Cochlear Implant Data Logs Predict Children's Receptive Vocabulary

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Abstract

Objectives. The data logs of Cochlear™ Nucleus® cochlear implant (CI) sound processors show large interindividual variation in children's daily CI use and auditory environments. This study explored whether these differences are associated with differences in the receptive vocabulary of young implanted children.

Design. Data of 52 prelingually deaf children, who had received a CI before three years of age, were obtained from their clinical records. In total, 73 Peabody Picture Vocabulary Tests (PPVT) and CI data logs for one year preceding each test were collected. The data logs were used to determine the children's average daily amount of CI use and exposure to speech, speech in noise, noise, music, and quiet. Additionally, information was collected about other potential predictors of language abilities, namely gender, age, age at implantation, etiology of deafness, educational placement, and implantation mode (unilateral, bilateral). Model selection with Akaike's information criterion was used to determine which data-logging metrics, other variables, and combinations of both best predict receptive vocabulary scores.

Results. The data showed a strong positive association between receptive vocabulary and daily CI use, and a negative association between receptive vocabulary and daily exposure to music. Associations with the data logs' speech and noise metrics were less clear. The most important other variable was educational placement. The best model performance was achieved when data logs and other information were combined.

Conclusions. The results emphasize the importance of consistent CI use and a rich auditory environment for the early language development of young CI users. The study also

shows that CI data logs capture information about children's environment and CI use that are related to language performance and can help to detect and address problems and improve their auditory rehabilitation.

Cochlear Implant Data Logs Predict Children's Receptive Vocabulary

Worldwide, around 215,000 children with profound hearing loss (HL) use a cochlear implant (CI) to access their auditory environment (Cochlear Ltd., 2017). These children can achieve spoken language outcomes on par with their normal hearing (NH) peers, but their performance scores show large interindividual variation, and not all children with CIs reach age-adequate language levels (Kral, Kronenberger, Pisoni, & O'Donoghue, 2016; van Wieringen & Wouters, 2015). Some variation in the performance of children who use a CI or hearing aid (HA) can be explained by environmental factors (Houston et al., 2012; Markman et al., 2011) such as socioeconomic status (SES; Geers et al. 2011; Le Normand & Moreno-Torres 2014), educational placement (Moog & Geers, 2010; Sparreboom, Langereis, Snik, & Mylanus, 2015; Wie, Falkenberg, Tvete, & Tomblin, 2007), family composition (Geers et al., 2011; Macaulay & Ford, 2013), communication mode (Boons et al., 2012; Le Normand & Moreno-Torres, 2014; Wie et al., 2007), parent-child interactions (Holt, Beer, Kronenberger, & Pisoni, 2013; Niparko et al., 2010; Quittner et al., 2013), or linguistic input (Cruz, Quittner, Marker, DesJardin, & the CDaCI Investigative Team, 2013; DesJardin & Eisenberg, 2007; VanDam, Ambrose, & Moeller, 2012). To some extent, these factors are reflected in children's daily auditory environment—for instance, the amount of exposure to spoken language, or the presence of background noise.

CI users' auditory environment and CI use can be analyzed automatically with the Cochlear™ Nucleus® 6 CI sound processor (N6; Cochlear Ltd., Sydney, Australia). N6 keeps a *data log*, in which it tracks—among other things—time spent in different auditory environments (speech, speech in noise, noise, quiet, music, and wind), use of accessories like personal frequency modulation (FM) systems, and overall CI use (also known as *time on air*). To distinguish between auditory environments, N6 uses an *auditory scene classifier* that has been trained through supervised machine learning—that is, using a database of labeled recordings (Mauger, Warren, Knight, Goorevich, & Nel, 2014). Knowing the user's current auditory environment allows the sound processor to automatically optimize the signal path, for example, by activating noise reduction in noisy environments or enabling directional microphones when speech is presented in background noise. The data log is stored on the sound processor and can be read out at the CI clinic (for more details see the Methods section). Clinicians can use data logs to monitor CI users' daily auditory environment and usage behavior between clinic visits. With pediatric CI patients, such measurements might help to detect and address problems before they affect language acquisition, social and cognitive development, or academic achievement (Ambrose, VanDam, & Moeller, 2014; Barker et al., 2009; Connor & Zwolan, 2004; Holt et al., 2013).

