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Does Auditory Deprivation Impairs Statistical Learning in the Auditory Modality?

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Abstract.

Early sensory deprivation allows assessing the extent of reorganisation of cognitive functions, well beyond sensory processing. As such, it is a good model to explore the links between sensory experience and cognitive functions. One of these functions, statistical learning – the ability to extract and use regularities present in the environment – is suspected to be impaired in prelingually deaf children with a cochlear implant. However, empirical evidence supporting this claim is very scarce and studies have reported contradictory results. This might be because previous studies have tested statistical learning only in the visual modality and did not make clear distinctions between multiple types of statistical regularities. To overcome these problems, we designed a modified serial reaction time task where cochlear implanted children and normal hearing children had to react to auditory sequences that embed multiple statistical regularities, namely transition probabilities of 0th, 1st or 2nd order. We compared the reaction times of the children with the output of a simple computational model that learns transition probabilities. First, 6-12 years old children were able to learn 0th and 1st order transition probabilities but not 2nd order ones. Second, there were no differences between cochlear implanted children and their normal hearing peers. **These results indicate that auditory statistical learning is preserved in congenitally deaf children with cochlear implants. This suggests in turn that early auditory deprivation might not be crucially detrimental for the normal development of statistical learning.**

Keywords : cochlear implants, auditory deprivation, statistical learning, transition probability, serial reaction time, modelling

Introduction.

Auditory deprivation early in development induces a vast reorganisation of cortical functions (Bavelier & Neville, 2002; Bavelier et al., 2006; Kral et al., 2016). Because of the complex interdependencies between cortical functions and developmental windows, this may result not only in perceptual but also in cognitive deficits. Indeed, early deafness is associated with deficits beyond the mere processing of acoustic signals, such as problem solving (Luckner & McNeill, 1994), concept formation (Castellanos et al., 2015) or executive functions (Beer et al., 2014; Figueras et al., 2008; Kronenberger et al., 2013, 2014; Remine et al., 2008). In this paper, we focus on deficits in statistical learning, the ability to extract and use statistical regularities present in the environment, because it is a general cognitive ability that has been suggested to be impaired by early auditory deprivation (Conway et al., 2011).

Early deafness is associated with a poor ability to process temporal or serial order information in different modalities: the ability to detect visual targets in visual sequences (Horn et al., 2005), to reproduce or complete visual sequences (Greppe et al., 2019; Knutson et al., 1991; Myklebust & Bratten, 1953; Todman & Seedhouse, 1994), to reproduce tactile sequences (Bharadwaj et al., 2012), to perceive and reproduce complex auditory rhythms (Hidalgo et al., 2020; Rileigh & Odom, 1972), to reproduce complex motor sequences (Schlumberger et al., 2004), and to anticipate speak turns (Hidalgo et al., 2017, 2019). Early empirical observations have led to the formulation of the “auditory scaffolding hypothesis” (Conway et al., 2009): early sound exposure would provide a necessary experience in bootstrapping the development of general cognitive abilities, and, in particular, the tracking of sequential patterns in the environment. Consequently, a lack of auditory input in infancy might impair the normal developmental trajectories of the “general cognitive abilities related to representing temporal or sequential patterns” (Conway et al., 2009). Statistical learning may therefore be one important contributing factor underpinning the delayed language development observed in cochlear implanted children (Deocampo et al., 2018; Houston et al., 2012) and the important variability in the language outcomes after implantation (Markman et al., 2011; Niparko et al., 2010; Tomblin et al., 2007). Further, the importance of statistical learning abilities in critical periods for language acquisition (Werker & Hensch, 2015) has been subject to debate. In particular, perceptual narrowing, the rapid attunement of the perceptual system to specific sensory input, engenders a decline of non-native speech while improving native language speech perception. On one hand, statistical learning is believed to be the main mechanism by which infants slowly wither non-native speech perception (Kuhl et al., 2008). On the other hand, prior knowledge impacts statistical learning performance by shaping expectations on occurrence and co-occurrence of auditory and visual items (Siegelman et al., 2018). It is thus unclear whether early auditory deprivation will impact statistical learning abilities, especially with non-speech stimuli.

The seminal study supporting the auditory scaffolding hypothesis (Conway et al., 2011) used a visual sequence reproduction task, with sequences in the test phase being generated or not by the same “grammar” as the sequences in the learning phase. Cochlear implanted children did not benefit from the grammaticality of the visual sequences in the test phase, contrary to normal hearing children, suggesting that they did not extract the statistical regularity in the learning phase. However, a direct replication of this study have failed to demonstrate a difference between cochlear implanted and normal hearing children (Hall et

al., 2018) and studies using a similar visual sequence reproduction task have shown mixed results (Bharadwaj & Mehta, 2016; Grempe et al., 2019; Torkildsen et al., 2018). Furthermore, implicit learning paradigms, such as the serial reaction time task (Nissen & Bullemer, 1987), did not demonstrate a deficit of visual statistical learning in cochlear implanted children (Hall et al., 2018; Klein et al., 2019).

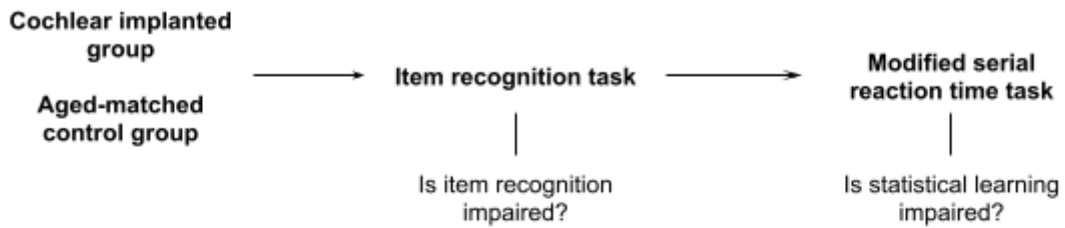
The auditory scaffolding hypothesis makes two strong assumptions. Firstly, statistical learning is a domain general, modality independent ability. This is why studies have used non-auditory stimuli, *i.e.* mostly visual stimuli. However, this assumption can be questioned. Indeed, several studies investigated whether overall performance in statistical learning tasks is similar across different types of stimuli (Conway & Christiansen, 2006; Johansson, 2009), whether there is transfer of learning across modalities (Conway & Christiansen, 2005; Emberson et al., 2011; Redington & Chater, 1996; Tunney & Altmann, 1999), whether there is statistical learning of coherent patterns across modalities (Mitchel & Weiss, 2011) or whether individual capacities in a variety of statistical learning tasks are correlated (Siegelman & Frost, 2015). Contrary to the most intuitive predictions, the pattern of results across these studies claims rather for modality specificity and sometimes even stimulus specificity (see (Frost et al., 2015) for an extensive discussion). The second assumption is that statistical learning is a homogeneous ability, with no distinction between different types of regularities. Indeed, the previously cited studies have used without clear distinction triplets of items, 1st order transition probabilities and sequences of repeating patterns. However, this second assumption can also be questioned (Daikoku, 2018). The notion of “transition probability”, a mathematical tool to capture time dependencies, is helpful to identify different types of regularities. A 1st order transition probability corresponds to the probability of observing an “A”, given the fact that a “B” was observed just before, $P(A|B)$. Similarly, a 2nd order transition probability corresponds to the probability of observing an “A” given the fact that the duplet “BA” was observed just before, $P(A|BA)$. By generalization, a 0th order transition probability corresponds to the probability of observing an “A” without taking into account the immediate context, $P(A)$. Transition probabilities of high order can capture more complex sequences, but are more difficult to track because the number of probabilities grows exponentially with the order. Recent works have shown that the brain is efficiently computing multiple order of transition probabilities at different latencies (Maheu et al., 2019; Pesnot Lerousseau & Schon, 2020).

