compared to infants with different inputs (i.e., with caregivers who experience very different transition patterns). For example, if an infant has observed that their caregiver is unlikely to transition from sadness to happiness, they should process this transition differently from an infant who frequently observes this transition in their caregiver. Relatedly, an infant whose caregiver has very atypical emotion transitions would likely process transitions differently from the average infants in our sample. An alternative possibility is that infants do not rely on learning emotion transitions from those around them, but instead expect, by default or via their own emotion experiences, to see within-valence emotion transitions more than between-valence ones. If so, they would show knowledge of likely versus unlikely emotion transitions, but their processing of transitions would not be shaped by the local patterns they observe.

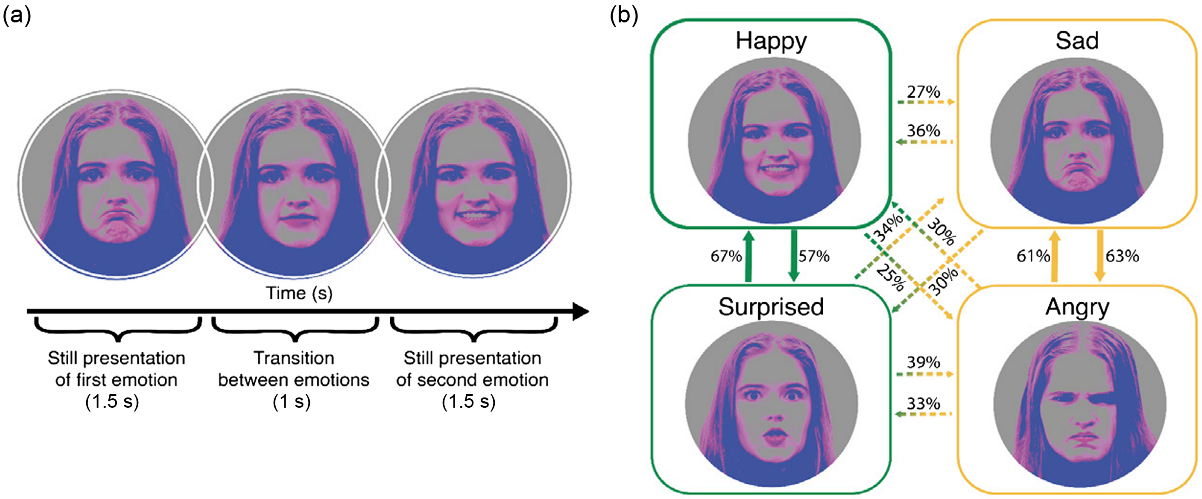
To test these hypotheses, we combined two sources of data: self-reports of caregivers' own emotion transition experiences and infants' processing of video clips displaying emotion transitions in the lab. We asked caregivers to report how frequently they experienced various emotion transitions that are known to vary in frequency based on prior research with adults (Thornton & Tamir, 2017). We then presented infants with audiovisual displays of the same emotion transitions (Figure 1). Half were high-frequency, within-valence transitions (e.g., sad → angry), and half were low-frequency, across-valence transitions (e.g., sad → happy), as reported by the general population (Thornton & Tamir, 2017), and the current sample of caregivers. During the experiment, all transitions were presented with equal frequency.

We used pupillometry to measure how infants process emotion stimuli in the lab, in two ways: First, we measured pupil size in order to test whether infants actively predicted which emotion was likely to follow next. Pupil size has been associated with prediction errors across a wide range of predicted events in both social and nonsocial domains (Berger & Posner, 2023; Gredebäck et al., 2018; Zhang & Emberson, 2020; Zhang et al., 2019). If infants track the likelihood of emotion transitions, they should experience larger prediction errors—marked by greater pupil dilation—when observing less likely transitions (e.g., happy to angry, or sad to surprised).

Second, we measured pupil size synchrony—the alignment in pupillary responses across participants—which has been shown in prior studies to be positively associated with attention to or similar processing of a stimulus (Hasson et al., 2004, 2008; Kang & Wheatley, 2017; Nencheva et al., 2021; Piazza, Cohen, et al., 2021; Piazza, Nencheva, & Lew-Williams, 2021). Synchrony in neurophysiological responses across participants is commonly used to investigate (a) how participants process a given stimulus on average as well as (b) individual differences in how participants process a stimulus. When a participant attends to a stimulus that unfolds over time, their neurophysiological responses (such as pupil size) become time-locked to the dynamics of that stimulus (Kang et al., 2014; Smallwood et al., 2011). Prior work has shown that people tend to converge on a similar time-locked way of processing stimuli (Hasson et al., 2004). Stimuli that are more engaging tend to elicit greater synchrony, for example, engaging moments in a story (Kang & Wheatley, 2017) or engaging intonation patterns (Nencheva et al., 2021). When a person does not attend to the stimulus, the temporal

Figure 1

Study Design



Note. (a) Frames and the timeline from an example transition between *sad* and *happy*. (b) Still frames of the four emotions in the study. Positive emotions are marked with green, and negative emotions with yellow. Solid arrows indicate transitions within the same valence; dashed lines indicate transitions across valence, resulting in 12 distinct transition trials. The average adult transition probabilities (based on caregiver ratings) are indicated over each transition arrow. Photo copyright Luke Walthour. See the online article for the color version of this figure.

structure of their responses does not follow the dynamics of the stimulus as closely (Kang et al., 2014; Smallwood et al., 2011). For example, moments of task-unrelated thought (or mind wandering) have been shown to disrupt the coupling between neural responses and the dynamics of the stimulus (Baird et al., 2014).