Similar technology has long been available in hearing aids (Mueller, 2007). Moreover, there are dedicated tools for automatic naturalistic measurements of the auditory environment—perhaps the best-known of which is the Language Environment Analysis system (LENA; Gilkerson et al., 2017). Researchers have used such methods to explore the influence of the environment on language development (Ambrose et al., 2014; Gilkerson et al., 2018; Walker, Holte, et al., 2015), and clinicians are using them for the fitting of hearing devices, counseling, and intervention (Archbold et al., 2015; Leffel & Suskind, 2013; A. McMillan, Durai, & Searchfield, 2017; Muñoz, Preston, & Hicken, 2014; Suskind et al., 2016). To determine whether N6 CI data logs can help improve the auditory rehabilitation of children with CI, it is crucial to understand how the captured information relates to rehabilitation outcomes. Regarding language development, three data logging metrics are particularly interesting: daily CI use, exposure to spoken language, and exposure to noisy environments.

Daily CI Use

Several studies have investigated the impact of hearing-device use on rehabilitation outcomes—either through data logs or through subjective reports—and have found that consistent hearing-device use is associated with better functional language outcomes and language growth in children with a HA (Tomblin et al., 2015; Walker, Holte, et al., 2015) and with better speech perception in children with CIs (Easwar, Sanfilippo, Papsin, & Gordon, 2018; Wie et al., 2007). One explanation for this is that hearing-device use creates opportunities for language exposure and learning. Furthermore, low or inconsistent hearing-device use might indicate trouble adjusting to the device or a lack of support, and can foreshadow poor use or nonuse (Archbold, Nikolopoulos, & Lloyd-Richmond, 2009). Inconsistent use can also be related to the child's state (e.g., mood, fatigue, or illness; Walker et al., 2013), frequent removal of the CI's magnetic coil (Easwar, Sanfilippo, Papsin, & Gordon, 2016), and caregivers struggling to manage the hearing device (Muñoz et al., 2015) or monitoring its use (Walker, McCreery, et al., 2015; Walker et al., 2013).

The amount of CI use can be measured automatically and objectively with N6 data logs. Busch et al. (2017), for example, analyzed N6 data logs of 510 children and found that it increased from a median of 8.5 hrs/day in the first 6 years of life to more than 11 hrs/day for older children (Busch et al., 2017). The interindividual variation was considerable, with interquartile ranges (IQRs) beyond 3 hrs/day, and a difference of roughly 10 hrs/day between the top and bottom 5% of the distribution in all age groups (Busch et al., 2017).

Similar distributions of daily CI use were found in other large samples of N6 CI data logs (Cristofari et al., 2017; Easwar et al., 2016, 2018; Oberhoffner et al., 2018; Wiseman & Warner-Czyz, 2018).

Exposure to Spoken Language

Child language development is driven by language input and facilitated by qualitative aspects—such as child-directedness, linguistic scaffolding, and interactivity (Hoff, 2006; Tamis-LeMonda, Kuchirko, & Song, 2014; Zauche, Thul, Mahoney, & Stapel-Wax, 2016). Various studies have recorded and analyzed naturalistic parent-child interactions, and some of them have used LENA to make comprehensive naturalistic measurements. Their results indicate, that the language development of children with CIs is related to their parents' mean length of utterance (MLU; DesJardin & Eisenberg 2007), lexical diversity, and use of facilitative language techniques (Cruz et al., 2013; DesJardin & Eisenberg, 2007), as well as maternal sensitivity and linguistic quality of parent-child interactions (Quittner et al., 2013). To our knowledge, an association between the sheer quantity of language input and language performance has not been observed for children with a CI, but for children with NH and HAs (Hurtado, Marchman, & Fernald, 2008; VanDam et al., 2012; Weisleder & Fernald, 2013).