In the present work we used auditory stimuli in order to test statistical learning in cochlear implanted children without assuming that statistical learning is a domain general ability. We took advantage of the fact that today, the majority of young children who experience severe to profound sensorineural hearing loss are treated with cochlear implantation (Maggs et al., 2017): after an early period of sensory loss, these children have regained access to auditory inputs. We adopted a modified serial reaction time task and designed auditory sequences to probe three types of regularities, namely three order of transition probabilities: 0th, 1st and 2nd order transition probabilities (see Figure 1). Importantly, we relied on modelling tools (Pesnot Lerousseau & Schon, 2020) to define the degree of surprise of each sequence, depending on the order of transition probabilities of interest (see Methods). Here, “surprise” has a precise mathematical definition, but it corresponds to the intuitive notion of surprise: a “surprising” sequence is a sequence that is hard to predict/learn whereas an “unsurprising” sequence is easy to predict/learn. The task allowed collecting reaction times in cochlear implanted children and normal hearing children.

This allowed tracking the changes in reaction times during the task and thus capture continuous learning. We made the assumption that if children are learning transition probabilities of a given order, their reaction times will decrease for “unsurprising” sequence and increase for “surprising” sequence (“surprising” and “unsurprising” depends on the given order of transition probabilities). We made the hypothesis that if auditory deprivation induces a loss in auditory statistical learning abilities, then we should observe a reduction of the reaction time difference between “unsurprising” and “surprising” sequences in cochlear implanted children compared to their normal hearing peers. Furthermore, if early deafness selectively impairs the ability to detect some regularities but not others, we should observe a group difference for one specific order of transition probabilities and not others.

If the auditory scaffolding hypothesis is true and given the seminal study of (Conway et al., 2011) — showing that children with hearing loss have a statistical learning deficit at the 1st order transition probabilities —, we expect to observe a difference in the learning of 1st order transition probabilities between groups. However, Conway has recently suggested the existence of two subsystems of statistical learning, one for simple statistics (0th order transition probabilities for example) and one for more complex statistics (2nd order transition probabilities for example) (Conway, 2020). The first system would be innate and relatively independent of sensory input while the second would mature during the development and would rely on sensory inputs. This would make the second system particularly vulnerable in children with early auditory deprivation. We therefore expect no difference between groups for the 0th order and a difference for the 1st and 2nd order transition probabilities.

A Paradigm



B Modified serial reaction time task

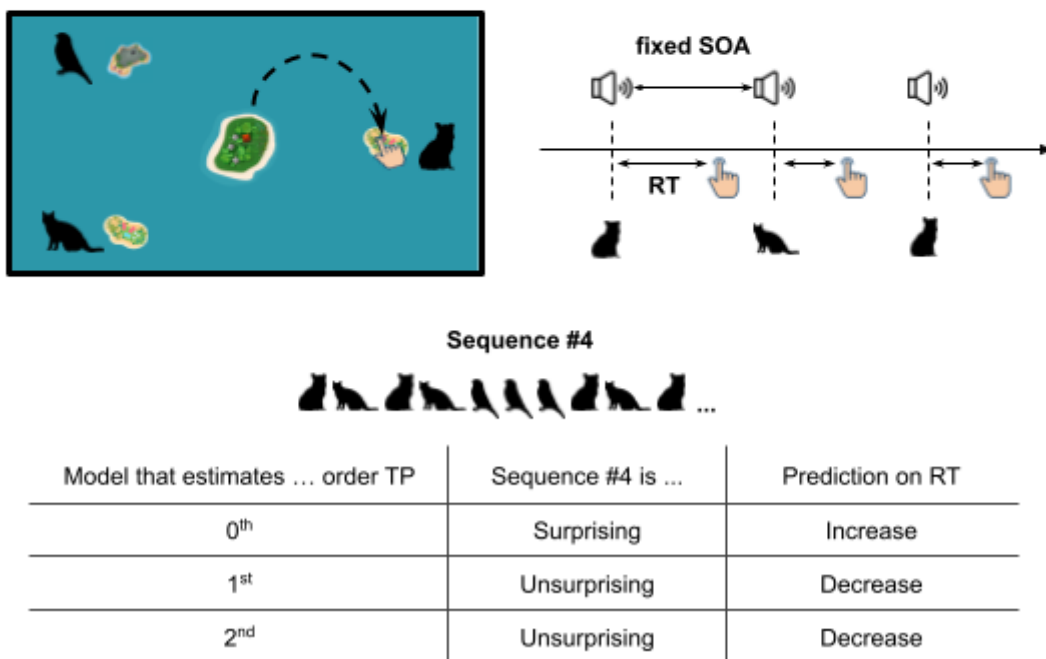


Figure 1. Overview of the study. A. Paradigm. Two tasks were presented to cochlear implanted children and age-matched normal hearing children. The first task was an auditory item recognition task (animal calls of dog, cat or bird), designed to ensure that items were easily recognizable and to measure inter-individual differences in the auditory recognition process speed. The second task was a modified serial reaction time task, designed to measure auditory statistical learning. **B. Modified reaction time task. (top left)** Children had to press on the correct “island” (*i.e.*, the island where the animal lives) every time a sound was presented (dog, cat or bird). The sounds were presented at a fixed stimulus onset asynchrony. **(top right)** Reaction times were recorded for each sound. **(bottom)** The sounds were arranged in sequences that embed 0th order, 1st order and 2nd order transition probabilities (a portion of the sequence #4 is shown). Sequences were classified as “surprising” or “unsurprising” given a model that learns 0th order, 1st order or 2nd order transition probabilities. The reaction times were expected to increase when the sequence was “surprising” and decrease when it was “unsurprising”, conditioned on a particular order of transition probability. SOA: stimulus onset asynchrony. RT: reaction time. TP: transition probabilities.

Material and methods.

Participants.

27 cochlear implanted children (mean age 10.3 y., standard deviation \pm 1.5, range [7, 12]) were recruited at the Institut Provençal du Suivi des Implantés Cochléaires (IPSIC) and in the paediatric ENT of la Timone in Marseille (see Table 1). 28 age-matched normal hearing children (mean age 9.7 y., standard deviation \pm 1.5, range [6, 12], difference between groups β = -0.6 ± 0.5 y., p = 0.17) were recruited from two elementary schools in Marseille. Normal hearing children were french native speakers with no known visual, speech, cognitive or hearing disorder. 7 participants (5 cochlear implanted children, 2 normal hearing children, misunderstanding of the task, technical problems and tedium) did not complete the entire experiment and were therefore removed from the analyses (difference between groups in dropping rate, X^2 = 1.601, p = 0.21). This study was carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki. This experiment has been approved by the ethics committee Sud Méditerranée I (n°ID RCB: 2015-A01490-49). Parents gave informed consent on behalf of their children, who were compensated for their participation with a gift.

