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# Early Caregiver Predictability Shapes Neural Indices of Statistical Learning Later in Infancy

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## ABSTRACT

Caregivers play an outsized role in shaping early life experiences and development, but we often lack mechanistic insight into *how* exactly caregiver behavior scaffolds the neurodevelopment of specific learning processes. Here, we capitalized on the fact that caregivers differ in how predictable their behavior is to ask if infants' early environmental input shapes their brains' later ability to learn about predictable information. As part of an ongoing longitudinal study in South Africa, we recorded naturalistic, dyadic interactions between 103 (46 females and 57 males) infants and their primary caregivers at 3–6 months of age, from which we calculated the predictability of caregivers' behavior, following caregiver vocalization and overall. When the same infants were 6–12-months-old they participated in an auditory statistical learning task during EEG. We found evidence of learning-related change in infants' neural responses to predictable information during the statistical learning task. The magnitude of statistical learning-related change in infants' EEG responses was associated with the predictability of their caregiver's vocalizations several months earlier, such that infants with more predictable caregiver vocalization patterns showed more evidence of statistical learning later in the first year of life. These results suggest that early experiences with caregiver predictability influence learning, providing support for the hypothesis that the neurodevelopment of core learning and memory systems is closely tied to infants' experiences during key developmental windows.

## 1 | Introduction

Early life is marked by rapid learning and neurodevelopment, both of which are profoundly influenced by our experiences. Experiences during this window guide *what* we learn, and influence *how* we learn. While our primary caregivers clearly play an outsized role in shaping our early life experiences and development, we often lack mechanistic insight into *how* exactly their behavior scaffolds the neurodevelopment of specific learning processes. Here, we capitalized on the fact that caregivers differ in the predictability of their behavior to test the idea that more predictable early environmental input trains an infant's later ability to learn about predictable information.

Variability in caregiver behavior is a major influence on child developmental outcomes, and thus likely on infant learning. As

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A complete list of authors that were part of the Khula South Africa Data Collection Team can be found in our supplementary material.

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**Summary**

- Caregiver predictability during dyadic interaction predicted neural responses during statistical learning 5 months later.
- The longitudinal relationship between caregiver predictability and neural responses during statistical learning was most evident in the same sensory modality.
- These results show that differences in infants' early experiences shape the neurodevelopment of relevant learning and memory systems early in life.
- These results extend much work with Western populations to an ecologically valid, and historically under-represented African context.

one example, caregivers show variation in the predictability of their long-term and moment-to-moment behavior (see Davis and Glynn 2024; Ugarte and Hastings 2023; Young, Frankenhuis, and Ellis 2020, for recent reviews), with documented impacts on offspring development across species (Davis et al. 2017, 2019, 2022; Demaestri et al. 2022). In humans, moment-to-moment caregiver predictability influences both child psychopathology, where less predictable caregiver signals precede negative mental health outcomes in children (e.g., Davis and Glynn 2024), and cognitive development, including effortful control in 2-year-olds (Holmberg et al. 2022), and memory performance in 6-year-olds (Davis et al. 2017). Such moment-to-moment predictability has been studied in multiple global contexts (although to our knowledge, not yet in an African setting, as we do here), implying the predictability of infants' early sensory input may be a globally ubiquitous predictor of later development (Aran et al. 2024; Klein and Feldman 2007; Montirosso et al. 2010). We reasoned that a mechanistic possibility explaining these links between cognitive development and caregiver predictability is that early experience with predictable information teaches infants to attend to (Munakata, Placido, and Zhuang 2023; Suarez-Rivera, Smith, and Yu 2019; Yu and Smith 2016) and thus learn from predictable information, thereby shaping learning and memory systems in the brain while they are highly malleable.

One learning process that might be especially shaped by the regularity of our experiences, including the predictability of caregiver input, is statistical learning or learning about the statistically predictable information in our environment (see Aslin 2017; Johnson 2020; Saffran 2020; Saffran and Kirkham 2018 for recent reviews on statistical learning in infancy). Seminal work indicated that infants can use only the statistical properties of their auditory input to support language learning. Specifically, Saffran, Aslin, and Newport (1996) demonstrated that after 8-month-old infants listened to an artificial language with no breaks between "words," they adjudicated between a series of syllables that predictably appeared together (a "word") and a series of syllables which had appeared together less predictably. Subsequent investigations have demonstrated that learners of all ages (Campbell et al. 2012; Fló et al. 2019, 2022; Saffran et al. 1997; Teinonen et al. 2009) can use the regularities naturally present in their environment to track statistical patterns across sensory domains highlighting the broad importance of this learning mechanism (Conway and Christiansen 2005; Fiser and Aslin 2002; Kirkham, Slemmer, and Johnson 2002; Saffran et al. 1999). Although there are both individual differences (Siegelman and Frost 2015) and developmental changes in statistical learning (Forest, Abolghasem, et al. 2023; Forest, Schlichting, et al. 2023; Jung, Walther, and Finn 2020; Raviv and Arnon 2018), this process is well-known to support much of the environmental learning which pervades early life, and predicts later behaviors such as reading ability (Arciuli and Simpson 2012; Spencer et al. 2015) and linguistic performance (Boeve, Zhou, and Bogaerts 2023; Kidd and Arciuli 2016; Misyak and Christiansen 2012; Shafto et al. 2012; Singh, Reznick, and Xuehua 2012).

Notably, statistical learning is shaped by prior experience with statistical regularities—both on relatively short and long timescales—making it a prime candidate for understanding how differences in caregiver experience shape learning. For instance, adults shift their attention to successively more complex statistical regularities as they gain experience in an environment (Forest et al. 2022), and infants look at the location of a display that is most informative for their learning at any point in time based on their prior experience (Poli et al. 2020). Prior learning of environmental regularities over longer timescales also shapes future statistical learning. For example, adults fail to learn statistically when an artificial language conflicts with the statistics of their native language (Finn and Hudson Kam 2008), potentially because prior learning of one set of statistics inhibits attending to, or learning about, a different distribution of sounds down the line (Bulgarelli and Weiss 2016; Gebhart, Aslin, and Newport 2009). This phenomenon has been well documented in language learning, where the early ability to differentiate between non-native phonemic contrasts disappears by the end of the first year of life, once infants have had extensive experience with the statistics of their own language (Maurer and Werker 2014; Werker and Hensch 2015; Werker and Tees 1984). Collectively, these examples highlight that our statistical experiences guide *what* we learn in the moment, and form the foundational knowledge which guides later learning (see also Amso and Kirkham 2021; Forest and Amso 2023).

Crucial for the hypothesis that experience with statistical regularities shapes the underlying neural systems used for future learning, variability in statistical learning performance has also been shown to relate to variability in neural development. In children, the thickness of the inferior frontal gyrus (Finn et al. 2019) and size of the hippocampus (Finn et al. 2019; Schlichting et al. 2017) relate to statistical learning performance. Evidence from electroencephalography (EEG) tasks demonstrates that the extent to which 6-month-old infants' (Choi et al. 2020) and adults' (Batterink and Paller 2017, 2019) neural oscillations align with the frequency of predictable auditory information relates to their later knowledge of a statistical structure. Initial evidence further suggests that variability in maternal experiences, like stress, relate to the way that toddlers' brains respond to predictable information during a statistical learning task (Pierce, Carmody Tague, and Nelson 2021). These examples suggest that variability in the psychological experiences that relate to statistical learning performance could also shape the neural substrates used for later learning, but this link has yet to be directly investigated.