Compared to their NH peers, children with CIs face additional challenges in language learning. First, they experience sensory deprivation during a crucial phase of neuronal development: Cortical pathways begin to form in utero, and synaptogenesis peaks between the first and fourth year of life. Hearing deprivation during this sensitive period affects the development of the auditory system and higher-order neurocognitive and psychosocial processes (Kral et al., 2016). Second, HL disrupts social-affective processes behind peer communication and caregiver-guided language learning (Markman et al., 2011). Although caregivers often compensate for a child's HL—for example by speaking more clearly (Houston et al., 2012)—the amount and interactivity of spoken language interactions between caregivers and children decrease with increasing severity of HL (VanDam et al., 2012). Moreover, parental spoken language input to children with a HL is often more directive and less responsive—which is associated with poorer language outcomes (Ambrose, Walker, Unflat-Berry, Oleson, & Moeller, 2015; Nittrouer, 2010). Additionally, the high prevalence of behavioral problems among children with HL (Barker et al., 2009; Quittner et al., 2010; Topol, Girard, Pierre, Tucker, & Vohr, 2011) might contribute to parenting stress, which in turn affects mother-infant interactions and children's language skills (Quittner et al., 2010; Vohr et al., 2010).

Children's exposure to spoken language (speech and speech in noise) can be quantified with N6 data logs. Busch et al. (2017) showed that, before the age of six, children with CI were exposed to around 4 hrs/day of speech, while 6-18 year-olds heard around 5 hours of speech per day. Similar results were reported by others (Cristofari et al., 2017; Easwar et al., 2016; Oberhoffner et al., 2018). Note however, that N6's speech counts include not only the spoken language that is presented to children by their environment, but also their own language production. All studies showed large variability within age groups: In Busch et al. (2017), for example, the difference in average daily exposure to speech between children in the top and bottom quartiles of the distribution was 2 hrs/day. This variation likely reflects sustained differences rather than temporary fluctuations, because N6 data logs normally represent long time periods—namely the period between the CI user's visits to their CI clinic. In the sample used by Busch et al. (2017), data logs covered between two weeks and over a year, with a median of 48.9 days. Moreover, most participants had contributed multiple data logs.

Exposure to Noisy Environments

Background noise can impede auditory and cognitive performance, and affect language learning (Klatte, Bergström, & Lachmann, 2013; Kujala & Brattico, 2009; B. T. M. McMillan & Saffran, 2016). CI users are particularly vulnerable to noisy listening conditions, because, compared to NH listeners, the signal that they receive is highly degraded. This affects speech comprehension in noise (Davies, Yellon, & Purdy, 2001; Moreno-Torres, Madrid-Cánovas, & Blanco-Montánez, 2016), hampers incidental learning (Vermeulen, De Raeve, Langereis, & Snik, 2012), and causes more cognitive fatigue (Pichora-Fuller et al., 2016). At the same time, noise is omnipresent in many children's environments (Evans, 2004; Pujol et al., 2012; Shield & Dockrell, 2008) and children with CIs are no exception: Data log data of Busch et al. (2017) show that the time spent in noisy environments was around 3.4 hrs/day for children under six years of age, and around 5 hrs/day for school-aged children. The variation in exposure to speech was large, too: The 25% of children who spent the most time in noisy environments were exposed to around 2 hrs/day more noise than the 25% of children who spent the least time in noisy environments. On average, around 2.5–3.5 hrs of children's daily exposure to noisy environments were accounted for by speech in noise. In fact, about two thirds of the speech that children were exposed to was presented in background noise. Again, similar numbers were reported by other studies (Cristofari et al., 2017; Oberhoffner et al., 2018).

Assistive listening devices like remote microphones can alleviate the effects of noise in the classroom (Bertachini et al., 2015; Davies et al., 2001) and facilitate parent-child communication in difficult acoustical situations (Allen et al., 2017). Yet, Busch et al. (2017) found that before the age of six, only one in five children with a CI was using assistive listening devices, and among those who did, the median duration of use was just around 17 min per day. Furthermore, only half of the school-aged children used such devices, and most of those who did, only used them for around 30–40 min per day. Notably, some sounds that N6 classified as noise could be speech with a low signal-to-noise ratio (SNR), such as background conversations and might actually contribute to language learning, because it has been shown that children can pick up new words from overheard speech (Boderé & Jaspaert, 2017).