Measures of pupil size synchrony across participants allowed us to probe two aspects of infants' processing of emotion displays in the lab. First, we can test if infants are sensitive to average transition frequencies. That is, do infants find emotion transitions to be more engaging if they are more versus less frequent in general? If infants track the likelihood of emotion transitions in their environment, they should show greater pupil size synchrony for high (vs. low) frequency transitions, which we interpret as an index of preferential attention (see Nencheva et al., 2021). We expected greater time-locked attention to high-frequency transitions given that this is a relatively complex task (Hunter & Ames, 1988).

Second, we can test if infants are sensitive to the specific emotion transition frequencies in their primary caregiver (Figure 2). Though processing is often time-locked to a stimulus, individuals bring their own expectations and interpretations to stimulus processing. Thus, synchrony (or lack thereof) between two people may vary based on prior experiences and can, therefore, reveal important individual differences. For example, people who hear different beginnings to a story show lower synchrony when listening to the end of the story (Nguyen et al., 2019). If infants' real-time processing of emotion transitions is shaped by the pattern observed in their own primary caregiver, then infants whose caregivers show similar patterns of emotion transitions should process emotion transition displays in the lab more similarly—marked by greater pupil size synchrony. Similarly, infants whose caregivers have more typical transitions would, on average, have greater pupil size synchrony with the other infants in our sample. Taken together, this investigation advances our understanding of how infants break into the statistical patterns of the social world and how statistical learning mechanisms could give rise to individual differences in emotion development.

Method

Open Science and Transparency

Data and Code Availability

The data, analysis code, stimuli, and additional online material are available at https://osf.io/2xytq/ (Nencheva, Tamir, & Lew-Williams, 2024).

Preregistered Analyses

The preregistration for this study can be found at https://aspredicted.org/QNQ_9LK. To address the question of how infants track transitional probabilities between different emotional states, we preregistered two sets of analyses: (a) comparing two pupillometry measures (percent change in pupil size and pairwise pupil size synchrony across participants) in more versus less frequent emotion transitions and (b) seeing if this effect differed with the age of the participants (with two age groups 4–7 months, and 7–10 months).

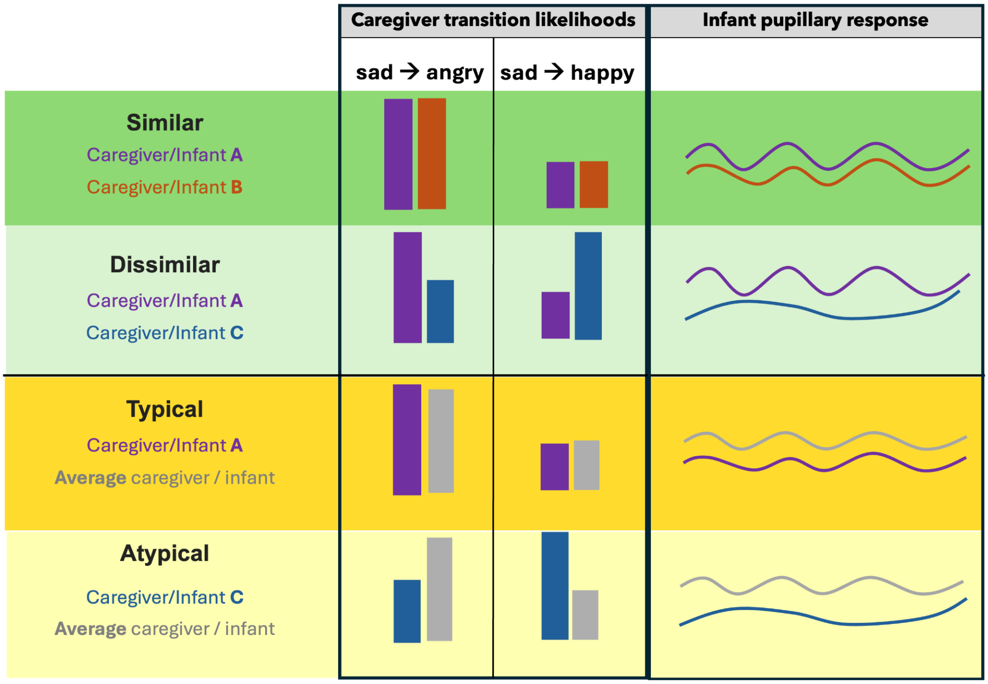
Deviations From Preregistration

In addition to preregistered analyses, we carried out exploratory analyses of individual differences.