ID	Age	Sex	MHL right ear (500-1000-2000-4000 Hz)	MHL left ear (500-1000-2000-4000 Hz)	Age of first hearing aid	Age at deafness onset	Age of right CI	Age of left CI	Kept in the analysis
1	105	M	90	90	20	congenital	57	23	✓
2	102	M	100	70	12	NA	21	-	✓
3	132	M	110-110-120-120	85-100-100-120	12	congenital	-	69	✓
4	112	F	100-105-110-120	100-105-110-120	20	congenital	20	-	✓
5	118	M	80-95-120-120	20-65-110-102	58	congenital	90	-	✓
6	112	F	110	110	7	congenital	15	107	✗
7	136	M	80	90	12	congenital	139	-	✓
8	113	F	100-120-120-120	100-110-120-120	7	NA	19	51	✓
9	84	F	120-120-120-120	120-120-120-120	12	congenital	52	30	✗
10	90	F	80-100-80-80	90-90-90-100	10	congenital	75	-	✗
11	138	M	110	110	24	congenital	27	-	✗
12	150	M	80-100-120-110	70-95-120-120	36	congenital	39	-	✓
13	147	F	80-75-70-65	120-120-120-120	35	congenital	-	71	✓
14	113	F	110-120-120-120	110-110-120-120	21	NA	67	24	✓
15	126	F	100	100	20	NA	42	120	✓
16	138	F	100	100	21	congenital	26	95	✓
17	124	F	120-120-120-120	120-120-120-120	24	congenital	39	96	✓
18	87	F	65-70-75-80	60-70-75-70	65	NA	82	75	✗
19	94	F	65-120-120-120	55-110-115-120	NA	congenital	-	10	✓
20	116	M	75-115-120-120	85-105-115-115	5	congenital	34	-	✓
21	142	F	115-120-120-120	90-120-120-120	39	22	-	47	✓
22	104	F	115-120-120-120	90-115-120-120	6	congenital	36	13	✓
23	139	M	65-70-65-55	110-120-120-120	20	18	-	21	✓
24	141	F	95-120-120-120	105-120-120-120	NA	congenital	24	87	✓
25	131	M	80-100-115-120	95-115-120-120	8	congenital	15	-	✓
26	146	M	120-120-120-120	120-120-120-120	NA	congenital	15	84	✓
27	128	M	80-85-100-85	75-85-100-85	60	congenital	60	60	✓

Table 1. Demographic data of the cochlear implanted children group. Ages are indicated in months. M: male. F: female. MHL: Mean hearing loss before implantation. Audiogram: single numbers are average auditory loss over frequencies. NA: unknown.

Stimuli.

3 animal sounds were used in the experiment: a bird whistle, a cat meow and a dog bark. All sounds had the same loudness and duration. Each sound was 400 ms long, with a cosine ramp on and off of 10 ms. Using these sounds, sequences of items (A, B and C) of different length and order were built (see below). The mapping between the items and the sounds was randomized across participants.

General procedure.

Participants were seated in a calm room in front of a tablet and a loudspeaker. Participants were told that they were zookeepers, whose goal was to catch animals (birds, cats and dogs) hidden on different islands. In order to catch the animals, they were told to listen carefully, because no visual cues were present (“the animals are hidden”). Catching an animal was composed of two actions: first, tap on the island where the animal lives (“capture the animal”) and second, tap on the central island (“release the animal in the zoo”). The “animal” islands were equidistant from each other, and equidistant from the central island. This ensured that the participants had to travel the same distance with their finger at each trial. Participants received feedback at the end of each sequence, indicating how many animals they had captured. Every 3 sequences, they had the opportunity to trade the captured animals against images of exotic animals, to enrich their zoo.

Participants were familiarized with the task and the stimuli in 3 small practice sequences of 10 items. In the first sequence, visual cues were present to help the participants. In the second sequence, visual cues progressively disappeared, to orient the child toward an auditory strategy. In the third sequence, no visual cues were present, as in the rest of the experiment.

Participants then did the item recognition task and the modified serial reaction time task. The order of the tasks was fixed across participants.

The sounds were presented binaurally to participants at an adjusted comfortable level (~70 dB) using a loudspeaker. Stimuli presentation and data collection was controlled with Epyriment for Android (Krause & Lindemann, 2014) and Python custom scripts, running on a Samsung Galaxy Tab A tablet with Android 9.0.

The entire experiment was ~30 minutes long.

Item recognition task.

1 sequence of 50 items was presented in the item recognition task, at a fixed, long, stimulus onset asynchrony of 2300 ms. The order of the items was random, with a roughly equal amount of A, B and C.

Differences in the reaction time distribution could potentially introduce a bias in the modified serial reaction time task, with differences in the item recognition process being confounded with differences in statistical learning abilities. In order to account for this potential bias, we adjusted the stimulus onset asynchrony in the modified serial reaction time task for each participant. The asynchrony was set to $\mu + 2\sigma$, where μ and σ are the mean and standard deviation of the reaction times in the item recognition task. Assuming a Gaussian

distribution of the reaction times, this threshold is supposed to keep ~98% of the responses if the child does not change its speed, and thus it equalizes task difficulty across individuals.

Modified serial reaction time task.

27 sequences of 17 to 25 items were presented in the modified serial reaction time task. The SOA was adapted to each participant. This was done to equate task difficulty across participants and to control for potential group differences in the perceptual/cognitive processes involved in the mere recognition of the sounds. It was based on the distribution of their reaction times in the item recognition task, and defined as $\mu + 2\sigma$, where μ and σ are the mean and standard deviation of the reaction times in the item recognition task (SOA in the cochlear implanted children group 1711 ± 302 ms, range [1202, 2297], SOA in the normal hearing children group 1521 ± 204 ms, range [1228, 2060], difference between groups $\beta = -190 \pm 75$ ms, $p < 0.05$, $\Delta\text{BIC} = 2.4$, $\text{BF}_{\text{BIC}} = 3$).

Classical serial reaction time tasks comprise two types of sequences (Nissen & Bullemer, 1987): “regular” sequences, that are composed of a repeating pattern, and “random” sequences. Learning is usually measured as the differences in reaction time or accuracy between “regular” and “random” sequences. Here, we generalized the idea to study multiple regularities – here, multiple orders of transition probabilities – at the same time. We relied on modelling tools and information theory (Shannon, 1948) to classify the sequences as “unsurprising/surprising” for each order of transition probabilities that we were interested in (0th, 1st and 2nd). Indeed, there is no a priori way of classifying the trials into “regular” or “random”: a sequence can appear “random” for transition probabilities of low order but “regular” for transition probabilities of higher order. Take the sequence $S_1 = \text{ABABABABABAB}...$: at the 0th order, S_1 is described by $P(A) = P(B) = 0.5$. This means weak expectations on the forthcoming item, hence 0th order transition probabilities encode no information about S_1 . However, at the 1st order, S_1 is described by $P(A|B) = P(B|A) = 1$ and $P(A|A) = P(B|B) = 0$. This gives strong expectation on the forthcoming item, hence 1st order transition probabilities capture a lot of information about S_1 . Similarly, take the sequence $S_2 = \text{AABBAABBAABB}...$: at the 1st order, S_2 is described by $P(A|A) = P(A|B) = P(B|A) = P(B|B) = 0.5$ (it is equally likely to observe an A or a B after an A). This means weak expectations on the forthcoming item, hence 1st order transition probabilities encode no information about S_2 . At the 0th order, S_2 is described by $P(A) = P(B) = 0.5$ (it is equally likely to observe an A or a B), hence 0th order transition probabilities encode no information about S_2 . However, at the 2nd order, S_2 is described by $P(A|BB) = P(A|BA) = P(B|AB) = P(B|AA) = 1$ and $P(A|AA) = P(A|AB) = P(B|BA) = P(B|BB) = 0$. This gives strong expectation on the forthcoming item, hence 2nd order transition probabilities capture a lot of information about S_2 .

Formally, the surprise was defined as $-\log_2 P(x_i)$ where $P(x_i)$ is the posterior predictive probability $P(s_t = x_i | s_{0:t-1}, M_k)$ on the presented item s_t , and M_k is an agent that is estimating transition probabilities of order K (see Model). We then averaged the surprise of each agent M_k in each sequence. Using a median-split on the average surprise of each sequence, we classified the sequences in two sets for each agent M_k : “unsurprising” ($\neg S$) and “surprising” (S) sequences. We designed the sequences so that the correlation between the surprise of M_0 , M_1 and M_2 was low (all spearman’s $\rho < 0.2$), meaning the “surprising/unsurprising” sequences were not the same for each agent. **The range of transition probabilities estimated by the agents spanned from ~0.01 to ~0.99 for each agent and each type of sequence.** More specifically, the following sequences were presented:

- sequences $S_0 - S_1 - S_2$ (surprising for M_0 , M_1 and M_2)
- sequences $S_0 - S_1 - \neg S_2$ (surprising for M_0 , M_1 but not for M_2)

- sequences $S_0 - \neg S_1 - \neg S_2$
- sequences $S_0 - \neg S_1 - S_2$
- sequences $\neg S_0 - S_1 - \neg S_2$
- sequences $\neg S_0 - S_1 - S_2$
- sequences $\neg S_0 - \neg S_1 - S_2$
- sequences $\neg S_0 - \neg S_1 - \neg S_2$

We measured whether the reaction time of the children were modulated accordingly. The rationale is that if the child is estimating transition probabilities of K^{th} order, then his reaction times will resemble the surprise of an agent that is estimating transition probabilities of K^{th} order: his/her reaction times will be low in “unsurprising” sequences and high in “surprising” sequences.