Can Data Logs Predict Language Outcomes?

In summary, better spoken language outcomes would be expected for children who use their CI consistently, receive enough spoken language input, and experience little background noise. In all three aspects, N6 data logs show large variation, and it stands to reason that this explains some variance in language outcomes. However, there is still little evidence for associations between children's CI data logs and their language performance. The only published study is one by Guerzoni and Cuda (2017), who logged speech exposure for the first year after implantation. Although all ten participants had received their CI between 10 and 24 months of age, and used it throughout waking hours, there were vast differences in their average daily exposure to speech (0.9–2.6 hrs/day) and speech in noise (0.8–4.8 hrs/day). Exposure to speech below 70 dB explained 72% of the variance in vocabulary skills one year after implantation. However, the environmental differences and their correlation with language outcomes may have been driven by uncontrolled mediating variables—such as the amount of CI use. A multivariate analysis is required to further explore associations between the auditory environment and rehabilitation outcomes of children with CIs, and the explanatory value of N6 data logs.

Aim of the Study

This study investigates associations between children's N6 CI data logs and their language performance, specifically their receptive vocabulary. We conducted a multivariate analysis to determine whether data logs can explain variance beyond that explained by other common predictors of language development—such as chronological age, age at implantation, educational placement, or implantation mode (i.e., unilateral vs. bilateral implantation). Because little is known about potential associations between CI data logs and language performance, we used model selection to explore a wide range of competing hypotheses, and model averaging to account for modeling uncertainty.

If differences in data logs are associated with differences in vocabulary, this would provide further evidence for an association between the auditory environment and the language outcomes of children with CI. It would also show that CI data logs can help to identify and address problems in children's environments, making them a useful tool for intervention and naturalistic research. The absence of such associations might indicate that the link between environment and language outcomes is weak or that the current data logging system does not capture these associations and requires further improvements.

MATERIALS AND METHODS

This was a cross-sectional, retrospective analysis, based on a convenience sample of pediatric CI patients. The children's data had been collected as part of the clinical routine at the Radboud UMC Nijmegen (The Netherlands). Prior to the data collection, parents of all participants had given informed consent for the use and publication of their child's assessment data. The study was approved by the UZ Leuven / KU Leuven Medical Ethical Committee (approval number B322201523779) and was conducted in accordance with the Radboud UMC's ethical standards.

Final Sample

The final sample contained n = 73 Peabody Picture Vocabulary Test (PPVT) results, data logs for the year preceding each test, and other information about the children from n = 52 children with CIs (21 female, 31 male). The dependent variable was the children's receptive vocabulary. It was measured with the PPVT Standard Score (SS), which has a mean of 100 and a *SD* of 15 in the age-matched norm population. Details on the data selection and pre-processing are provided below.

Selection of Participants and PPVT Test Results

At the Radboud UMC, there were 211 children who used an N6 CI sound processor. From these, we excluded children who were implanted after the age of three (n = 49), postlingually deaf (i.e., after 1.5 years of age; n = 2), not from a predominantly orally communicating Dutch speaking home (n = 16), or diagnosed with intellectual disability or severe motor deficits (n = 10). For all others, we gathered their Peabody Picture Vocabulary Test (PPVT) results from the clinical records and extracted their sound processor data logs from the clinic's Custom Sound® CI fitting software (Cochlear Ltd., Sydney, Australia). We included results from all PPVTs taken before 14 years of age, and where CI data logs were available for the year before the test. Nine of the 85 PPVT results that met these criteria were excluded, because less than 70% of the preceding year were covered by data logs—likely, because the children had only recently received their CI or upgraded their sound processor. For the remaining PPVT results, the preceding year was completely or almost completely covered by data logs (*M*=98%, *SD*=0.06).