Note that we intended to carry out preregistered analyses for a second research question using two additional tasks. Initially, we had planned on presenting the tasks in a counterbalanced order. However, after piloting, we decided to prioritize the task used for the research reported here, and we always presented it first. Because infants frequently grew inattentive or fussy during the two follow-up

Figure 2

Schematic Illustrating Pupillometry Measures



Note. This schematic illustrates the logic of our measures of similarity and typicality, based on individual differences in caregivers' emotion transitions and infants' processing of transition displays. The top panel (green) depicts our measure of similarity in the emotion transitions of three hypothetical caregivers and the pupillary responses of their infants. In the "Similar" panel, if Caregivers A (purple) and B (orange) report a similarly high likelihood of transitioning from sad to angry, then their infants should have similar pupillary responses when they observe a transition from sad to angry. On the other hand, Caregivers A (purple) and C (blue) in the "Dissimilar" panel report very different likelihoods of transitioning from sad to angry, and their infants would have different pupillary responses when watching a transition from sadness to anger. The bottom panel (yellow) depicts our measure of typicality in the overall emotion transition patterns of caregivers and mock pupillary responses of their infants. The average caregiver in the sample might have a fairly high likelihood of transitioning from sad to angry and a relatively low likelihood of transitioning from sad to happy. In the "Typical" panel, the typical Caregiver A (purple) has similar transition likelihoods to the average (gray), and their infant's pupillary responses should approximate the group average as well. In contrast, in the "Atypical" panel, an atypical Caregiver (C; in blue) might have very different transitions from the average (gray), and their infant's pupillary responses should be different from the group average. See the online article for the color version of this figure.

tasks, there was insufficient usable pupillometry data for the key change trials. Specifically, 78% of participants did not meet the preregistered exclusion criteria for the follow-up tasks.

Participants

This investigation analyzed data from 70 full-term infants (range = 4.1–10.2 months) with no known vision or hearing impairments and their primary caregivers. As preregistered, data collection covered two age ranges: 4- to 6-month-olds and 7- to 10-month-olds, with 35 participants in each age group. This age range was selected to capture infants' emerging ability to differentiate facial displays of emotion (Geangu & Vuong, 2023; Kotsoni et al., 2001; Nelson & Dolgin, 1985; Prunty et al., 2022).

The preregistered sample size was determined based on a power analysis using the *pwr* package in R (Champely et al., 2018) based on a *t*-test comparing frequent versus infrequent transitions in 10 infants in measures of percent change in pupil size and pairwise pupil size synchrony. Based on this power analysis, a sample size of 35 participants resulted in a power greater than 80% in both analyses (pupil size: power ~ 81.6%; pupil size synchrony: power ~ 88.8%).

The sample consisted of 17% Asian participants, 7% Black, 7% Hispanic, 57% White, 3% Other, and ethnicity information was missing for 9% of participants. There were approximately equal numbers of male and female infants (45.7% female and 54.3% male).

An additional 12 participants (not included in the final participant count) were excluded based on three preregistered criteria: (a) equipment errors or malfunction that affected the pupillometry recording (five participants), (b) unwillingness to sit on the caregiver's lap or other fussiness preventing completion of the study (one participant); and (c) after data processing, the participant had fewer than one codable trial in each trial category (three participants). We excluded three additional participants from any analyses involving parent reports of emotion transitions due to missing parent survey data.

Context of Data Collection

Participants were recruited through the Princeton Baby Lab participant pool, which consists of families in Central New Jersey and neighboring areas. Forty-four percent of participants were tested before the COVID-19 pandemic, with the remaining sample collected after research facilities reopened following the pandemic.

Pupillometry Task

Stimuli

We recorded a White female actor showing transitions between canonical facial displays depicting four emotions (*happy*, *surprised*, *sad*, and *angry*), with 12 transitions total (Figure 1b). Each video clip displayed a single transition between two distinct emotions. Based on prior adult data (Thornton & Tamir, 2017), we selected transitions that are experienced by adults with different frequencies. Specifically, transitions between similar states (e.g., *happy* and *surprised* or *sad* and *angry*) occur relatively frequently in adults. In contrast, transitions across these two pairs (e.g., between *happy* and *sad*) are less frequent. Although surprise can have ambiguous valence (Kim et al., 2017), we treated it as positive for this study because of its higher transition probability with happiness compared to anger and sadness (Thornton & Tamir, 2017). The facial emotion displays for each video clip were validated using Microsoft Azure Face Application Programming Interface. This automated face processing tool detects canonical facial expressions by assigning a confidence score of how well a given facial configuration fits the canonical expressions for anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. For all the final video clips included in the study, we ensured that the still frame of the target emotion received the highest confidence score for the intended emotion (e.g., that a still frame of an angry display scored the highest in the anger category).