Model.

The model was based on a previously published model IDyOM (Harrison et al., 2020; Pearce & Wiggins, 2012), an n-gram model (Chen & Goodman, 1999) that we reframed and extended in a Bayesian framework. The goal of the model is to infer the probability of each item given the preceding context. Formally, the model is exposed to a sequence of T items $s_{0:T-1}$ of vocabulary Ω of size 3. The context is given by the last K items of the sequence. As a Bayesian ideal observer, she uses Bayes rule to update her belief:

$$P(\theta|s_{0:T-1}) \propto P(s_{0:T-1}|\theta)P(\theta)$$

The transition probability matrix θ describes how likely each element is, given its preceding context. This learning process consists in estimating θ from the sequence $s_{0:T-1}$. This computation is based on the matrix N that contains the number of occurrences of each $(K+1)$ -uplets of items in the sequence $s_{0:T-1}$. The matrix N is a matrix of size 3×3^K where each row designates a particular item and each column a particular K -uplets of items. N_{ij} designates the number of occurrences of the $(K+1)$ -uplet corresponding to the cell (i, j) of the matrix N (the j^{th} K -uplet followed by the i^{th} item). The predictive posterior probability of the model for each item is, rather naturally:

$$P(s_T = x_i | s_{0:T-1}) = P(s_T = x_i | s_{T-K:T-1}) = \frac{N_{ij} + 1}{\sum_{v=1}^3 N_{vj} + 1}$$

where $P(s_t = x_i | s_{0:T-1})$ is the probability of the element $x_i \in \Omega$. It corresponds to the ratio of two scalars:

- $N_{ij}+1$: the number of times that the context (j^{th} column), *i.e.* the last K elements of the sequence, *i.e.* $s_{T-K:T-1}$, and the element x_i (i^{th} row) have been observed together plus one,
- $\sum_v (N_{vj}+1)$: the number of times that the context $s_{T-K:T-1}$ (the sum of the j^{th} column) has been observed plus 3.

The size of the context, K , is the key parameter of the model. It corresponds directly with the notion of order of a Markov chain. If $K = 1$, the estimated statistics is of the form $P(s_t = x_i | s_{t-1})$. Similarly, if $K = 2$, the estimated statistics is of the form $P(s_t = x_i | s_{t-2} s_{t-1})$. By generalization, if $K = 0$, the estimated statistics is of the form $P(s_t = x_i)$. Note that Markov transition probabilities of higher order can track more complex sequences than probabilities

of lower order. Note further that the number of transition probabilities to be tracked grows exponentially with the parameter K . This makes M_2 predictions (3×3^2 probabilities to track) much harder to make than M_1 predictions (3×3^1 probabilities to track).

Statistical analyses.

Statistical analyses were done using R and the package lme4 (Bates et al., 2014). In the item recognition task, the effect of the group was estimated using mixed-effect models. Fixed effects were Intercept and Group (normal hearing : 0, hearing impaired : 1). Random effects were restricted to a random intercept for each participant. Accuracy was modelled using a logistic regression on the probability of being correct (incorrect : 0, correct : 1). Reaction times and reaction time standard deviation were modelled using linear regressions.

In the modified reaction time task, the effect of the group, of the surprise and their interaction were also estimated using mixed-effect models. Fixed effects were Intercept, Group (normal hearing : 0, hearing impaired : 1), Surprise (“unsurprising” : 0, “surprising” : 1) and their interaction. Random effects were restricted to a random intercept for each participant. Reaction times were modelled using linear regressions. As we were interested in intra-individual variability, we z-scored the reaction times of each participant prior to the analysis.

For all analyses, model complexity was monitored using the Bayesian Information Criterion and Akaike Information Criterion, two standard measures to arbitrate between complexity and accuracy. Reported p-values are Satterthwaite approximations. We also report the Bayes factor, a measure that quantifies the relative support of the alternative hypothesis over the null hypothesis. For example, when comparing the accuracy of two groups, $BF_{BIC} = 0.07$ means that the hypothesis “there is a difference in accuracy between groups” is supported by the data 0.07 times “more” than the hypothesis “there is no difference in accuracy between groups” – or, similarly $1/0.07 = 14$ times “less”. The Bayes Factor associated with a particular fixed effect was approximated using the difference between Bayesian Information Criterion of the model with the effect BIC_1 and the model without the effect BIC_0 and defined as $BF_{BIC} = \exp((BIC_0 - BIC_1)/2)$.

Results.

Cochlear implanted children show a greater reaction time variability than normal hearing children at recognizing sounds.

We first ensured that all children were able to recognize the sound items before analyzing the results of the modified serial reaction time task. Indeed, a trivial prerequisite for statistical learning is the ability to recognize the items that are presented. For that, the children completed an item recognition task before the main experiment (see Methods). In this task, they had to recognize the sound items, and click on the corresponding island on the screen, *i.e.* the island where the heard animal lived (see Figure 1A). Items were presented in a randomized order, with a relatively long stimulus onset asynchrony to allow good accuracy (2300 ms). All children were able to do the task, with excellent accuracy (see Figure 2A) for both normal hearing children ($99.1 \pm 1.5 \%$) and cochlear implanted children ($98.1 \pm 2.6 \%$), and no difference between groups ($\beta = -0.73 \pm 0.46$, $p = 0.12$, $\Delta\text{BIC} = -5.4$, $\text{BF}_{\text{BIC}} = 0.07$). Average reaction times in correct trials (see Figure 2B) were similar between normal hearing children (1078 ± 104 ms) and cochlear implanted children (1090 ± 141 ms, $\beta = 11.9 \pm 36.1$ ms, $p = 0.74$, $\Delta\text{BIC} = 1.3$, $\text{BF}_{\text{BIC}} = 0.5$). However, the variance of the reaction times in correct trials (see Figure 2C) was higher for cochlear implanted children (310 ± 96 ms) than for normal hearing ones (221 ± 64 ms, $\beta = 89.0 \pm 23.9$, $p < 10^{-3}$, $\Delta\text{BIC} = 8.8$, $\text{BF}_{\text{BIC}} = 80$).