Furthermore, three PPVT results were excluded because the average daily CI use in the year before the test was below 2.3 hrs/day. A mean daily CI use of 2.3 hrs/day is more than 1.5 IQRs below the mean daily CI use in the large sample used by Busch et al. (2017), and might have been the result of technical or medical problems. It is also possible, that, between their regular visits at UMC Nijmegen, the CI had been fitted at a different clinic, which would have reset the data log and therefore decreased the daily averages. However, to the knowledge of the audiologists at Radboud UMC, this was not the case for any of the children in the sample. In one of the three cases in question, the child had been ill, and hence used their CI for just 0.37 hrs/day. In the other two cases, we were unable to find an explanation for the low CI use (0.90 and 2.27 hrs/day, respectively), but we nevertheless chose to exclude them because a simple 12-month average would likely misrepresent these children's day-to-day auditory input: Our analysis is based on the assumption that children receive a more or less steady auditory input over the course of a year, with a relatively stable mix of the various auditory environments.

Aggregation of CI Data Logs

The final sample contained 456 N6 CI data logs, with a median duration of 96 days (*IQR* = 235, range: 1–779 days). On average, each child contributed 8.33 data logs (*SD* = 5.52), with a mean length of 203 days (*SD* = 109). Based on these data logs, we calculated children's average daily amount of CI use for the year leading up to each PPVT test moment, and obtained information about their auditory environment—namely their average daily exposure to speech, speech in noise, noise, all speech (speech in quiet + speech in noise), all noise (speech in noise + noise), music, and quiet.

Each N6 CI data log covers the time between two consecutive clinic visits, and contains a counter for each auditory environment that N6 can distinguish. These counters track the time that users spend in these environments, even if the scene classifier is not used to adjust the signal path—that is, if the so-called *SCAN* feature is not activated. However, when accessories, such as FM or telecoil, are used, all input is counted towards a dedicated accessory counter. Total CI use can be calculated as the sum of the time spent in all auditory environments plus the time using accessories. Whenever the sound processor is connected to the clinic's Custom Sound CI fitting software, the counter values are transferred to a database on the clinic's computer, and the sound processor data log is reset. Because the duration of the data log is known (i.e., the time since the last clinic visit), the counters can be converted into daily averages.

To aggregate all data logs from a given 12-month window into a single average, some preprocessing was necessary: If a data log exceeded the 12-month window, we first reduced its counter values for CI use and time spent in each auditory environment proportional to the excess. If the 12-month window was not fully covered by data logs, counters for the gap were estimated from the average of the previous and next log, weighted by their respective durations. If two data logs overlapped (e.g., data logs from bilateral CI users), the higher one of the corresponding counters was used for the overlap, respectively. Eventually, the corrected counters for each 12-month window were summed and divided by 365 to obtain average hrs/day for all data-logging variables.

Other Variables

For each child, information was retrieved from clinical records about their date of birth, gender, age at implantation, and etiology of deafness. We also determined the children's implantation mode—that is, whether they were currently using one or two CIs (i.e., bilateral implantation), and what their educational placement was at the time of the data collection. Table 1 shows the sample characteristics.

We categorized etiology of deafness as either genetic (*n* = 25), infection (*n* = 9), or unknown (*n* = 18). The children's implantation mode was categorized as unilateral (*n*=16) if they were using only one CI, bilateral simultaneous (*n* = 17) if there had been less than one-year between implantations, and bilateral sequential (*n* = 19) if there was more than one year between implantations. This grouping is in line with results from Gordon & Papsin (2009), who found that outcomes of bilateral implantation were best—and similar to those of simultaneous implantation—when the inter-implant delay was one year or less. A child's educational placement was categorized as mainstream (*n* = 27) if the child attended a mainstream school or daycare with at most a so-called *light educational arrangement*. This means that the child follows a regular curriculum in a mainstream classroom, potentially with some special measures to compensate for the HL and occasional support from a co-teacher, sign language interpreter, or note-taker. All other educational arrangements were categorized as special (*n* = 25), including one child who did not yet attend daycare at 2.8 years of age. Since all children in our sample were predominantly orally communicating, all education placements were also predominantly oral. Notably, implantation mode and educational placement could only be determined for the time of the data collection and could have been different for a child's earlier PPVT test moments, for example if the children had since changed their educational setting or received a second CI. We had initially planned to use audiological test results as a surrogate for factors like pre-implant and residual hearing, or the quality of the electro-neural interface. Unfortunately, these tests had not been conducted uniformly enough to be used in the analysis.