People can display their internal emotional states in a variety of ways, including their facial movements, vocal tone, words, and body language. In this study, we focused only on easily recognizable canonical facial and vocal displays of these emotions. Each video clip captured an actor dynamically switching from one facial expression to another. The video clips were edited to show a still frame of the first emotion display for 1.5 s, then a transition to the ending emotion display for 1 s, followed by a still frame of the second emotion display for another 1.5 s (4 s total; Figure 1a). During the starting and ending facial expression, a sound corresponding to the facial expression was played (laughter for happiness, a gasp for surprise, crying for sadness, and a grunt for anger, modeled after the vocal affect map constructed by Cowen et al., 2019). The sound clips were all normed to a loudness of 60 dB. All video clips were modified to be isoluminant to ensure that changes in pupil size were not the result of changes in the luminance of the stimulus (de Groot & Gebhard, 1952).

Procedure

During the task, infants sat on their caregiver's lap in front of a 17-in. monitor, where the stimuli were presented. For the task's duration, caregivers were instructed to close their eyes to avoid influencing the infant's behavior. The infant's pupil size was recorded at a sampling frequency of 500 Hz using an EyeLink 1000 Plus eye tracker. Before the task, infants were shown a brief Muppet Show clip during the eye tracker setup, followed by a 3-point horizontal calibration, with a video of a laughing baby as the calibrating clip.

The task consisted of two blocks. All 12 transition videos were displayed in each block, separated by random intertrial intervals between 0.5 s and 1 s after each trial. After every four clips, participants saw a short, isoluminant attention-getting clip. The order of the videos was counterbalanced in eight pseudorandom orders.

At the end of the study, participants completed an additional preregistered task where they saw isoluminant still images that varied in their identity and facial displays of emotion. However, data from these tasks are not included in the current investigation.

Caregiver Emotion Transition Survey

Transition Likelihood

The primary caregiver of each infant completed a brief questionnaire either before or after the study reporting how often they experience each of the transitions in the study and how often they think their child experiences each transition in their daily lives (modeled after Nencheva et al., 2021; Thornton & Tamir, 2017). For example, they might rate how likely they are to feel sad next if they are currently feeling happy. Caregivers rated the likelihood of each transition from 0 to 100 using a slider.

Emotion Frequency

Next, caregivers were asked to indicate how frequently they and their child experienced each emotion using a slider from 0 (*not at all*) to 100 (*very frequently*).

Emotional Expressivity

Caregivers also reported their own emotional expressivity on a 17-item Emotional Expressivity Scale (Kring et al., 1994). Emotional expressivity was used in an exploratory analysis reported in additional online material (https://osf.io/2xytq/).

Analysis

Preprocessing of Pupil Size

The raw pupil size values recorded by the EyeLink 1000 Plus eye tracker were converted from arbitrary units into percentages relative to baseline (computed over the second 250 ms into the trial). Potential artifacts caused by partial blinks were detected by analyzing fluctuations in pupil size using a sliding window of 0.05 s. Any intervals within this window that showed a change exceeding 15% were considered artifacts and subsequently removed from the data (Merritt et al., 1994). Missing data intervals smaller than 200 ms were interpolated using Stineman interpolation (Stineman, 1980). Intervals longer than 200 ms were left as missing data in subsequent calculations of average pupil size or pupil synchrony. We excluded trials in which more than half of the data were missing, following a procedure from Nencheva et al. (2021). On average, participants had 18.0 (out of 24) trials that met these inclusion criteria, approximately 1.7 (out of two) trials per unique transition. There were no differences in the direction of the reported results when the missing data threshold was increased (75%) or decreased (25%). The analysis window of interest included data from 1.5 s after the onset of the trial (the end of the still presentation of the first emotion display and the beginning of the transition) to 100 ms after the offset of the transition video.

As preregistered, we examined two features of infants' pupillary responses: (a) average pupil size, which is generally thought to reflect prediction error or surprisal, and (b) pairwise pupil size synchrony across infants, which is generally thought to reflect engagement. To compute average pupil size, we averaged the pupil size (relative to baseline) for the analysis window described above for each usable trial for each participant, after preprocessing. We computed the pairwise pupil size synchrony during each trial for all possible pairs of participants, following procedures from Nencheva et al. (2021). We used a dynamic-time-warping distance, a measure of the difference between two time series, to compute the difference between participants' responses on the same trial. We then flipped the sign of this estimate to estimate the synchrony in pupillary responses instead. This measure was *z*-scored. Note that in the preregistration, there was an additional intermediate step that subtracted dynamic time-warping distance from a nonzero constant. Since the constant canceled out in the *z*-score computation, we skipped this extra step in the final analysis.

Similarity and Typicality of Emotion Transitions

In two exploratory analyses, we explored individual differences in caregivers' emotion transitions. First, we did a pairwise analysis, where we quantified how different/similar two parents (Parent A and Parent B) are in their likelihood of transitioning between two specific emotions (e.g., from happy to sad). This was measured as the difference in the transition likelihood indicated by Parent A and the likelihood reported by Parent B for the same transition. In the text, for ease of interpretation, we report these analyses in terms of similarity between the two parents (i.e., the opposite of difference).