Here, we tested the idea that relevant, regular early experiences shape the operation of core learning processes when these systems are highly malleable in the infant brain, by asking if natural variability in caregivers' predictability shapes infants' subsequent statistical learning months later. To do this, we recorded naturalistic, dyadic interactions between 2- and 6-month-old South African infants and their primary caregiver which we used to calculate the entropy of caregiver behavior as a measure of unpredictability (Davis et al. 2017). Approximately 5 months later (near the end of the first year of life), we recorded continuous EEG while the same infants completed an auditory statistical learning task. Following past research (Pierce, Carmody Tague, and Nelson 2021), we compared neural responses to predictable and unpredictable auditory information during the task. Finally, we longitudinally related both caregiver entropy following the behaviors in the matching modality (auditory) and overall caregiver entropy to differences in infants' neural responses to predictable versus unpredictable auditory information later in the first year of life.

## 2 | Methods

### 2.1 | Participants

#### 2.1.1 | Cohort Study Description

The data presented herein were collected as part of an ongoing longitudinal study, designed to chart the development of executive function from 0 to 1000 days, in an African context typically under-represented in developmental and psychological research. As part of the longitudinal study, families were recruited through health clinics in Gugulethu, an informal settlement near Cape Town, South Africa, to participate in prenatal and (five) postnatal visits. Local university Health Research Ethics Committees approved all protocols. These protocols varied by timepoint, but included medical assessments, magnetic resonance imaging (MRI), rest and task-based EEG, and behavioral questionnaires (see Zieff et al. 2024, for complete longitudinal protocol). Before participating, caregivers provided informed consent on behalf of themselves and their infant in the family's preferred language.

#### 2.1.2 | Current Sample

Our main research question was how the predictability of infants' early caregiver interactions might shape the ongoing brain development of relevant learning systems. Thus, we explored the relationship between caregiver entropy during naturalistic caregiver–infant interactions at the first postnatal visit ("Visit One," approximately 4 months after infants were born) and EEG responses during statistical learning at the second postnatal visit ("Visit Two," approximately 9 months after infants were born, see Table 1). Of the families who participated in the larger study, 262 participated in the caregiver–infant interaction session at Visit One. Most often, the caregiver present at this visit was the infant's mother. A total of 183 families participated in the EEG statistical learning task at Visit Two. Of these, 129 infants provided usable EEG data (see Supplementary Material, "EEG Data Quality Control Procedure"). The overlap of subjects who participated in both the caregiver–infant interaction task at Visit One, and had usable statistical learning EEG data from Visit Two was 103 subjects ($M_{\text{Age Visit One}} = 3.8$ months, $SD = 0.8$ months, range = 2–5.8 months; $M_{\text{Age Visit Two}} = 9.1$ months, $SD = 1.4$ months, range = 6.3–12.0 months). For all analyses, we present results with the largest sample size possible. For example, when reporting EEG results from the statistical learning task, we report results from all 129 participants with EEG data, rather than just the 103 subjects for whom we also had caregiver entropy data (see Table 1 for sample size information and Table 2 for family demographics).

#### 2.1.3 | Sample Size Justification

The most computationally intensive analysis we ran, and the analysis for which we had the fewest number of subjects, was to analyze the longitudinal relationship between caregiver entropy at Visit One and neural measures of statistical learning at Visit Two. Specifically, we planned to run a linear model that included seventeen total predictors (this encompasses five main effects terms, their two- and three-way interactions, and one additional control term; see Section 2.4). A power analysis (run in G*Power, Faul et al. 2007) indicated achieving 80% power in detecting a medium-sized effect ($f^2 = 0.15$) in this model would require a sample of at least 95 participants. Thus, the 103 subjects' data we analyzed here surpass the minimum sample size required for medium and large effects.

### 2.2 | Caregiver Predictability Metrics

#### 2.2.1 | Caregiver-Infant Interaction Recordings

To measure the entropy of infants' early interactions with their primary caregiver, we recorded infants and their caregivers during naturalistic, dyadic interaction for about 5 minutes during Visit One. Caregivers were instructed to play with their infants as they would at home in a quiet, private space in the testing center. This space held three tripods, each with a Logitech C920 Pro HD Webcam camera. One camera directly faced the infant, one faced the caregiver, and the final camera captured a side view of the dyad. The video and audio signals from each computer were temporally aligned using ManyCam (https://manycam.com/) during the recording session.

#### 2.2.2 | Hand-Annotation of Caregiver Behavior

Following data collection, we hand-annotated caregiver behavior in Datavyu (Datavyu Team 2014), following a protocol used previously to characterize moment-to-moment caregiver behaviors (Davis et al. 2017), and which can be referenced in full in their Supporting Information for readers who wish to adapt this approach to their work. This protocol involves frame-by-frame annotating of the onset and offset of each instance of five caregiver behaviors which can be processed by infants' sensory systems: vocalizing (auditory signal), holding the baby, touching the baby (tactile signals), holding an object in the room, and pointing (visual signals). Alongside these five caregiver behaviors, we also annotated infant eye-gaze toward the caregiver as a measure of infant attention, which we included as a covariate in relevant analyses.

**TABLE 1** | Sample size and number of included subjects for each task.

| Task | Completed task | Useable data | Mean age in months (useable data) |
|---|---|---|---|
| Caregiver-interaction recording (Visit One) | 262 | 255 (118 F, 137 M) | 3.8 (range: 2–5.8) |
| Statistical learning during EEG (Visit Two) | 183 | 129 (60 F, 68 M) | 9.1 (range: 6.3–12) |
| Overlap in final sample | — | 103 (46 F, 57 M) | 5.2 (between Visits One and Two) |

**TABLE 2** | Family demographic characteristics.

| | Visit One (*N* = 256) | Visit Two (*N* = 129) | Longitudinal sample (*N* = 103) |
|---|---|---|---|
| Maternal place of birth | | | |
| South Africa | 250 | 126 | 101 |
| n the African continent (not South Africa) | 5 | 2 | 2 |
| Missing | 1 | 1 | — |
| Primary spoken language | | | |
| Xhosa | 246 | 125 | 100 |
| English | 3 | — | — |
| Sotho | 2 | 1 | 1 |
| Afrikaans | 2 | 1 | 1 |
| Shona | 1 | 1 | 1 |
| Ndebele | 1 | — | — |
| Missing | 1 | 1 | — |
| Maternal age (in years) at infant birth | | | |
| Mean (*SD*) | 28.9 (5.8) | 29.2 (5.8) | 29.5 (5.9) |
| Median [Min, Max] | 28.7 [18, 44.1] | 29.0 [18, 44.1] | 29.1 [18, 44.1] |
| Missing | 1 | 1 | — |
| Maternal educational attainment | | | |
| Completed Grades 6–7 | 6 | 4 | 4 |
| Completed Grades 8–11 | 114 | 62 | 49 |
| Completed Grade 12/High school | 103 | 45 | 37 |
| Some postsecondary education | 20 | 9 | 8 |
| Completed postsecondary education | 12 | 8 | 5 |
| Missing | 1 | 1 | — |
| Household monthly income (South African Rand, ZAR)[a] | | | |
| <R1000 | 48 | 24 | 20 |
| R1000–R5000 | 115 | 56 | 44 |
| R5000–R10,000 | 59 | 29 | 24 |
| >R10,000 | 12 | 4 | 4 |
| Missing or unknown | 22 | 16 | 11 |

[a] At the time of writing (March 19, 2024), 1 United States Dollar (USD) = 18.68 South African Rand (ZAR).