For each PPVT test result, we calculated the child's chronological age and hearing age at the test moment, where hearing age refers to the time since the implantation of the first CI. The mean chronological age at the PPVT test moment was M = 7.2 years (SD = 3.6, range: 2.1–13.9 years of age). The age distribution was bimodal, with a gap around six years. This was because children who were implanted about 5 years prior to the data collection were still using a sound processor of the previous generation, without the data logging feature.

Model Selection and Averaging

To find the best combinations of data-logging variables and other variables to predict receptive vocabulary (i.e., PPVT SS) we used model selection based on the small-samples corrected Akaike's information criterion (AICc; Burnham & Anderson, 2002). The AICc combines a likelihood-based measure of model fit with a penalty for model complexity. We used AICc to evaluate a set of candidate models and rank them by their difference in AICc from the best model in the set (ΔAICc). Models with ΔAICc<2 are commonly considered to be as well supported by the data as the best model (Symonds & Moussalli, 2011). Using this threshold, we obtained three subsets of models that best predicted the PPVT SS:

(1) Models that did not include data-logging variables, but any combination of other variables

(2) Models using a combination of data-logging variables and age

(3) Models combining data-logging variables and other variables

Additionally, *AICc-weights* were computed for each model, representing the degree of belief that it is the best model in its set (Wagenmakers & Farrell, 2004). These weights were used to determine the relative importance of each predictor and compute a weighted average model for each of the three sets. For the calculation of the averages, coefficients that did not occur in a submodel were treated as if it they were zero. These so-called *full averages* cause shrinkage and thus produce more conservative average coefficients.

All continuous predictors were *z*-standardized. Because some children had taken multiple PPVT tests, all models contained random intercepts for participants (most children had taken one [*n* = 34] or two [*n* = 16] PPVTs. For two children, results were available from three and four tests, respectively). Due to the limited number of repeated measurements, random slopes for age could not be estimated. Notably, PPVT SSs lower than 55 had been recorded as 55 (i.e., left-censored). Because this only concerned three data points, we used these left-censored scores as is. To quantify variance in PPVT SSs explained by each model, we used marginal R^2 for mixed models, R_m^2 (Nakagawa & Schielzeth, 2013). All analyses were carried out in R (version 3.5.0; R Core Team, 2018). The models were fit using lme4 (version 1.1-17; Bates, Mächler, Bolker, & Walker, 2015) and maximum-likelihood estimation. Model selection was performed with the MuMIn package (version 1.40.4; Bartón, 2017).

RESULTS

Descriptive Statistics

For each of the *n* = 73 PPVT SSs in our sample (see also Table 1), we aggregated information about the 12 months before the test from the child's CI data logs, namely their average daily exposure to different auditory environments and overall CI use. The variation in the data logs was large: For example, CI use ranged from 3.04–14.18 hrs/day (*IQR* = 4.07), exposure to speech (all speech) from 1.37–7.43 hrs/day (*IQR* = 1.95), and exposure to noise (all noise) from 0.87–5.86 hrs/day (*IQR* = 1.46; see Table 2 and Supplemental Digital Content, Figure S1, which shows the distributions of the data logging variables). There were strong, positive associations between many data logging variables. Accordingly, a given data logging variable could often be used to predict other data logging variables—with standardized regression coefficients that were frequently far exceeding $\beta = .5$, (e.g., speech in noise and CI use, $\beta = 0.89$, $p<.05$; see Supplemental Digital Content, Figure S2, which shows pairwise associations between data logging variables).