In a second analysis, we looked at the atypicality/typicality of the general pattern of emotion transitions of a given parent compared to the group (of all other parents in the sample). Atypicality was measured as the average difference (described above) across all transitions of a given parent. For ease of interpretation, we report these analyses in terms of typicality (i.e., the opposite of atypicality).

Controlling for the Amount of Pixel Change in Transition Videos

We computed two measures of pixel change in the video using MATLAB: (a) the average pixel value difference between the first and the last frame of the video (Ambrus et al., 2021) and (b) the average frame-by-frame pixel difference over the whole video (Hard et al., 2011; Kosie & Baldwin, 2021). We then averaged these two measures to get an overall estimate of pixel change in the video. This estimate was used as a control variable.

Model Selection

For all analyses (except for individual differences analyses), we used mixed effects models (*lme4* package; Bates et al., 2015) with random effects by participant (for pupil size) or participant pair (for pairwise pupil size synchrony analyses). We included random slopes if doing so did not lead to a lack of convergence of a singular fit error.

Results

Before testing if infants track the patterns of emotion transitions, we needed to confirm that within-valence transitions were more likely than across-valence transitions in our sample and that infants could differentiate between each of the emotions on display in this study. Caregivers reported that they were more likely to experience transitions between same-valence emotions than between opposite-valence emotions (see additional online Figure 2 at https://osf.io/2xytq/). Caregivers reported that their infants were also more likely to experience same-valence transitions (see additional online Figure 2 at https://osf.io/2xytq/). Further, infants successfully differentiated between positive and negative displays (see additional online Figure 1 at https://osf.io/2xytq/). With these prerequisites in place, we could investigate our main question: Are infants attuned to the emotion transition patterns of their environment?

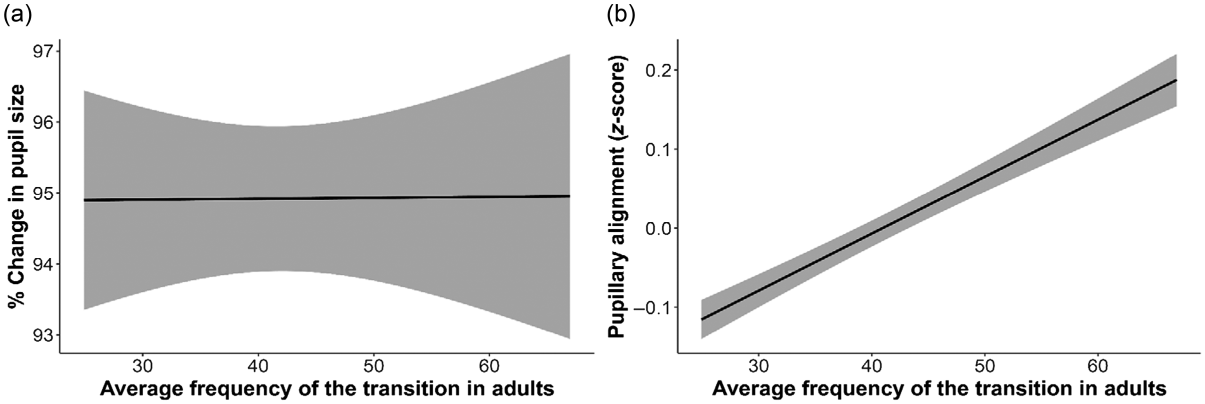
Infants Differentiate Between High- Versus Low-Frequency Emotion Transitions

In the main preregistered analyses, we examined whether infants tracked the average frequency with which adults reported experiencing these transitions (based on their caregivers' ratings). First, we compared infants' average pupil size for displays of transitions experienced by caregivers with high versus low frequency on average (with frequency as a continuous variable). We did not observe an effect on pupil size, $\beta = 0.001$, $t(1186.04) = 0.1$, $p = .72$ in a mixed effects model with random intercepts by the participant, controlling for the amount of pixel change in the video (Figure 3a). There was also no interaction with age, $\beta = 0.02$, $t(1187.88) = 0.28$, $p = .78$, or main effect of age, $\beta = -0.02$, $t(316.83) = -0.2$, $p = .84$. Further, in a supplementary analysis, the transition likelihoods reported by the infants' own caregiver did not relate to pupil size. These results suggest that infants did not experience a prediction error in response to low-frequency transitions.