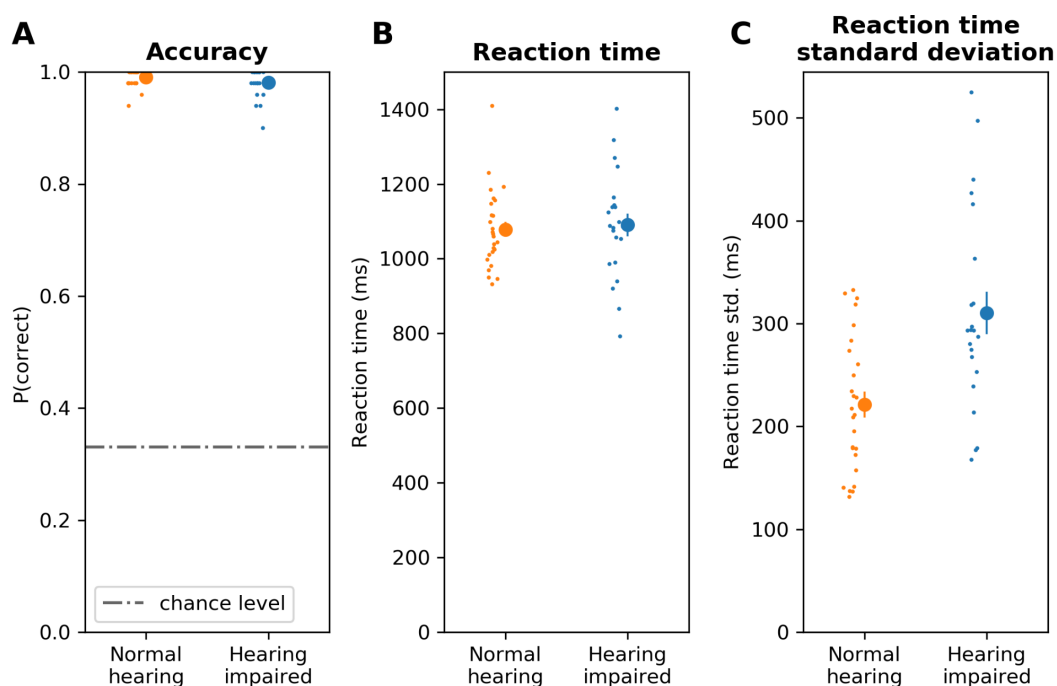


Figure 2. Accuracy and reaction times in the item recognition task. **A.** Accuracy in the auditory item recognition task as a function of the group. Chance level is at 33% (dotted line). There is no difference between groups ($\beta = -0.73 \pm 0.46$, $p = 0.12$, $\Delta\text{BIC} = -5.4$, $\text{BF}_{\text{BIC}} = 0.07$). **B.** Average reaction times in correct trials in the auditory item recognition task as a function of the group. There is no difference between groups ($\beta = 11.9 \pm 36.1$ ms, $p = 0.74$, $\Delta\text{BIC} = 1.3$, $\text{BF}_{\text{BIC}} = 0.5$). **C.** Standard deviation of the reaction times in correct trials in the auditory item recognition task as a function of the group. Cochlear implanted children have a higher reaction time variability than normal hearing children ($\beta = 89.0 \pm 23.9$, $p < 10^{-3}$, $\Delta\text{BIC} = 8.8$, $\text{BF}_{\text{BIC}} = 80$). Large points are the group averages, small points are individual data. Error bars represent the standard error of the mean.

In order to account for this potential bias, we adjusted the stimulus onset asynchrony in the modified serial reaction time task for each participant (see Methods). On average, the subject-specific stimulus onset asynchrony in the modified serial reaction time task was set to 1521 ± 204 ms in the normal hearing group and 1711 ± 302 ms in the cochlear implanted group ($\beta = -190 \pm 75$ ms, $p < 0.05$, $\Delta\text{BIC} = 2.4$, $\text{BF}_{\text{BIC}} = 3$).

Overall, the item recognition task was used as a calibration phase and ensured that (1) items were easily recognizable ($\sim 100\%$ accuracy) and (2) inter-individual differences in the recognition process speed were equalized.

Cochlear implanted children and normal hearing children have similar auditory statistical learning abilities, for multiple orders of transition probabilities.

We then asked whether cochlear implanted children have impaired auditory statistical learning abilities, and so, for multiple orders of transition probabilities. For that, we presented them with the modified serial reaction time task. As we were interested in intra-individual variability, we normalized the reaction times of each participant prior to the analysis. We first classified the sequences in two halves according to the surprise computed for a model that estimates transition probabilities of 0th order, *i.e.* probabilities of the form “P(A)”, *i.e.* the mere frequency of occurrence (see Figure 3A). On average, participants were faster in the “unsurprising” sequences than in the “surprising” sequences ($\beta = 0.26 \pm 0.018$, $p < 10^{-16}$, $\Delta\text{BIC} = 488.9$, $\text{BF}_{\text{BIC}} = 1 \times 10^{106}$). This was true for normal hearing children (-0.13 ± 0.070 vs 0.14 ± 0.079) as well as cochlear implanted children (-0.12 ± 0.057 vs 0.14 ± 0.066). There was no difference between group ($\beta = 0.0051 \pm 0.016$, $p = 0.76$, $\Delta\text{BIC} = -17.2$, $\text{BF}_{\text{BIC}} = 0.0002$), and no interaction either ($\beta = -0.019 \pm 0.024$, $p = 0.63$, $\Delta\text{BIC} = -15.5$, $\text{BF}_{\text{BIC}} = 0.0004$). Note that we complemented standard parametric tests with Bayes Factors in order to distinguish between an insensitive statistical test (not providing evidence in favour or against the null hypothesis) from a genuine absence of difference between groups (see Methods). A Bayes factor of ≤ 0.33 provides significant evidence in favor of the null hypothesis (Kass & Raftery, 1995). Overall, this analysis suggests that cochlear implanted children were able to extract transition probabilities of 0th order from auditory sequence, similarly to the normal hearing children.

We then ran the same analysis, this time splitting the trials in two halves according to the surprise computed for a model that estimates transition probabilities of 1st order, *i.e.* probabilities of the form “P(A|B)” (see Figure 3B). On average, participants were faster in the “unsurprising” sequences than in the “surprising” sequences ($\beta = 0.19 \pm 0.018$, $p < 10^{-16}$, $\Delta\text{BIC} = 256.7$, $\text{BF}_{\text{BIC}} = 5 \times 10^{55}$). This was true for normal hearing children (-0.096 ± 0.081 vs 0.107 ± 0.088) as well as cochlear implanted children (-0.082 ± 0.071 vs 0.091 ± 0.076). There was no difference between group ($\beta = 0.015 \pm 0.017$, $p = 0.36$, $\Delta\text{BIC} = -17.2$, $\text{BF}_{\text{BIC}} = 0.0002$), and no interaction either ($\beta = -0.030 \pm 0.024$, $p = 0.21$, $\Delta\text{BIC} = -14.2$, $\text{BF}_{\text{BIC}} = 0.0008$). Similar to the 0th order transition probabilities, this result suggests that cochlear implanted children were able to extract 1st order transition probabilities from auditory sequence, similarly to the normal hearing children.

Finally, we splitted the trials in two halves according to the surprise computed for a model that estimates 2nd order transition probabilities, *i.e.* probabilities of the form “P(A|BA)” (see Figure 3C). No difference in average reaction times were observed between

“unsurprising” sequences and “surprising” sequences ($\beta = -0.021 \pm 0.018$, $p = 0.25$, $\Delta\text{BIC} = -13.4$, $\text{BF}_{\text{BIC}} = 0.001$). This was true for normal hearing children (0.024 ± 0.06 vs -0.023 ± 0.057) as well as cochlear implanted children (0.020 ± 0.077 vs 0.091 ± 0.076). There was no difference between group (-0.0026 ± 0.017 , $p = 0.88$, $\Delta\text{BIC} = -17.2$, $\text{BF}_{\text{BIC}} = 0.0002$), and no interaction either ($\beta = 0.0053 \pm 0.025$, $p = 0.83$, $\Delta\text{BIC} = -15.7$, $\text{BF}_{\text{BIC}} = 0.0004$). Contrary to the results for the 0th order and 1st order transition probabilities, this result suggests that cochlear implanted children and normal hearing children were not able to extract 2nd order transition probabilities from auditory sequences.