Descriptively, children in mainstream education used their CI for about 1 hr/day more than children in special education (mainstream: 10.56 hrs/day, *SD* = 2.65, special: 9.54 hrs/day, *SD* = 2.47), and it was therefore no surprise that they also had slightly higher average daily exposure to almost all auditory scenes—with music being the only exception (mainstream: *M* = 0.96 hrs/day, *SD* = 0.52, special: *M* = 1.15 hrs/day, *SD* = 0.45; see Table 2 and Figure 1). This difference in music exposure was especially pronounced for older children (>6 yrs of age; Figure 1).

The age-related changes in children's average auditory environments were similar to those in Busch et al. (2017)'s much larger sample. There were, for example, an increase in noise and speech in noise exposure during primary school age, and a decrease of music exposure throughout childhood. Nevertheless, for any auditory scene, children with very low or high exposure could often be found across the entire age range (Figure 1).

The PPVT SS—our dependent variable—was approximately normally distributed, with M = 91.4 and SD = 16.5 (Figure 2a). Descriptively, there was no discernible effect of chronological age on PPVT SSs (Figure 2b), which is unsurprising because the PPVT SS is normalized by chronological age. However, SSs of children in special education (M = 83.5, SD = 17.5) differed from those of children in mainstream education (M = 98.6, SD=11.6; see Table 1). While the lowest SS of any child in mainstream education was 81, 40% of children in special education had scores that were lower than that (Figure 2).

With regards to the aim of our study, we were most interested in the association between data-logging variables and the PPVT SS. The scatterplots in Figure 3 give some indications of such associations: for example, there appears to be a positive association between average daily CI use and the PPVT SS. Moreover, it seems that the children who have had the least exposure to music tended to have the highest PPVT SSs. However, as mentioned above, to fully understand the connection between the environment and the language outcomes one should consider all data-logging variables and other variables (e.g., age, educational placement) simultaneously. Moreover, the clustering of observations within subjects must be accounted for. To this end, we used hierarchical linear models, model selection, and model averaging to determine how well PPVT SSs can be predicted from different combinations of data-logging variables, other variables, and both.

Best Models Without Data-Logging Variables

The first set of models predicted the PPVT SS without using data-logging variables but using any possible combination of the other variables—that is, chronological age, educational placement (special vs. mainstream), gender, age at implantation, implantation mode (unilateral CI vs. bilateral CI), and etiology (genetic, infection, other). Hearing age was not used as a predictor, because it was strongly correlated with chronological age, r(70) = .99, ($p < .001$).

The model with the best (lowest) AICc explained R_m^2 = 24% of the variance in PPVT SSs, using only educational placement as a predictor. The other two models in the best model subset (i.e., with ΔAICc<2) also included chronological age and gender, respectively, but they did not fit substantially better and had lower AICc-weights. Accordingly, the most important predictor in the average model was educational placement. The predicted difference in PPVT SSs between a child in special and mainstream education was b = 16.1 points (SE = 3.9), whereas chronological age and gender had comparatively small effect sizes and large standard errors (see Table 3).

Best Models with Only Data-logging Variables

The second set of models predicted the PPVT SS using any combination of chronological age and data-logging variables, namely daily CI use and average daily exposure to speech, speech in noise, all speech, noise, music, and quiet. We did not include exposure to all noise as a potential predictor, because it was strongly correlated with exposure to speech in noise, r(70) = .99, $p < .001$ (see also Supplemental Digital Content, Figure S2). We also allowed for interactions of chronological age with any data-logging variables, interactions of daily CI use with exposure to speech, speech in noise, and all speech, and interactions of exposure to all speech with exposure to speech and speech in noise.

All but one of the seven best models contained chronological age, daily CI use, daily exposure to music and an interaction between music exposure and age. This combination of predictors also had the lowest ΔAICc and explained R_m^2= 32% of the variance in PPVT SSs. In addition to these variables, other models also included daily exposure to speech, speech in noise, all speech, and noise—yet never at the same time. All these models had a similar model fit. Only model 6 fits the data considerably better ($R_m^2 = 41\%$), albeit at the cost of parsimony: Compared to the model with the lowest ΔAICc, this model additionally included daily exposure to speech, as well as interactions of chronological age with daily CI use and daily exposure to speech. The penalty that is associated with this high number of parameters is the reason why model 6 did not outperform other models in terms of AICc. Conversely, model 5 had a comparable AICc value to the best model in the set, but a much poorer fit ($R_m^2 = 21\%$), using nothing but daily exposure to quiet as a predictor. Because daily exposure to music and daily CI use were consistently included in the best models, the averaged model coefficients further emphasized their relative importance compared to other data-logging variables (see Table 4).