Operationally, this annotation was completed offline for each video. First, each video was evaluated for image resolution and audio clarity. Then, each behavior was annotated, one at a time by trained annotators (e.g., caregiver vocalizing was marked first, and infant eye-gaze was annotated completely separately). This approach serves two important functions. First, annotating each behavior separately helps to avoid mistakes in annotation. Second, it ensures any relationships observed between different caregiver behaviors reflect real co-occurrence of these behaviors, rather than annotators' interpretations of co-occurrence.

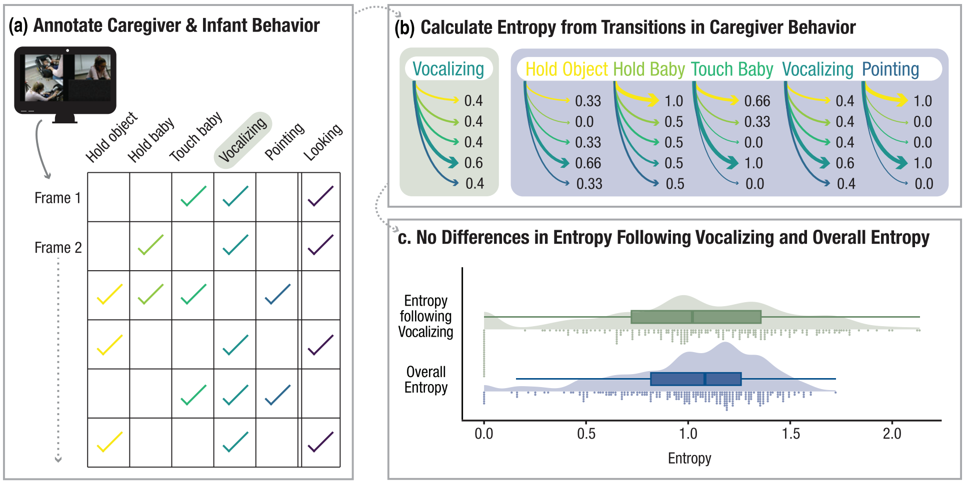

**FIGURE 1** | Measuring caregiver predictability. (a) Caregiver–infant interactions were recorded from three cameras which were aligned temporally before hand-annotating five caregiver behaviors (hold object, hold baby, touch baby, vocalizing, and pointing) and one infant behavior (looking) on each frame of the video. On each frame (*y*-axis of the table), the presence or absence of each behavior (*x*-axis of the table) was marked (colored check marks in each box), resulting in a frame-by-frame annotation of caregiver behavior. (b) These annotation matrices were then transformed into Markov models, capturing the probability of a caregiver transitioning from one behavioral state to another. Markov models were generated independently for each caregiver, and could be used to understand how predictable her behavior was by examining the transitional probability from one behavioral state to any other. Panel (b) shows an example calculation of the predictability for the caregiver in Panel (a) from behavioral states which include each behavior to states which include each other behavior. For example, following frames in which the caregiver was vocalizing (green outline, first column), she transitioned to a behavioral state that included Holding an object twice (40% of the time), Holding her baby twice (40% of the time), Touching her baby twice (40% of the time), Vocalizing three times (60% of the time), and Pointing twice (40% of the time). Note that these probabilities were calculated for specific behavioral states which could be either single behaviors or combinations of behaviors (i.e., what proportion of the time did a caregiver switch from "Touching Baby and Vocalizing" to "Holding baby and Vocalizing"), but for simplicity in the figure we have collapsed the transitional probabilities across all states involving each behavior rather than listing them separately. Thickness of arrows reflects strength of the transition; color of arrows indicates the behavior present in the state the caregiver transitioned to. These transitional probabilities were then fed into the standard calculation for Shannon Entropy, using all possible behaviors (Blue Background, "Overall Entropy"), or just based on the transitions following behavioral states in which the caregiver was Vocalizing (Green Background, "Entropy Following Vocalizing"). (c) Entropy (*x*-axis) was computed for every caregiver both overall and following vocalizing (*y*-axis, color). There was no difference in the distribution of entropy values by entropy type (overall or following vocalizing). Dots represent individual caregivers, box-plots represent the median and interquartile range (excluding outliers), and shading represents density of caregiver entropy values along the *x*-axis.

Instances of the same behavior less than 500 ms (holding baby, touching baby, holding an object, or pointing) or 1000 ms apart (vocalizing and infant eye-gaze) were identified as a single event, and behaviors occurring further apart in time were annotated as separate occurrences. The intervals for vocalizing were chosen to be 1000 ms based on past work (see Davis et al. 2017), and because there were some instances of caregiver vocalizing in our data which included pauses longer than 500 ms while still being part of the same utterance. The interval for separate infant eye movements was likewise set to 1000 ms to account for the fact that at 4-months the infant visual system still requires more time to plan and execute eye movements than later in life. If any behavior was unclear, this time point was marked as "unknown" and excluded from analysis (caregiver behavior was not codable 1.54% of the time on average, and infant behavior was not codable 2.93% of the time on average). This process resulted in a frame-by-frame (33 Hz) annotation which reflected the occurrence and duration of caregiver actions and infant attention toward the caregiver (Figure 1a).

To ensure annotations were consistent across our sample, we trained each new annotator until their annotations matched an experienced annotator's with at least 85% accuracy in eight training videos. For these videos, the accuracy match was computed for each behavior separately using an automatic process built-in to DataVyu. If a training annotator did not match the experienced annotators' annotations the trainee was re-trained and re-annotated that behavior in all videos until this match was achieved. We also confirmed continued inter-annotator reliability across our seven total annotators by implementing a quality control procedure on a subset (10%) of all videos. These videos were annotated by two people instead of one. If the inter-annotator reliability was less than 80% for any caregiver or infant behavior, the behavior of concern was re-coded in all videos that had been annotated by the discrepant annotator (note that this happened just once, where one person's annotations of "holding baby" clearly deviated from the other annotators'). The final inter-annotator reliability for this 10% of videos resulted in a Cohen's Kappa of 0.75, which reflects high inter-rater reliability (McHugh 2012).

### 2.2.3 | Calculating the Entropy of Caregiver Behavior

Our hand-annotation process resulted in a data frame that detailed the presence and timing of five caregiver behaviors and infant eye-gaze toward the caregiver for the entire naturalistic interaction (Figure 1a). We then assigned each timepoint a behavioral "state" which reflected the caregiver behavior(s) that were active at that time. A state could reflect the caregiver doing either zero, one, or multiple behaviors. For example, a caregiver might have been holding her baby (one state), and then switch to vocalizing while touching her baby (a second state, e.g., "Frame 1" in Figure 1a).

We then used this sequence of states to model the entropy of caregiver behavior (e.g., how predictably does she transition from vocalizing to touching her baby?) by constructing Markov models representing the transitions from one behavioral state to another. Figure 1b illustrates example transitional probabilities for the behaviors visualized in Figure 1a, collapsed across all behavioral states that include the caregiver behavior of interest to behavioral states with every other caregiver behavior, rather than separately listing all possible behavioral states (i.e., the transitional probabilities visualized for "Vocalizing" reflect that this Caregiver transitioned 40% of the time to a behavioral state that included "Holding an object," rather than that she transitioned 40% of the time to only "Holding an object"). These models allowed us to quantify the consistency of caregiver transitions using the formula for Shannon Conditional Entropy (denoted as $H(Y|X) = \sum_{x\in X, y\in Y} p(x,y)(log\frac{p(x,y)}{p(x)}$). This formula models the uncertainty in transitioning from one state to another, given the frequency of all states and the transitions between them (Davis et al. 2017; Vegetabile et al. 2019). The resulting outcome, termed "conditional entropy," indicates how unpredictable a caregiver's next action is, based on her current state (i.e., how likely is it that a caregiver will transition to "Holding baby while Vocalizing" if she is currently "Touching the baby"). In other words, the higher the entropy of a caregiver's behavior, the *less* predictable she was. We calculated both the *overall entropy* of caregiver behavior, by including all possible states in the entropy calculation (Figure 1b, blue; i.e., averaging the predictability of her transitions from any behavioral state to any other), and *entropy following caregiver vocalizing* alone, by restricting our calculation of conditional entropy to only include transitions following caregiver vocalizing (Figure 1b, green). Because behaviors can also occur in tandem, we chose to include any state which includes vocalizing in this calculation, rather than states where the caregiver was *only* vocalizing. Of note, these calculations mean that the measure of predictability we are using reflects transitions between behavioral states, like switching from vocalizing to touching the baby, or from vocalizing while touching the baby to holding an object, rather than the predictability of the auditory information itself, as is more typically done in statistical learning research. This data processing was done with custom Python (version 3.9) scripts via Jupyter Notebook (Kluyver et al. 2016).