Second, we tested whether the average adult frequency of emotion transitions is reflected in the infants' pupil size synchrony. We compared pupil size synchrony for video displays of transitions experienced by adults with high versus low frequency (with frequency as a continuous variable). Higher transition frequency was associated with greater infant pupil size synchrony in a mixed-effects regression with random intercepts by participant pair, controlling for the amount of pixel change in the video, $\beta = 0.09$, $t(11859.12) = 9.88$, $p = 6.41 \times 10^{-23}$; Figure 1b. There was also a main effect of age, such that older infants had overall more consistent pupillary responses, marked by great pupil size synchrony between participants, $\beta = 0.11$, $t(11180.5) = 4.39$, $p = 1.17 \times 10^{-5}$. We did not observe an interaction

Figure 3

Infants Process Frequent Transitions More Similarly Compared to Less Frequent Transitions



Note. In both panels, the average transition frequency reported by caregivers in the study is plotted on the *x*-axis. (a) There was no association between the transition frequency and the average pupil size across a trial (as a % relative to baseline), plotted on the *y*-axis, with a 95% confidence interval shaded region. (b) There was a positive association between the transition frequency and the pupillary size synchrony across infants on a given trial (plotted on the *y*-axis as a *z*-score), with a 95% confidence interval shaded region.

between frequency and participant age, $\beta = -0.03$, $t(11794.9) = -1.03$, $p = .30$, suggesting that both older and younger infants are similarly more engaged by high-frequency transitions. These results suggest that infants processed high-frequency transitions more similarly, possibly indicating greater engagement.

In an exploratory analysis, we probed whether infants' pupillary responses reflected their parents' specific transition likelihoods by computing the consistency in how the same infants responded across multiple experiences of the same transition video. We computed pupil size synchrony between the same infants' pupil size time-course for the same transition display in Block 1 and Block 2 respectively, where such data was available (a subset of 27 participants who had at least two complete overlapping trials with high and at least two complete overlapping trails with low transition likelihood). Infants were more consistent in their pupillary responses to transition videos that depicted transitions that their caregiver experienced with higher (vs. lower) frequency, $\beta = 0.15$, $t(204.54) = 2.31$, $p = .02$. Importantly, this was not the case, when we replaced the infants' own caregivers' transition likelihood with that of a random other caregiver in the sample for the same transition, $\beta = -0.01$, $t(182.07) = -0.08$, $p = .93$. That is, the time course of infants' pupillary responses during transition videos reflected the pattern of transition of the infants' own caregiver with specificity.

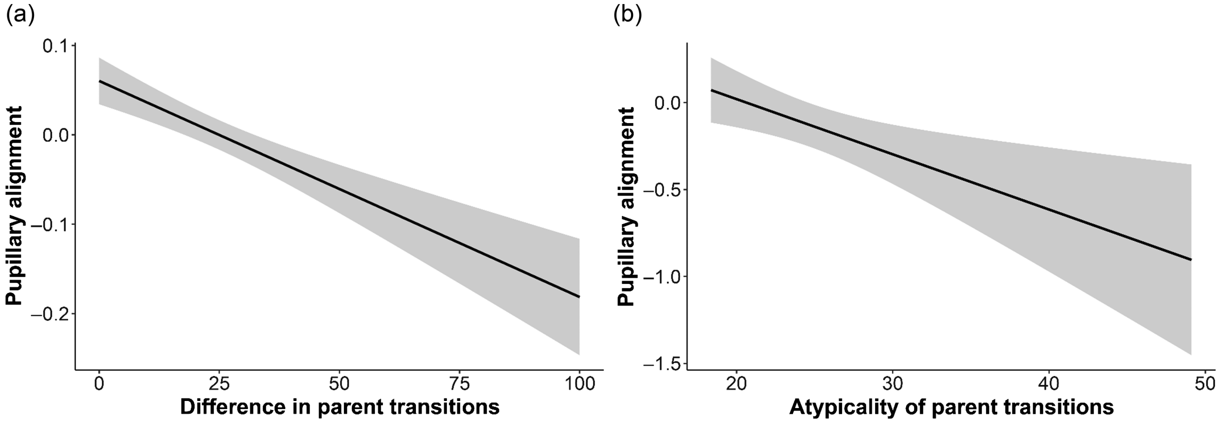
Emotion Transitions in the Home Shape How Infants Process Transitions in the Lab

Next, we carried out two more sensitive exploratory analyses to further probe whether infants show learning of the frequency with which emotion transitions occur in their own primary caregiver. First, we tested whether infants whose caregivers showed similar emotion transition patterns processed emotion transition displays in the lab more similarly. For example, if two of the parents in our sample rated their likelihood of experiencing a transition between happiness and sadness as highly unlikely (e.g., both 12 out of 100), we expected their infants to process the video transition between happiness and sadness more similarly to each other, compared to a third infant whose caregiver rated the transition as more common (e.g., 52 out of 100). We used a mixed effects regression to predict pairwise pupil size synchrony between infants at each trial from the difference in caregiver-reported transition probabilities for the given transition. We included random intercepts by the valence of the starting emotion and controlled for the average frequency of the transition. We found that infants whose caregivers reported more similar transition probabilities had more aligned pupillary responses, $\beta = 0.05$, $t(14175.02) = 6.19$, $p = 6.04 \times 10^{-10}$; Figure 4a. However, in an exploratory analysis, infants whose own emotion transitions were more similar (as reported by caregivers) did not have more aligned pupillary responses, $\beta = 0.02$, $t(14224.99) = 1.61$, $p = .11$. This suggests that infants who observed similar emotion dynamics in the home processed emotion transitions in similar ways.