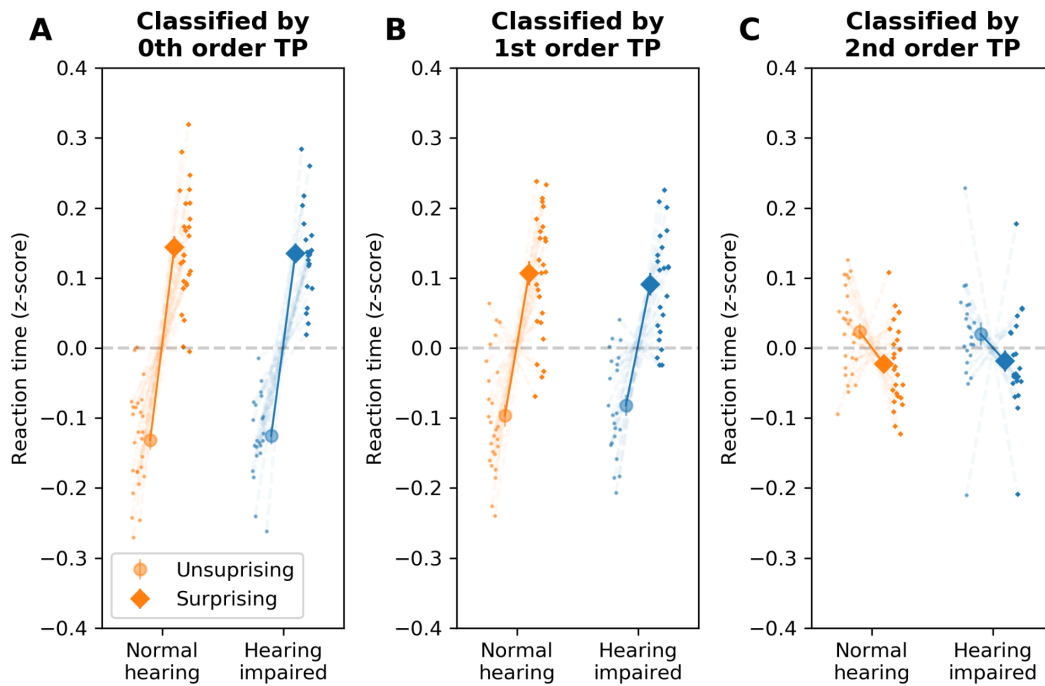


Figure 3. Reaction times in the modified serial reaction time task. **A.** Reaction times were lower for “unsurprising” than “surprising” sequences, as classified by a model that estimates 0th order transition probabilities ($\beta = 0.26 \pm 0.018$, $p < 10^{-16}$, $\Delta\text{BIC} = 488.9$, $\text{BF}_{\text{BIC}} = 1 \times 10^{106}$), with no difference between groups and no interaction. **B.** Reaction times were lower for “unsurprising” than “surprising” sequences, as classified by a model that estimates 1st order transition probabilities ($\beta = 0.19 \pm 0.018$, $p < 10^{-16}$, $\Delta\text{BIC} = 256.7$, $\text{BF}_{\text{BIC}} = 5 \times 10^{55}$), with no difference between groups and no interaction. **C.** Reaction times were similar for “unsurprising” than “surprising” sequences, as classified by a model that estimates 2nd order transition probabilities, with no difference between groups and no interaction. Large points are the group averages, small points are individual data. Error bars represent the standard error of the mean. TP: transition probabilities.

These results are robust, as we found the exact same pattern when analyzing the reaction times without normalization (see Supp. Fig. 1), or normalized by the subject-specific stimulus onset asynchrony (see Fig. Supp. 2). The results were also the same when using the continuous values of the surprise instead of the median-split (see Supplementary Results). Furthermore, we ensured that the difference in stimulus onset asynchrony between groups does not explain the result we obtain in the modified serial reaction time: including the subject-specific stimulus onset asynchrony as a fixed effect did not change the results and did not influence the reaction times (for all models, $p > 0.05$, $\text{BF}_{\text{BIC}} < 0.33$). Including the index of the sequence as a fixed effect to account for fatigue and long-term learning effects did also not change the results and did not influence the reaction times (for all models, $p > 0.05$, $\text{BF}_{\text{BIC}} < 0.33$). Note that such an effect would only capture a “meta-learning” of the task, as the model already describes the continuous learning by constantly updating predictions as a function of the context.

We finally asked whether the effects of the surprise at different orders interact with each other. The interaction between the surprise at the 1st order and the surprise at the 0th order was statistically significant ($\beta = -0.252 \pm 0.025$, $p < 10^{-16}$, $\Delta\text{BIC} = 85.5$, $\text{BF}_{\text{BIC}} = 7 \times 10^{36}$). The negative sign indicates that the effect of the surprise at the 0th order is reduced when the sequence is surprising at the 1st order. This suggests that the two systems indeed interact or at least share common resources. There was no evidence of a difference between groups concerning this interaction, as shown by the non-significant triple interaction ($\beta = 0.005 \pm 0.050$, $p = 0.92$, $\Delta\text{BIC} = -14.3$, $\text{BF}_{\text{BIC}} = 3 \times 10^{-7}$).

Similarly, the interaction between the surprise at the 2nd order and the surprise at the 1st order was statistically significant ($\beta = -0.103 \pm 0.025$, $p < 10^{-5}$, $\Delta\text{BIC} = 1.54$, $\text{BF}_{\text{BIC}} = 2.3$). Again, the effect of the surprise at the 1st order is reduced when the sequence is surprising at the 2nd order. There was no evidence of a difference between groups concerning this interaction, as shown by the non-significant triple interaction ($\beta = -0.007 \pm 0.050$, $p = 0.88$, $\Delta\text{BIC} = -14.3$, $\text{BF}_{\text{BIC}} = 3 \times 10^{-7}$).

Discussion.

We designed a modified serial reaction time task with auditory sequences embedding three types of regularities, in the form of three orders of transition probabilities: 0th, 1st and 2nd order. We made the assumption that the reaction times of the children reflect their ability to learn a given order of transition probabilities: their reaction times should increase in “surprising” sequences and decrease in “unsurprising” sequences. We made the hypothesis that if auditory deprivation induces a loss in auditory statistical learning abilities, we should observe a reduction of the difference of reaction times between “surprising/unsurprising” sequences in hearing impaired children compared to normal hearing children. This difference could be restricted to one or more order of transition probabilities. The results show that both normal hearing children and hearing impaired children between 6 and 12 years are able to learn 0th order and 1st order transition probabilities from auditory sequences, but not 2nd order transition probabilities. Furthermore, we do not reveal any group difference in this modified serial reaction time task. Finally, the results cannot be explained by inter-individual differences in the speed of the recognition processes, as we adjusted the timing of the experiment on an individual basis to equalize this potential bias (subject-specific stimulus onset asynchrony). Overall, our results indicate that auditory statistical learning is preserved in congenitally deaf children with cochlear implants. We discuss these results in regard to the auditory scaffolding hypothesis. We also propose three lines of thoughts on: the developmental trajectory of statistical learning, the group difference in the recognition processes and the link between statistical learning and language in hearing impaired children.

The auditory scaffolding hypothesis (Conway et al., 2009) states that early sound exposure provides a crucial experience for the development of cognitive sequencing abilities, such as statistical learning or motor planning. It makes the assumption that the cognitive sequencing abilities are modality independent/domain general. This implies that a lack of auditory input in infancy may impair general cognitive abilities beyond auditory processing. In this respect, the most elegant way to test the auditory scaffolding hypothesis is to show an impairment not specific to the auditory modality, and therefore to use non-auditory stimuli. Several studies have used visual stimuli on statistical learning tasks in hearing impaired children. However, these studies have shown mixed results (Bharadwaj & Mehta, 2016; Conway et al., 2011; Gremp et al., 2019; Hall et al., 2018; Klein et al., 2019; Torkildsen et al., 2018). Furthermore, the assumption of the modality independence of statistical learning can be questioned (Frost et al., 2015). A more direct prediction of the auditory scaffolding hypothesis is that a lack of auditory input in infancy may impair statistical learning in the auditory modality. Using auditory sequences and a task that involves statistical learning in cochlear implanted children, we show that this is not the case. This implies that early sound exposure is not a necessary condition for the normal development of auditory statistical learning abilities. This result is consistent with studies on the development of language production in cochlear implanted children, that have shown that these children exploit the statistical biases present in the language, as usually observed in normal hearing children (phonotactic probability and neighborhood density, (Guo et al., 2015); lexical frequency, (Faes et al., 2017); and consonant clusters, (Faes & Gillis, 2017)). However, although behavioral results of the hearing impaired children and the normal hearing children look similar, hearing impaired children could achieve “normal” behaviour

through compensatory mechanisms. These mechanisms could be unobservable at the behavioral level but yet present and observable using neural measures. Further research with brain imaging methods is necessary to elucidate this question. Regarding the auditory scaffolding hypothesis, statistical learning is just one of the cognitive sequencing abilities that could be impacted by early auditory deprivation. As stated in the original article (Conway et al., 2009), sound is the privilege modality for processing sequences of events in time, and it is very likely that early sound exposure is necessary for the normal development of multiple cognitive sequencing abilities. Auditory statistical learning might not be one of them, but others remain to be tested, such as chunking, motor planning or problem solving.