## 2.3 | Statistical Learning During EEG

### 2.3.1 | EEG Data Acquisition

EEG data at Visit Two were recorded while infants sat on their caregiver's lap in a dimly lit, quiet room. EEG data were collected using high-density (128-channel) HydroCel Geodesic Sensor Nets (Magstim EGI, Whitland, UK). Nets with modified taller (9.3 mm) pedestals designed for improving the inclusion and experience of infants with curly, coiled, and/or coarsely textured hair were used as needed (Mlandu et al. 2024). EEG data were recorded at a sampling rate of 1000 Hz and online referenced to the vertex (channel Cz) via NetStation 5.4 software (Magstim EGI) connected to a Net Amps 400 Series high-input impedance amplifier. Impedances were aimed to be kept below 100 KΩ under the impedance capabilities of the amplifier.

### 2.3.2 | Statistical Learning Task

The auditory statistical learning task we used was adapted from prior research in toddlers (Pierce, Carmody Tague, and Nelson 2021), and similar to many prior statistical learning studies (especially Kudo et al. 2011; Saffran et al. 1999 which used the same auditory stimuli). The task was presented via E-prime 3.0 on a Windows 10 Pro PC. During the task, an experimenter silently blew bubbles, played a silent video, or showed toys to the infants to keep them calm and engaged while the auditory stimuli played.

The statistical learning task presented infants with a series of 12 unique pure tones, one at a time, for approximately 7 min (Figure 2a). Each tone lasted 50 ms, with no ISI (0 ms). Although tones sounded one-at-a-time, they were presented in a statistically predictable order. Specifically, tones were grouped into sets of three, which formed tone "triplets" (tone triplets were F#A#D; CG#C#; EGD#; AFB). Within a triplet, the tones always appeared in the same order (e.g., F# always preceded A#, which always preceded D). Triplets then appeared in a pseudo-random order such that no triplet followed itself. Three of the triplets appeared 80 times each during the task, and one of the triplets appeared 40 times during the task. In all cases, the triplets appeared an equal number of times in the first and second half of the task (40×/half for frequent triplets, 20×/half for the infrequent triplets). Thus, the transitional probability for tones within a triplet (e.g., F# → A#, or A# → D) was 1.0, while the transitional probability for tones spanning a triplet boundary (e.g., D → C) was 0.33 (note, this is true despite one triplet appearing half as often as the others). There were no breaks between triplets that could have indicated any grouping structure to participants. Thus, if infants in our sample show evidence of having learned the relationship between tones, this must be due to the statistical pattern in the order they were played.

Most statistical learning studies rely on a separate test phase (see Batterink et al. 2015; Liu et al. 2023; Siegelman, Bogaerts, and Frost 2017 for discussions), completed after exposure to structured information, to test participants' knowledge of the statistics they experienced. That said, a growing number of studies have relied on neural measurements to understand the statistical learning process as it unfolds (Batterink and Paller 2017, 2019; Batterink and Zhang 2022; Koelsch et al. 2016; Sanders, Newport, and Neville 2002; Sanders, Ameral, and Sayles 2009; Soares et al. 2020, 2022), especially in young learners (e.g., Choi et al. 2020; Fló et al. 2022; Kabdebon et al. 2015). We likewise relied directly on EEG data collected during the exposure phase as our neural measure of infant learning. Specifically, we capitalized on the fact that if infants learned the structure of the tone stream, some of the tones would become predictable (the 2nd and 3rd tones in a triplet) after having heard the first tone. The first tone, on the other hand, would remain unpredictable, since any triplet could follow the third tone of the previous triplet (Figure 2b). Past research (Pierce,

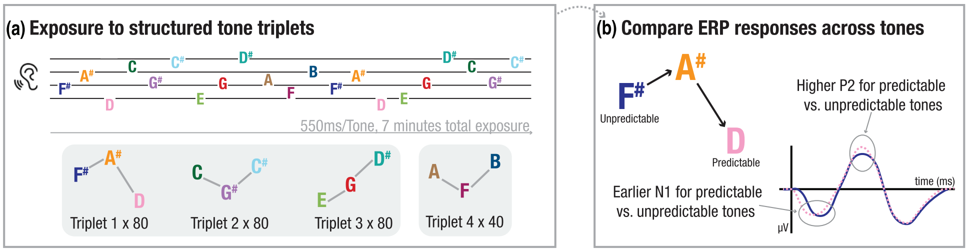

**FIGURE 2** | Statistical learning task and measurement. (a) Statistical learning task structure. Infants were exposed to a continuous stream of 12 tones which each played for 550 ms. These tones were secretly grouped into four "tone triplets" (shaded panel), such that within each triplet tones always appeared in the same order. These triplets then appeared in a pseudo-random order for about 7 min, with the caveat that no triplet immediately followed itself. Three of these triplets (F$^{\#}$A$^{\#}$D; CG$^{\#}$C$^{\#}$; EGD$^{\#}$) appeared 80× during the course of the task, while one triplet (AFB) appeared half as frequently (40× during the task). (b) Indexing statistical learning in infants via EEG responses. EEG was recorded during the statistical learning task, to compare ERP responses to unpredictable (e.g., First position tones, like Tone F$^{\#}$, Navy ERP wave) and predictable tones (e.g., Second and Third Position tones, like Tone A$^{\#}$ and D, pink dashed ERP wave) over the course of learning. Past research has indicated that two ERP features differ as a function of tone predictability: N1 latency (earlier for predictable) and P2 amplitude (higher for predictable). The example ERP figure is adapted from Pierce, Carmody Tague, and Nelson (2021), and reflects ERP responses (in microvolts, *y*-axis) across time (in milliseconds, *x*-axis).

Carmody Tague, and Nelson 2021) has demonstrated that two ERP features, namely the latency of the N1 and the amplitude of the P2 differ as a function of whether a tone is predictable or not in this statistical learning task. In particular, the N1 is thought to reflect auditory detection and discrimination (Tomé et al. 2015), while the P2 may reflect learning more specifically (Tremblay et al. 2014) and has been shown to increase as a function of stimulus predictability (Picton 1992). Thus, by recording EEG, which has an appropriate temporal resolution for measuring responses on the sub-second level, we could ask whether there were differences in neural responses to predictable compared to unpredictable tones which emerged after infants had the opportunity to learn about the structure of the tone sequence.