As an extension of the previous analysis, we examined whether infants whose caregivers, on average, have more typical (i.e., similar to the group) emotion transitions showed greater pupil size synchrony with other infants. For example, two parents reported a very typical experience of transitioning from happiness to sadness (27 out of 100). The third caregiver, on the other hand, reported a relatively atypical likelihood of transitioning between the same two emotions (89 out of 100). If this pattern extends across other emotion transitions, does the infant of the third caregiver process video transitions differently from other infants in the group, given their less typical experience? A linear regression predicted the average pupil size synchrony between a given infant and all other infants in the group across all trials from the atypicality of their caregivers' emotion transitions (the average difference between their caregivers' reporter transition frequency and that of the group across all transition pairs). We found that infants whose caregivers had more typical (i.e., less atypical) transition probabilities were more aligned in their pupillary responses with other infants, $\beta = 0.34$, $t(64) = 2.9$, $p = .005$; Figure 4b. However, in an exploratory analysis, infants whose own transitions (as reported by caregivers) were more typical

Figure 4

Infants Whose Caregivers Have More Similar Emotion Transitions at Home Process Emotion Transitions More Similarly in the Lab



Note. (a) Pupil size synchrony between a given pair of participants on a given trial (*y*-axis) decreased based on how different their parents' self-reported transition probabilities were for the same transition (*x*-axis). (b) The average pupil size synchrony between a given participant and all other participants in the sample, across all trials (*y*-axis), also decreased based on how atypical their caregiver's transitions were, compared to those of the group. The latter was measured as the average difference between the transition likelihood reported by the parent and the likelihood reported by all other parents across all transitions.

(i.e., less atypical), compared to the rest of the infants in our sample, were not more aligned in their pupillary responses with other infants, $\beta = 0.07$, $t(64) = 0.55$, $p = .58$. That is, infants who observed typical emotion dynamics in the home processed emotion transitions in similar ways to their peers.

Discussion

How do babies learn to understand and predict others' emotions? We found that infants were sensitive to the frequency of emotion transitions documented in adult research as well as in their very local caregiving environment. Infants' pupil responses were more similar when watching audiovisual displays of more (vs. less) frequent transitions. Further, infants who observed similar emotion transitions at home responded similarly to those same transitions in our experimental task. Together, these results suggest that even very young infants are highly tuned to the dynamics of emotion transitions, and this sensitivity allows them to learn the specific emotion dynamics of their community.

Why were infants' pupillary responses more similar for emotion transitions that tend to be more versus less frequent among typical adults? One possibility is that this is somewhat automatic and/or reflects developmental maturation, where they converge onto adult-like patterns of emotion transitions independent of learning. Another possibility is that this reflects learning about a broad suite of observations of people in their kin network and that they found frequent transitions more engaging (Kang & Wheatley, 2017; Nencheva et al., 2021). This interpretation is consistent with prior work showing that young infants are more engaged by and prefer familiar experiences (Hunter & Ames, 1988). In future work, it will be important to determine how these moment-to-moment differences impact the quality of infants' social interactions, or at a more foundational level, how the range of alignment between infants maps onto meaningful behaviors. In contrast, we did not observe a difference in pupil *size* between more versus less frequent transitions. This suggests that infants did not experience greater prediction error (or surprisal) when the actor transitioned from sadness to happiness than from sadness to anger. Although infants' processing of emotion transitions seems to be influenced by how often these transitions happen on average, they might not actively *predict* which emotion comes next. This could result from nonnaturalistic features of the experimental design, for example, the fact that infants saw many transitions in quick succession with the same frequency. Relatedly, infants' prediction errors may be based on the more local pattern of transitions of the experiment (in which all transitions were presented with equal frequency), rather than on their prior experiences with these transitions outside of the lab. Regardless, this finding contrasts with research on adults, showing that adults actively predict which emotional states are likely to come next (Thornton et al., 2019).

As a test of whether infants learn by observing the emotion transitions of their local community, we measured infants' sensitivity to the dynamics of their own primary caregiver's specific emotion transitions. Within our sample, infants showed similar pupil responses to one another if their parents had more similar emotion transition patterns at home. For example, if a parent transitions to happiness 20% of the time after feeling sad, their infant would respond to this transition in ways that are similar to other infants whose parents also transitioned between sadness and happiness 20% of the time and would respond differently from infants whose caregivers experienced this transition either more or less frequently (e.g., 5% or 40% of the time). This implies that infants learn to understand and process emotion transitions by observing the statistical patterns in how their own caregivers transition between emotions. This aligns with broader views on the significance of statistical learning processes in emotion development (Plate et al., 2019; Ruba et al., 2022; Woodard et al., 2021). From their baseline models at home, infants could have a foundation for learning the typical emotion dynamics of other members of their kin network, as well as their broad community or culture.