The development of implicit learning abilities has been shown to involve two subsystems, namely sequence learning and statistical learning, that do not mature at the same rate (Janacsek et al., 2012; Simor et al., 2018). The distinction is that sequence learning requires the acquisition of order-based relationships between items while statistical learning is based on probabilistic associations between items. This dichotomy has been linked to the classical model-free/model-based distinction in the reinforcement learning literature (Daw et al., 2005). The asymmetric development of sequence learning and statistical learning has also been linked to an asymmetric development of basal ganglia (model-free learning), that mature quickly, and prefrontal cortex/medio-temporal lobe (model-based learning), that mature later during development. In the current study, we are only probing model-free learning and report differences with respect to the order of the transition probability to be learned. While 6-12 years old children are able to learn 0th and 1st order transition probabilities, they do not seem to learn 2nd order ones, at least at this relatively fast presentation rate, in this probabilistic setting and with relatively short sequences (few examples to learn). Using similar stimuli, recent data have shown that normal-hearing adults are able to learn 2nd order transition probabilities (Pesnot Lerousseau & Schon, 2020). Based on this comparison, we can speculate on a developmental trajectory inside the model-free realm, with more complex statistics developing after more simple ones. **We nonetheless note that 1st and 2nd order transition probability learning has been shown to both engage prefrontal cortex/medio-temporal lobes (Covington et al., 2018; Schapiro et al., 2017), indicating that the dichotomy between subsystems might not be clear cut.** The question of the interaction between subsystems is an open question and it is unclear whether the subsystems operate in a parallel manner or in a more sophisticated manner, for example by competing until one effectively manages to predict the sensory inputs (Dehaene et al., 2015). The model we used assumes a strictly parallel architecture without interactions between subsystems for simplicity. However, the data reveal an interaction between the surprises at different orders. Further research is needed to explore this interaction and to understand whether this reflects a true interaction between subsystems or an effect of external common sources such as attention.

We report that cochlear implanted children have more variable reaction times than normal hearing children in the item recognition task. It should be noted that this variability difference is not due to a difference in strategies regarding the speed accuracy trade-off. Indeed, there is no accuracy difference between groups, so a greater variability due to the presence of incorrect trials is excluded. Furthermore, we only considered correct trials in this analysis. Finally, participants had a relatively long time to respond (2300 ms) so they did not have to trade accuracy or speed. Nonetheless, this difference in the variability of the reaction times could potentially introduce a bias between cochlear implanted children and normal

hearing children, by putting a greater speed constraint on the hearing impaired children at equal stimulus onset asynchrony. This is why we have decided to control for this bias by adjusting the stimulus onset asynchrony on an individual basis, taking into account inter-individual differences in the speed of the recognition processes. Please note also that this manipulation did not explain the results we find concerning the statistical learning, as it was not correlated with any measure in the modified reaction time task. Although difficult to interpret, this higher variability could be linked to variability in the recognition process itself, for example degenerated accumulation of evidence (Ratcliff & McKoon, 2008), but it could also be linked to difference in sustained attention, for example with a higher frequency of lapse events. It is nonetheless less probable that this higher variability reflects general cognitive processes – such as sustained attention – as it does not correlate with the statistical learning measures. Further research is needed to illuminate this finding, and specify its origin.

Finally, our results do not imply that statistical learning is not involved in speech comprehension and production in cochlear implanted children. We did not measure speech abilities, and therefore we could not study correlations between statistical learning abilities and speech-related abilities. It is known that, at the group level, cochlear implanted children have difficulties in speech abilities (Niparko et al., 2010) and it is also known that statistical learning is correlated with measures of language acquisition (Arciuli & Torkildsen, 2012; Aslin & Newport, 2014; Romberg & Saffran, 2010). It has been suggested (Deocampo et al., 2018; Houston et al., 2012) that the link between statistical learning and language in hearing impaired children might be present at two levels. First, at the group level, hearing impaired children could systematically have deficits in statistical learning abilities, which explains why they have deficits in language abilities. Second, at the individual level, hearing impaired children could have more or less facilities in statistical learning, which explains why some have good language abilities and some not. Here, we show that statistical learning, at least in the auditory modality, is not impaired at the group level. However, and this is beyond the scope of this paper, studying inter-individual differences could still be a powerful tool to explain the considerable variance in language outcomes after a cochlear implantation. As stated above, it might be the case that children with poor statistical learning abilities have more trouble than others to adapt to the cochlear implant and more trouble to learn language (although causality links between statistical learning and language have never been established so far). Further, the study included only three sounds, for experimental constraints. However, speech involves many more sounds and a richer statistical structure. For these reasons, the lack of deficit that we report in this reduced set of stimuli may only partially generalize to the performance of the hearing impaired children in more complex environments.

In conclusion, our results suggest that auditory statistical learning at different complexity levels is preserved in congenitally deaf children with cochlear implants. This suggests in turn that early auditory deprivation might not be crucially detrimental for the normal development of statistical learning. Future research should try disentangling whether such learning is mediated by other modalities, takes place following cochlear implantation or both.

Supplementary Results.

Effect of surprise using continuous values.

We measured the effect of the surprise using the continuous values of the surprise instead of the median split.

The effect of the surprise of the 0th order transition probabilities was statistically significant ($\beta = 0.565 \pm 0.030$, $p < 10^{-16}$). The positive sign of the coefficient β indicates that sequences with higher 0th order surprise are associated with higher reaction times. There was no interaction with the Group ($\beta = 0.029 \pm 0.041$, $p = 0.49$).

The effect of the surprise of the 1st order transition probabilities was also statistically significant ($\beta = 0.305 \pm 0.024$, $p < 10^{-16}$). There was no interaction with the Group ($\beta = -0.025 \pm 0.032$, $p = 0.44$).

The effect of the surprise of the 2nd order transition probabilities was not statistically significant ($\beta = 0.027 \pm 0.190$, $p = 0.16$). There was no interaction with the Group ($\beta = -0.032 \pm 0.026$, $p = 0.21$).

Effect of age of the first hearing aid.

We measured whether the age of the first hearing aid (mean age 19.5 ± 14.0 m., range [7, 60]) had an impact on the reaction times and on the ability to learn 0th, 1st and 2nd order transition probabilities.

The main effect of age of the first hearing aid on the reaction times was not statistically significant ($\beta = 3 \times 10^{-18} \pm 0.0006$, $p = 1$, $\Delta\text{BIC} = -3 \times 10^4$, $\text{BF}_{\text{BIC}} < 10^{-100}$). There was no interaction between the age of the first hearing aid and the surprise at the 0th order transition probability on the reaction times ($\beta = -0.0009 \pm 0.001$, $p = 0.79$, $\Delta\text{BIC} = -20.7$, $\text{BF}_{\text{BIC}} = 3 \times 10^{-5}$). There was also no interaction with the surprise at the 1st order transition probabilities ($\beta = -0.002 \pm 0.001$, $p = 0.19$, $\Delta\text{BIC} = -19.6$, $\text{BF}_{\text{BIC}} = 6 \times 10^{-5}$) nor at the 2nd order transition probabilities ($\beta = 8 \times 10^{-5} \pm 0.001$, $p = 0.94$, $\Delta\text{BIC} = -21.3$, $\text{BF}_{\text{BIC}} = 2 \times 10^{-5}$).