### 2.3.3 | EEG Data Processing

EEG data were preprocessed using the Harvard Automated Processing Pipeline for EEG (HAPPE), an automated preprocessing software designed for infant EEG data (HAPPE and HAPPE+ER; Gabard-Durnam et al. 2018; Monachino et al. 2022). The HAPPE+ER pipeline with Version 4 of HAPPE software was run using MATLAB (2022b) and EEGLAB (2022.0, Delorme and Makeig 2004). Preprocessing parameters are available in Table S1. Prior to any data preprocessing, we removed electrodes from the outer rim of the net and eye electrodes (electrodes E125, E126, E127, E128, E48, E119, E43, E49, E56, E63, E68, E73, E81, E88, E94, E99, E107, E113, E120, E44, E38, E32, E25, E21, E14, E8, E1, E121, E114, and E17), which is common practice in infant EEG research (see Monachino et al. 2022). Electrical line noise at 50 Hz was removed using CleanLine (Mullen 2012) via a multi-taper regression, and data were filtered with a 0.5–30 Hz finite impulse response (FIR) bandpass filter. Bad channels were detected using HAPPE's automated algorithm. Data were then artifact corrected via wavelet-thresholding. The continuous data were then segmented into epochs spanning the presentation of each stimulus (100 ms before until 550 ms after the onset of each tone), and were baseline corrected by the average over the prestimulus period (−100 to 0 ms). Any segments with remaining artifact were removed using amplitude based (± 200 uV) and joint probability criteria. Bad channels were interpolated via spherical spline interpolation and data were rereferenced to the average reference.

As we were primarily interested in understanding how EEG measures of statistical learning related to infants' early experiences, rather than understanding how learning progressed differently for frequent versus less frequent stimuli, we restricted our analyses to the frequent triplets. We also excluded any participant with fewer than 10 epochs remaining for any tone position in the first or second half of the study (i.e., Positions 1, 2, or 3 tones; see Supplementary Material for a full description of EEG data quality control procedure). Preprocessed EEG data were then run through the generateERPs script (HAPPE+ER; Monachino et al. 2022) to extract event-related potentials (ERPs) for each tone. Data were extracted and averaged from 11 frontal electrodes (E3, E4, E11/Fz, E19, E23, E24/F3, E27, E28, E117, E123, and E124/F4; Figure S1) based on prior research (Pierce, Carmody Tague, and Nelson 2021) and visual inspection of the data. ERP features were generated separately for each tone position (Positions 1–3), and for each half of the experiment (first and second half), in each participant. Peak amplitude and peak latency were extracted for the N1 (30–100 ms) and P2 (100–300 ms) components. The grand average waveforms were then manually inspected to confirm that the peak of each ERP component occurred in the time windows we had prespecified. We then calculated a corrected P2 amplitude which accounted for the N1 amplitude, and a corrected P2 latency which accounted for the N1 latency, as is common in the literature (Conte et al. 2020; Conte and Richards 2021; Hoehl and Wahl 2012).

## 2.4 | Analysis Plan and Rationale

Our central research question was whether or not early experience with highly predictable (i.e., low entropy) input would shape neural engagement during future learning of predictable information. Thus, we analyzed caregiver entropy data from Visit One, EEG responses to predictable versus unpredictable information during statistical learning at Visit Two, and their relationship to one another. All analyses were carried out in R (version 4.2.3, R Core Team 2021).

First, we confirmed that caregiver entropy at Visit One differed across caregivers using measures of central tendency. Entropy scores can range from 0 (reflecting perfectly predictable behavior) to a theoretically infinite maximum based on the total number of behavioral states included in the calculation. Our sample had entropy scores ranging from 0 to 2.13 ($SD = 0.43$), suggesting sufficient variability existed for further analysis. As some evidence suggests that statistical learning develops on different timelines in different sensory modalities (Raviv and Arnon 2018; Shufaniya and Arnon 2018), and that individual differences in statistical learning are only weakly correlated across modalities (Siegelman and Frost 2015), we reasoned that the particular sensory learning system tapped during the learning task (auditory, in this case), might be most related to experience with predictability in the relevant sensory domain. Thus, we also compared caregiver entropy following vocalizing (i.e., entropy following behaviors in the matching sensory modality) with overall caregiver entropy using a paired-sample *t-test* to test whether these scores differed sufficiently enough to separately relate both measures to later learning.

Next, we asked whether there was evidence of statistical learning in the EEG data at Visit Two, as measured by different ERP responses to predictable tones and unpredictable tones. Although the tones used here have been used to measure statistical learning in infants (Kudo et al. 2011; Saffran et al. 1999) and toddlers (Pierce, Carmody Tague, and Nelson 2021), we needed to confirm there was evidence of sensitivity to statistical structure in these data before investigating any potential relationship with caregiver entropy. As mentioned, prior work with this task has indicated that the N1 latency and the P2 amplitude differ as a function of where in a statistical triplet the tone is positioned (Pierce, Carmody Tague, and Nelson 2021). We reasoned that if these differences reflect *learning*, they should emerge during the second half of the task. Thus, we fit two linear mixed-effects models to test for statistical learning in the EEG signal. These models were fit using the lme4 package (Bates et al. 2015) and are reported using the *Anova()* function from the Companion to Applied Regression ("car") package (Weisberg 2019). Our first model predicted N1 latency as a function of tone predictability (position 1 tone are "unpredictable" while Positions 2 and 3 tones are "predictable"), half (first and second), and age at EEG (continuous in days and mean-centered) as fixed effects, as well as their two- and three-way interactions. This model also included the percentage of EEG segments retained following preprocessing to account for potential effects of data quality, and random by-subjects effects of half and tone predictability. Second, we ran a parallel model to examine any effects on P2 amplitude (adjusted for N1 amplitude). Although N1 latency and P2 amplitude have been used in prior statistical learning work and thus comprised our central analyses, we also ran similar models for N1 amplitude and P2 latency (adjusted for N1 latency). These models did not show any clear signs of learning-related change across our sample, and are therefore presented in the Supplementary Material.

Finally, we asked whether caregiver entropy would shape neural responses to statistical information down the line. To do this, we calculated an "EEG statistical learning score" by subtracting each infant's ERP responses to unpredictable (Position 1) tones from the average of their ERP responses to predictable tones (i.e., Positions 2 and 3 tone responses were averaged), in the second half of learning. This provided us with a measure of how much infants' neural responses to tones differed as a function of predictability, after infants had the opportunity to learn their statistical structure. We then ran two linear models to examine whether this learning score related to caregiver entropy. One of these models predicted the EEG learning score as a function of infant age at Visit One (during the caregiver interaction), caregiver entropy following vocalizing (mean centered), the frequency of caregiver vocalizing, how much the infant looked at their caregiver during the interaction, and the two- and three-way interactions of these terms. The model also accounted for data quality in the EEG signal and infant age at Visit Two (during the EEG task). Infant looking was included in this model to account for the possibility that the extent to which an infant attends to their caregiver would moderate the relationship between her predictability and later learning. The frequency of caregiver vocalizing was included to account for the possibility that the total amount of caregiver vocalizations, rather than the predicable structure present following vocalizing, would relate to auditory statistical learning. We included infant age at Visit One to account for the possibility that how old an infant was when we measured their interactions with their caregiver might account for some variability in how the caregiver behaved. We also included infant age at Visit Two (during EEG) to ensure that any differences observed in the EEG index of learning were not simply attributable to age differences in the EEG signal. The second model was identical but replaced caregiver entropy following vocalizing with overall caregiver entropy (mean-centered) and removed the vocalization frequency term to understand the specificity of any observed effects from the auditory entropy model.