Learning how emotions unfold over time from observing caregivers would only help infants learn the typical transitions of their community if they observe typical transitions. If caregivers display atypical transitions, this would lead infants toward learning atypical patterns; among older children and adolescents, those who experience atypical patterns are at greater risk of mental health problems (Reitsema et al., 2019). A large risk factor for developing psychopathology is intergenerational transmission. For instance, children of depressed mothers are more likely to develop psychopathology (e.g., Goodman et al., 2011). Our lab task, although merely simulating real emotion transitions, highlights a potential learning mechanism for the intergenerational transmission of patterns of emotion dynamics, including atypical patterns. In this nonclinical sample, we found that infants who observed more atypical caregiver emotion transitions in the home also processed emotion transition displays in more atypical ways. The question remains as to whether early processing of atypical emotion patterns does or does not play a foundational role in later processing and/or emotion-related outcomes.

This investigation comes with several key limitations. First, the links we observed between emotion transitions in the home and infants' processing of emotion transitions in the lab are correlational. Therefore, it is impossible to establish whether infants learn from observing emotion transitions in the home or if other factors—such as shared genetics, physiological experiences, or other aspects of the home environment—link caregiver emotion dynamics and infants' processing of emotion transitions. Future longitudinal extensions of this work can help us understand the extent to which these early experiences with caregivers have a persistent versus fleeting influence on infants' processing of emotion transitions, as infants accumulate more diverse information about people's emotion transitions over the course of development.

Second, our study design focused on the emotion transitions of the primary caregiver, which is likely only part of the emotion dynamics observed by infants, as infants interact with many closer and more distant members of their kin networks (Okocha et al., 2024). Future research can investigate how infants integrate statistical information about the emotion dynamics of the adults and peers in their lives and even their own emotion transitions. Prior work has shown that infants' emotion transitions start off as more idiosyncratic and less organized by valence and converge onto the shared adult pattern over the course of development (Nencheva, Nook, et al., 2024). In adults, individual differences in emotion transitions are reflected in the processing of others' emotion transitions (Barrick et al., 2024; Barrick & Lincoln, 2024). How do these developmental changes interact with children's perception of emotion transitions? In our exploratory analyses, we did not find evidence that individual differences in infants' emotion transitions (as reported by caregivers) shaped infants' processing of emotion transition displays in the lab. However, this may be in part due to noisiness in caregivers' estimates of infant emotion transitions, as well as the relatively narrow age range of infants. Further, more research is needed to understand the extent to which infants extend their knowledge of the specific emotion transitions of their caregivers to predict the emotion transitions of new people in their lives. For example, the number of close others with whom an infant interacts on a regular basis has been shown to shape their language development (Okocha et al., 2024). Similar effects may be in place in the domain of emotion, where exposure to the emotion dynamics of one versus many individuals over time may have consequences for emotion development. Further research is also needed to understand the extent to which caregiver perceptions and caregiver experiences of emotion dynamics are stable measures of individual differences and how the role of primary (and secondary) caregiver emotion transitions changes over the course of development. Looking outside biologically related caregivers may also disentangle the effects of shared genetics versus learning from experience.

Third, our stimuli represented canonical facial and vocal displays of emotion, as is common in lab studies of infant emotion (for a review, see Ruba & Repacholi, 2020). Although our dynamic video displays go a step beyond the more traditional use of static pictures showing canonical facial expressions, they do not capture the real-world complexity of the emotion displays that infants observe. Caregivers most likely do not always pout when sad, or furrow their brows when angry, and may not show any outward displays that would allow infants to access their internal emotion experiences. Instead, inferences about the emotion that someone may be experiencing are constructed in multimodal and contextually rich displays. For example, alongside facial expressions, people can observe others' emotions through behaviors, posture, language, and other situational information. Further, the timescale of the transition displays in the lab may not match the timescale of real-world emotion experiences and displays. For instance, a transition away from a short-lived emotion like surprise may occur rapidly (matching the quickness of transitions in our stimuli), whereas a transition away from a stickier emotion like sadness may take considerably longer in the real world. These differences in timescale may affect not only the results of this study but also learning more broadly, drawing on different learning mechanisms that integrate regularities across longer and shorter timescales. Future research should aim to characterize in an ecologically valid way the sources and timescales of affective information that are reliably available to infants in order to understand how infants learn about the emotion dynamics of the people around them.

Last, our study is based on a relatively homogeneous U.S.-based convenience sample of caregivers and infants. The full spectrum of caregiver emotion dynamics and infants' perceptions across households, communities, and cultures remains unexplored. Future work exploring this variability can reveal rich insights into how infants fine-tune their processing of emotion dynamics.

Conclusion

From the first moments of life, infants navigate a dynamic world where emotions change from one moment to the next. Our findings suggest that they learn how emotions unfold over time by observing statistical patterns in the emotion experiences of those in their environment, even about their primary caregiver specifically. This investigation provides a new window into the cognitive mechanisms that support infants in integrating complex social patterns in their local community, which may help them form predictions about future emotion experiences and lay the foundation for individual differences in emotion development.

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Received March 14, 2024
Revision received January 21, 2025
Accepted April 3, 2025 ■