Supplementary Materials.

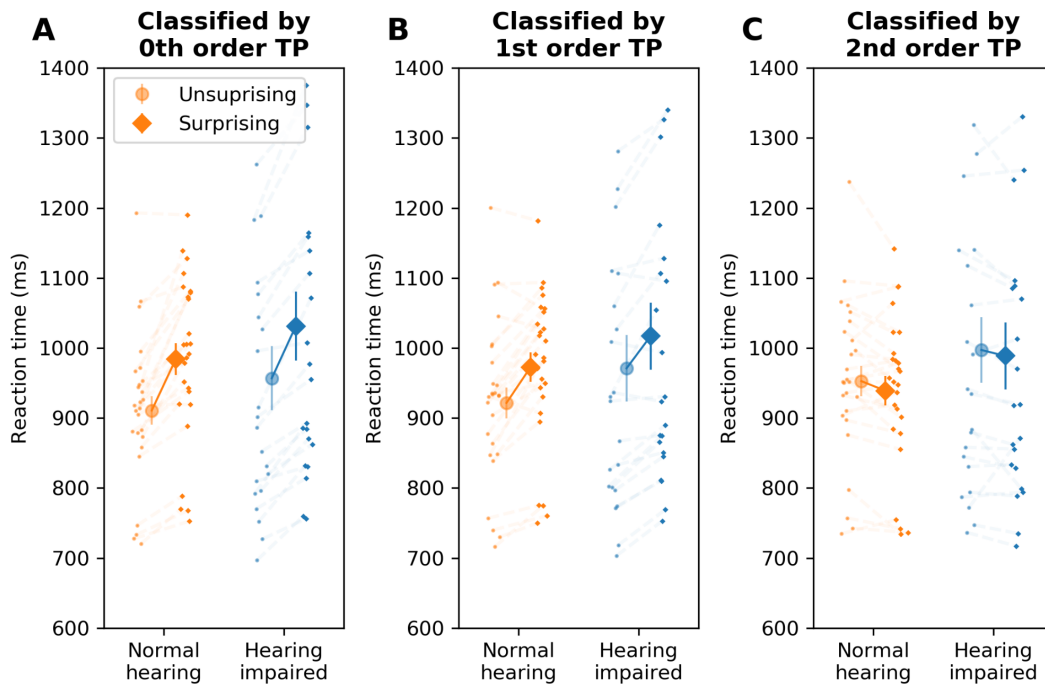


Figure Supp. 1. Raw reaction times in the modified serial reaction time task. **A.** Reaction times were lower for “unsurprising” than “surprising” sequences, as classified by a model that estimates 0th order transition probabilities ($\beta = 76.3 \pm 5.33$ ms, $p < 10^{-16}$, $\Delta\text{BIC} = 428.4$, $\text{BF}_{\text{BIC}} = 1 \times 10^{93}$), with no difference between groups and no interaction. **B.** Reaction times were lower for “unsurprising” than “surprising” sequences, as classified by a model that estimates 1st order transition probabilities ($\beta = 49.8 \pm 5.34$ ms, $p < 10^{-16}$, $\Delta\text{BIC} = 204.3$, $\text{BF}_{\text{BIC}} = 2.3 \times 10^{44}$), with no difference between groups and no interaction. **C.** Reaction times were similar for “unsurprising” than “surprising” sequences, as classified by a model that estimates 2nd order transition probabilities ($\beta = -2.79 \pm 5.36$ ms, $p = 0.60$, $\Delta\text{BIC} = -3.3$, $\text{BF}_{\text{BIC}} = 0.19$), with no difference between groups and no interaction. Large points are the group averages, small points are individual data. Error bars represent the standard error of the mean. TP: transition probabilities.

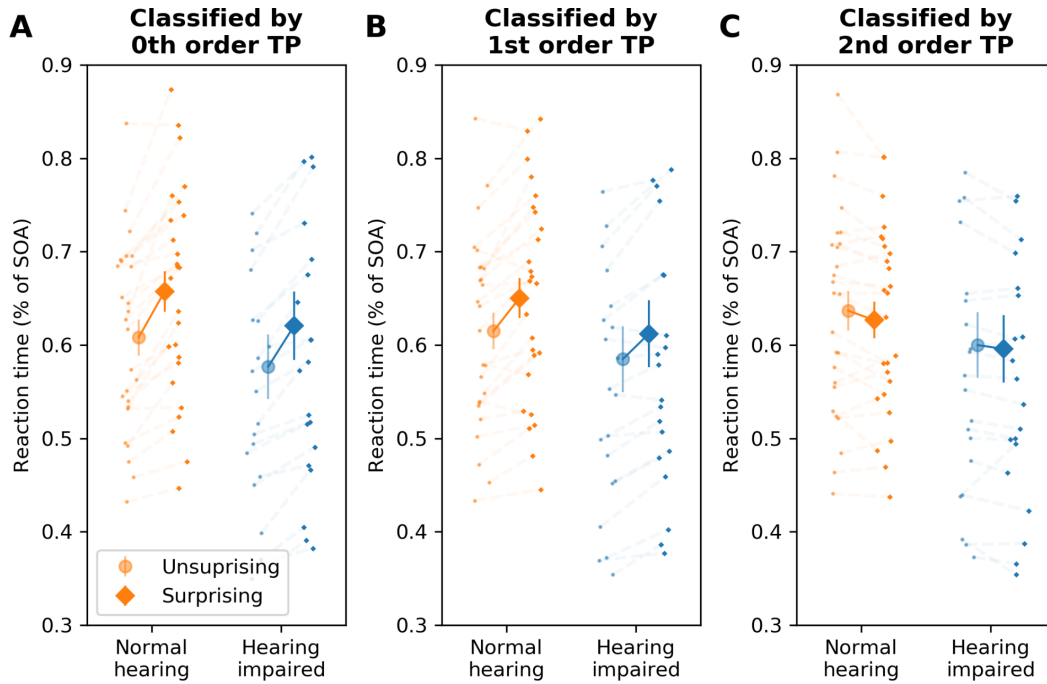


Figure Supp. 2. Reaction times normalized by the stimulus onset asynchrony in the modified serial reaction time task. **A.** Reaction times were lower for “unsurprising” than “surprising” sequences, as classified by a model that estimates 0th order transition probabilities ($\beta = 4.51 \pm 0.34$ %, $p < 10^{-16}$, $\Delta\text{BIC} = 404.7$, $\text{BF}_{\text{BIC}} = 5.4 \times 10^{87}$), with no difference between groups and no interaction. **B.** Reaction times were lower for “unsurprising” than “surprising” sequences, as classified by a model that estimates 1st order transition probabilities ($\beta = 2.94 \pm 0.34$ %, $p < 10^{-16}$, $\Delta\text{BIC} = 192.2$, $\text{BF}_{\text{BIC}} = 5.4 \times 10^{41}$), with no difference between groups and no interaction. **C.** Reaction times were similar for “unsurprising” than “surprising” sequences, as classified by a model that estimates 2nd order transition probabilities ($\beta = -0.08 \pm 0.34$ %, $p < 10^{-16}$, $\Delta\text{BIC} = -18.0$, $\text{BF}_{\text{BIC}} = 1.2 \times 10^{-4}$), with no difference between groups and no interaction. Large points are the group averages, small points are individual data. Error bars represent the standard error of the mean. TP: transition probabilities.

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