As some past work (mostly with Western samples) has reported correlations between sociodemographic variables and caregiver predictability across longer timescales, we also examined whether there were correlations between such variables and caregiver entropy following vocalizing in our sample that might account for variability in later learning. There were no significant correlations between caregiver age at enrollment ($r = 0.11$, $t(229) = 1.62$, $p = 0.11$), caregiver educational attainment ($r = 0.09$, $t(229) = 1.38$, $p = 0.17$), nor household income ($r = -0.06$, $t(229) = -0.93$, $p = 0.35$), and caregiver entropy following vocalizing. These variables were also not correlated in the subset of participants for whom we had both caregiver entropy following vocalizing measures at Visit One and EEG measures of statistical learning at Visit Two (entropy and caregiver age, $r = 0.11$, $t(96) = 1.07$, $p = 0.29$; entropy and caregiver educational attainment, $r = 0.03$, $t(96) = 0.32$, $p = 0.75$; entropy and household income, $r = -0.006$, $t(96) = -0.06$, $p = 0.95$). Thus, we did not include sociodemographic covariates in our models, to conserve as much power as possible given our sample size.

## 3 | Results

### 3.1 | Entropy Varies Across Caregivers

Our first analysis examined the consistency of caregiver entropy. This analysis served both to describe naturalistic behavior in our sample and to confirm that there was sufficient variability to ask how this early signal related to later learning. As in prior characterizations of this population (Forest et al. 2024), there

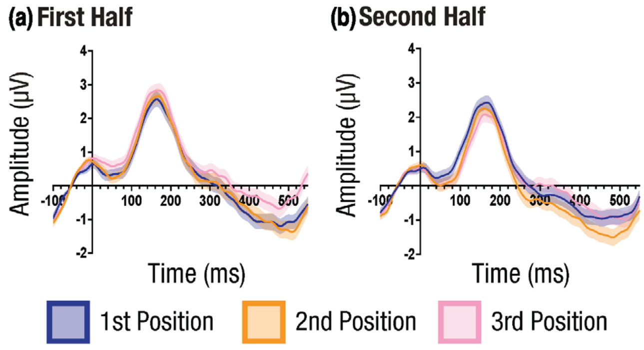

**FIGURE 3** | Raw ERP waveforms for each Tone Position in the (a) first and (b) second half of the experiment. The amplitude (*y*-axis) of EEG response at each millisecond (*x*-axis) for each tone position (color; 1st position tones, dark blue; 2nd position tones, orange; and 3rd position tones, pink). Colors match the example Tone Triplet in Figure 2b.

was a wide range of entropy across caregivers both following vocalizing ($M = 1.01$, $SD = 0.50$, range = 0.00–2.13) and overall ($M = 1.02$, $SD = 0.36$, range = 0.00–1.72). There was no significant difference in entropy following vocalizing and overall entropy ($t(232) = -0.91$, $p = 0.37$, Cohen's $d = 0.05$, Figure 1c), and these behaviors were moderately correlated ($r = 0.66$, $t(229) = 13.35$, $p < 0.001$). This correlation suggests that there is within-dyad consistency across predictability in one sensory domain and general predictability, but that there is still sufficient divergence in these metrics to examine the effect of each on later auditory statistical learning.

### 3.2 | P2 Amplitude Shows Evidence of Learning-Related Change

Next, we examined ERP responses to predictable and unpredictable tones across both halves of the experiment. The raw ERP waveforms are plotted in Figure 3. Our first ERP analysis examined if ERP N1 component responses during the statistical learning task, which may reflect the detection and discrimination of auditory inputs, differed as a function of tone predictability. The results of our model (described in Section 2.4) indicated there were no main effects of tone predictability ($\chi^2_1 = 0.25$, $p = 0.61$), half of the learning task (first or second; $\chi^2_1 = 0.26$, $p = 0.61$), age ($\chi^2_1 = 0.003$, $p = 0.96$), or EEG data quality ($\chi^2_1 = 0.08$, $p = 0.78$) on N1 latencies. There were also no interactions between age and tone predictability ($\chi^2_1 = 0.83$, $p = 0.36$), age and half of learning ($\chi^2_1 = 0.02$, $p = 0.90$), and no three-way interaction between age, half of learning, and tone position ($\chi^2_1 = 0.01$, $p = 0.92$). These results suggest no difference in the N1 response to predictable tones as a function of statistical experience (Figure 4a).

We then asked whether the amplitude of the P2 component (adjusted for N1 amplitude) differed by tone predictability. As for N1 latency, there were no main effects of age ($\chi^2_1 = 0.81$, $p = 0.37$), half of learning ($\chi^2_1 = 0.26$, $p = 0.61$), or tone predictability ($\chi^2_1 = 0.001$, $p = 0.96$) on P2 amplitude. There was, however, a three-way interaction between half of learning, age, and tone predictability ($\chi^2_1 = 4.72$, $p = 0.03$). There were no other significant main effects (EEG data quality, $\chi^2_1 = 1.09$, $p = 0.30$), or significant two-way interactions (tone predictability × age, $\chi^2_1 = 0.47$, $p = 0.49$; age × half, $\chi^2_1 = 2.14$, $p = 0.14$; tone predictability × half, $\chi^2_1 = 0.36$, $p = 0.55$). Follow-up linear mixed effects models comparing P2 amplitude as a function of age and tone predictability in each half separately (with random-by subject effects of tone predictability) confirmed that there were no effects of age, predictability, or their interaction in the first half (all $\chi^2$s 0.67 and $p$'s > 0.41), while there was a significant interaction between age and tone predictability in the second half ($\chi^2_1 = 4.33$, $p = 0.04$). In the second half alone, there were still no significant main effects of tone predictability ($\chi^2_1 = 0.49$, $p = 0.48$) or age ($\chi^2_1 = 0.07$, $p = 0.80$). Together, these results suggest that for older infants, P2 amplitude differs as a function of tone predictability *after* infants have had the opportunity to learn from the statistics of the auditory information. In other words, P2 amplitude shows evidence of learning-related change, in a manner consistent with past research, for older infants (Figure 4b).

### 3.3 | EEG Index of Statistical Learning Relates to Caregivers' Entropy Following Vocalization

Finally, we were interested in understanding how early experience with predictable structure modulates infants' statistical learning later in life. As the P2 amplitude showed learning-related change, we used this component to calculate our 'EEG learning score,' by subtracting the P2 amplitude for unpredictable 1st position tones from the average P2 Amplitude for predictable 2nd and 3rd position tones. A positive value thus reflects learning by indicating a greater P2 amplitude for predicted than unpredicted tones, while a negative value reflects greater P2 amplitude for unpredicted information. We investigated the longitudinal relationship between this learning score and caregiver entropy.

We reasoned that the development of neural responses to auditory structure might be most related to experience with predictability following auditory input. As such, we first examined the relationship between caregiver entropy following vocalizing and EEG learning scores, and found that, indeed, caregiver entropy following vocalizing significantly related to the EEG learning score months later (main effect of caregiver entropy following vocalizing, $F_{(1,79)} = 4.72$, $p = 0.03$). Specifically, infants whose primary caregivers displayed greater predictability (i.e., lower entropy) following vocalizing showed a larger EEG learning score (a larger difference in P2 Amplitude to predictable relative to unpredictable tones, Figure 5a). There was also a main effect of how much an infant looked at their caregiver ($F_{(1,79)} = 4.19$, $p = 0.04$) suggesting, intuitively, that the amount an infant attends to their caregiver also shapes their early learning. There was also a marginal main effect of how frequently a caregiver vocalized ($F_{(1,79)} = 4.07$, $p = 0.05$), but no main effects of age at Visit One ($F_{(1,79)} < 0.001$, $p = 0.99$), age at Visit Two ($F_{(1,79)} = 0.14$, $p = 0.71$), or EEG data quality ($F_{(1,79)} = 0.34$, $p = 0.56$). There were also no two- or three-way interactions (all $F$'s < 3.56, all $p$'s > 0.06). This pattern of results supports the hypothesis that caregiver predictability following auditory cues is related to the development of auditory statistical learning.

To test how specific to auditory input this effect was, we also examined whether overall caregiver entropy affected infants'

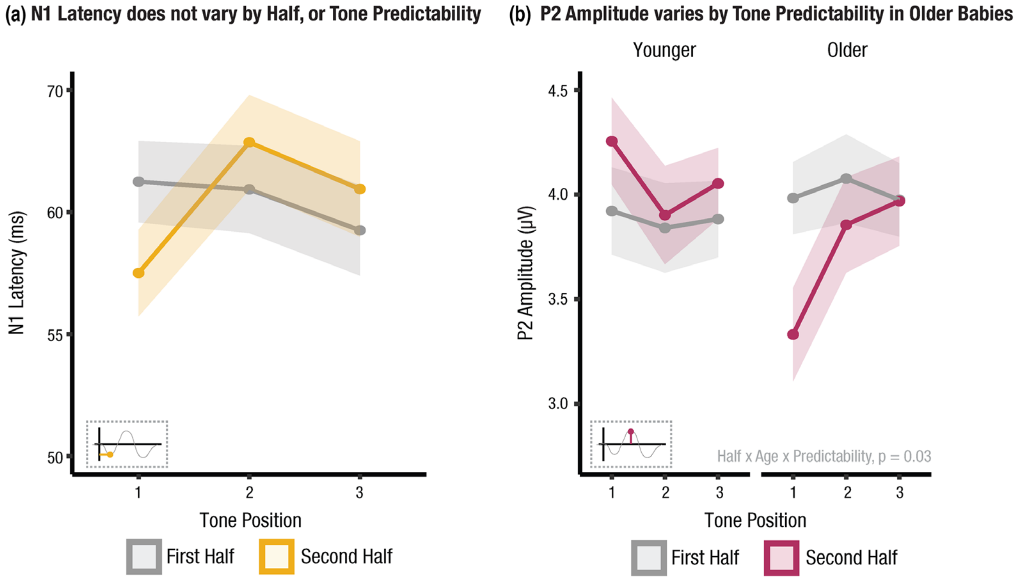

**FIGURE 4** | ERP results during the statistical learning task. (a) N1 latency (*y*-axis, milliseconds) does not differ as a function of Tone Predictability (*x*-axis), in either the first half (gray) or second half (yellow) of the statistical learning task. Inset depicts N1 latency in the context of an example ERP response to remind readers what this metric reflects. (b) P2 amplitude (*y*-axis, microvolts) differs as a function of Tone Predictability (*x*-axis), in the second half (pink) but not first half (gray) of the statistical learning task for older babies, but not in younger babies (vertical panels; note, age was modeled continuously and the median-split into older and younger groups is for visualization purposes only). *p* value reflects significant three-way interaction of half, age, and predictability from linear mixed effects model reported in the Results section. Inset depicts P2 Amplitude in the context of an example ERP response to remind readers what this metric reflects. In both panels, dots represent group means for the plotted ERP response, shading indicates 95% confidence intervals around the mean.

subsequent neural responses to structured auditory information. Overall caregiver entropy scores were not significantly related to the EEG learning scores ($F_{(1,87)} = 2.62$, $p = 0.11$, Figure 5b). There was a main effect of infant looking toward the caregiver ($F_{(1,87)} = 4.02$, $p = 0.05$), but no other significant main effects (age at Visit One, $F_{(1,87)} = 0.08$, $p = 0.78$; age at Visit Two, $F_{(1,87)} = 0.59$, $p = 0.44$; EEG data quality, $F_{(1,87)} = 0.09$, $p = 0.77$), nor two- or three-way interactions (all *F*'s < 2.38, all *p*'s > 0.13). Along with exploratory control analyses showing that caregiver entropy following non-auditory behaviors also does not predict auditory statistical learning (presented in the Supplementary Material), these results suggest that caregiver predictability within a particular sensory domain is more relevant than general caregiver predictability in shaping subsequent learning.

## 4 | Discussion

We tested the hypothesis that differences in the predictability of infants' early experiences shape the neurodevelopment of core learning and memory systems while they are highly malleable. Specifically, we examined predictability during dyadic caregiver–infant interactions and neural evidence of statistical learning months later in an under-studied African context. We found that the predictability of caregivers' sensory behaviors (here, following auditory signals) was associated with how infants' brains responded to novel, predictable statistical information in the auditory domain approximately five months later. The effect of caregiver predictability on later learning was most relevant in the matching sensory modality, providing support for the hypothesis that developmental trajectories in statistical learning are closely tied to relevant experience. We elaborate on each of these findings below.

First, we replicated past results suggesting that caregivers show a great deal of variability in how predictable they are (Aran et al. 2024; Davis et al. 2017, 2019; Davis and Glynn 2024; Demaestri et al. 2022; Holmberg et al. 2022; Klein and Feldman 2007; Ugarte and Hastings 2023; Vegetabile et al. 2019; Young, Frankenhuis, and Ellis 2020), both overall and following particular behaviors (here, vocalizing). Past work examining caregiver predictability in our longitudinal sample has also reported correlations between overall and behavior-specific entropy (Forest et al. 2024). Thus, rather than providing highly predictable signals in some aspects of behavior and highly unpredictable information in others, caregivers are relatively consistent in how much structure they provide their infant. We refer readers to Forest et al. (2024), for a more comprehensive description of caregiver predictability across cultural contexts in this African cohort, but note that for the purposes of this paper there was sufficient divergence in these metrics to examine the effect of each on later auditory statistical learning.

As such, we tested whether infants showed neural evidence of sensitivity to statistical structure by recording their EEG responses to predictable and unpredictable information during an auditory statistical learning task. Past research using the paradigm employed here has shown that in North American 2-year-olds, N1 latency and P2 amplitude are sensitive to whether a sound is predictable (Pierce, Carmody Tague, and Nelson 2021). In our data, N1 latency was not statistically related to tone predictability. This may be because this metric, which has been

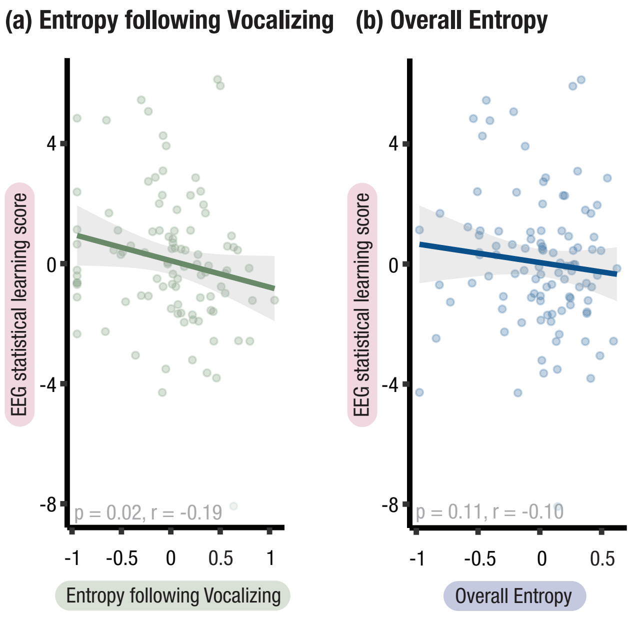

**FIGURE 5** | (a) Entropy following vocalizing (*x*-axis; values are mean centered) predicts EEG statistical learning scores (*y*-axis, the difference between P2 amplitude to predictable—unpredictable tones in the second half of learning). *p* value reflects the significant main effect of caregiver entropy following vocalizing on EEG statistical learning score from linear models reported in the Results section, simple Pearson's correlation between caregiver entropy following vocalizing and EEG statistical learning score is also noted for convenience. (b) Overall entropy (*x*-axis; values are mean centered) was not significantly related to EEG statistical learning scores (*y*-axis). In both panels, dots represent individual caregivers' entropy. Lines represent linear model fit of entropy as a function EEG learning score, shading indicates 95% confidence intervals around the model fit.

interpreted to signify early discrimination of stimulus categories or the processing of a stimulus' sensory features (Coull 1998; Heinks-Maldonado et al. 2005; Jeste et al. 2015; Soares et al. 2020), does not emerge as relevant to statistical learning until after the first postnatal year. This interpretation is consistent with work showing that although this component emerges during statistical learning in toddlers (Jeste et al. 2015; Pierce, Carmody Tague, and Nelson 2021) and children (Jeste et al. 2015; Soares et al. 2022), it changes more dramatically as a function of learning in adults than children (Soares et al. 2022).

In contrast, the amplitude of the P2 did differ as a function of the predictability of auditory information. Specifically, we observed a three-way interaction between tone predictability, half of the learning phase, and continuous age (in months), such that in the second half of learning, P2 amplitude differed by whether a tone was predictable in older infants. On the surface, this result is similar to past research, which has shown higher P2 amplitude to predictable versus unpredictable tones. However, we did not expect to observe age differences in this effect. Although this result may indicate that the younger infants cannot learn the statistical structure in the stream of tones, this seems unlikely given evidence that even neonates demonstrate statistical learning (e.g., Fló et al. 2022; Kudo et al. 2011; Teinonen et al. 2009). Alternatively, the learning rate of younger and older infants may differ as others have suggested (e.g., Forest, Schlichting, et al. 2023; Gomez 2016), such that younger infants learn more slowly than older ones. That is, the younger infants here may not have been provided with enough opportunity to learn the structure, but could do so with a longer exposure.

Given the P2 amplitude showed the most evidence of learning-related change in our sample, we used this metric to explore our central question of whether caregiver predictability would shape infants' subsequent statistical learning. Specifically, our "EEG statistical learning score" reflected infants' P2 responses to predictable versus unpredictable tones in the second half of the learning task. Caregiver predictability following vocalizing significantly predicted infant statistical learning in this auditory paradigm. That is, infants who had *more* predictable caregivers in the first few postnatal months showed more of a difference in P2 amplitude for predictable relative to unpredictable tones several months later. This finding is consistent with the idea that infants who have more predictable caregiver input have had more practice learning from highly predictable statistics, and thus show better learning during our task. These results thus provide one culturally agnostic mechanism by which caregivers shape their infant's learning.

Interestingly, we found that caregiver predictability following vocalizing predicted later statistical learning while overall caregiver predictability did not, suggesting subtle differences in how caregivers structure their behavior across sensory domains matters for infants' emerging learning abilities. This finding adds to a body of research aimed at understanding how statistical learning develops across modalities. In particular, while adult statistical learning shows stability and consistency within one sensory modality, performance is not correlated across modalities (Siegelman and Frost 2015). This suggests relative domain specificity (Siegelman et al. 2017), and hints that nuanced differences in prior experience across domains might shape unique learning trajectories. In that vein, some evidence suggests that auditory, linguistic statistical learning develops earlier than visual statistical learning, or nonlinguistic auditory statistical learning (Raviv and Arnon 2018), potentially because children receive a great deal of early, socially relevant (Ferguson and Lew-Williams 2016) experience with linguistic information. Our results are consistent with this idea, as they suggest individual differences in statistical learning are best predicted by experience following sensory behaviors in the relevant domain.

Fundamentally, our results also link extensive literatures highlighting the importance of early caregiving for later developmental outcomes with an emerging understanding of the exact ways in which the structure of caregiver–child interactions shapes learning. These relationships are crucial to understand, both for their broad applicability and their mechanistic insight. In regard to broad applicability, caregiver behavior is measurable across species and thus these approaches allow for linking advances in animal-models to human development (see Birnie and Baram 2022; Davis and Glynn 2024). As the behaviors coded to understand caregiver predictability are purely sensory, this approach also ensures the signal measured is culturally agnostic, and implies caregiver predictability is key to understanding how early experiences shape ongoing development across cultural contexts. While local variation in sensory signals, like the particular language spoken, may shape the exact dynamics of such learning there is no reason to suspect the African data presented here should be treated any differently than data collected in a Western context. This approach (and our sample) thus help to answer calls to broaden the scope of scientific research and theorizing beyond communities in the global North (Nketia, Amso, and Brito 2021).

On the mechanistic side, it has long been understood that children's learning is improved via scaffolding (Vygotsky 1978), but increasing evidence shows that caregivers and children *work together* to structure naturalistic, dyadic interactions in ways that are most useful for the child's learning (Franchak, Kretch, and Adolph 2018; Karmazyn-Raz and Smith 2023; Sameroff 2009). Most likely, rather than simply *expose* infants to predictable information, caregivers provide socially reinforced (Tummeltshammer, Feldman, and Amso 2019; Werchan and Amso 2021) opportunities to learn about environmental statistics, and promote attention on the part of their infants in rich, multimodal learning contexts (Lee and Lew-Williams 2023; Schroer and Yu 2022, 2023; Suarez-Rivera, Smith, and Yu 2019), thereby motivating the development of more specific learning mechanisms. This framework also suggests an alternative explanation of our results—given that our metric of caregiver predictability indexes how predictable caregivers are *following* vocalizing, rather than the predictability within the vocal signal itself as is more typical in statistical learning studies, one possibility is that caregiver vocalizing serves to capture infant attention and promote learning of what follows reliably, potentially by facilitating infants' active engagement. As other caregiver behaviors which might similarly capture attention, like touching the infant, did not predict later learning (see Supplementary Material) this seems to be most specific to vocalizing, or potentially multimodal combinations of parental behaviors which have been highlighted as key for early learning in other work (e.g., Schroer and Yu 2022, among others). Our results thus add to these converging lines of research which all emphasize just how fundamental early interactions with a caregiver are for setting-up long-term learning outcomes.

This study has a few limitations. First, we were focused on understanding how the brain responded to predictable information during a window of elevated plasticity for learning, rather than behavioral correlates of this process (Gee and Cohodes 2021; McLaughlin and Gabard-Durnam 2022; Ugarte and Hastings 2023). While we measured infants' interactions with a primary caregiver, infants who grow up in homes with shared caregiving responsibilities may spend less time with any particular caregiver than those who are cared for primarily by one person. It is also possible that within one caregiver–infant dyad, the predictability of caregiver behavior changes with the time of day, number of children present, or infant's age. Thus, future work will need to explore the stability of these differences in early experience, and their consequences for behavioral measures of statistical learning. And, given that we measured predictability following certain caregiver behaviors rather than the predictability within one sensory domain, future work might aim to understand how differences in the predictability and frequency of the auditory input itself work together to optimally shape later learning. Further research is also required to determine whether these effects persist beyond infancy as long-term individual differences, or whether caregiver predictability later in life, when learning and memory systems are less malleable demonstrates the same effects. Despite these limitations, our study provides mechanistic insights into how early experiences shape cognitive development around the world, by demonstrating that the ongoing development of neural processes which are crucial for learning in infancy and beyond are shaped in nuanced ways by infants' everyday caregiving experiences.

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## Conflicts of Interest

The authors declare no conflicts of interest.

## Data Availability Statement

Data may be shared following publication, via reasonable request to the authors.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section.