Best Models Combining Data-logging Variables and Other Variables

The third set of models predicted the PPVT SS using any combination of data-logging variables and other variables that appeared in the previous two best-model sets—namely chronological age, educational placement, gender, daily CI use, and daily exposure to speech, speech in noise, noise, music, all speech, and quiet. We also allowed for interactions of data-logging variables with age and educational placement.

All of the best models (i.e., with ΔAICc<2) included chronological age, music, daily CI use, and educational placement—the same four variables that had consistently appeared in the best models with only data-logging variables and only other variables. Notably, all models also contained at least one of the three speech metrics. The model with the lowest (best) AICc included daily exposure to speech in noise, its interaction with educational placement and an interaction of chronological age and daily exposure to music; it explained R_m^2 = 51% of the variance in PPVT SSs. The other models achieved comparable R_m^2, including daily exposure to all speech or daily exposure to speech as predictors. Because the AICc-weights were similar across all models in the set, the average model emphasized the importance of the four predictors that occurred in all models, whereas the less consistently included speech metrics had small average coefficients with large standard errors (see Table 5). We used the average model to predict mean PPVT SSs as a function of daily CI use and music exposure for both kinds of educational placement and for different exemplary ages, namely at the sample's mean chronological age and approximately 1 *SD* above and below the mean. The predictions are shown in Figure 4.

Decision Boundaries of the Auditory Scene Classifier

When interpreting the data logs, it should be kept in mind, that N6's auditory scene classifier relies on a combination of acoustical features and might activate the same environment in very different environments. For example, to distinguish speech, speech in noise, and noise, the classifier relies—to some extent—on the modulation depth of the signal as an approximation of the signal-to-noise ratio (SNR). This means that an environment classified as noise might contain spoken language at a low SNR (e.g., speaking in a noisy restaurant). Similarly, the music environment might be activated in situations which merely contain music as background noise, for example, from radio or TV. In order to better understand the auditory scene classifier's behavior, we determined the SNRs at which it switches between the speech, speech in noise, and noise scenes. To that end, we positioned an N6 sound processor in a sound booth and presented it with concatenated LIST sentences (Van Wieringen & Wouters, 2008) at 70 dBA. The speech signal was mixed with four-talker babble noise at decreasing SNRs. We found that the classifier transitioned from the speech environment to the speech in noise environment at around 15 dB SNR, and from speech in noise to noise at around -5dB SNR.

DISCUSSION

Like previous studies, we found wide interindividual variation in data logs of children with CI (Busch et al., 2017; Cristofari et al., 2017; Easwar et al., 2016; Oberhoffner et al., 2018; Wiseman & Warner-Czyz, 2018). Moreover, we showed that these differences are correlated with differences in language performance, particularly receptive vocabulary.

Effects of Data-logging Variables

The most strongly associated with vocabulary scores were the average daily amount of CI use and exposure to music. In the models that used data-logging variables and other variables (Table 5), a 1 *SD* increase in daily CI use was, on average, associated with an increase in the PPVT SS of $b = 13.2$ points, which is almost 1 *SD* of the PPVT SS in the norm population. This finding is in line with the literature, which stresses the importance of consistent hearing device use for auditory rehabilitation (Walker, Holte, et al., 2015; Wie et al., 2007). For example, Easwar et al. (2018) have found that longer daily CI use is associated with better speech perception abilities in children with a CI. Specifically, a one hour increase in daily CI use was associated with a 2.6% increase in speech perception test scores when factors like age and length of CI experience were controlled for.

The strong negative effect of music exposure, on the other hand, came as a surprise. A 1 *SD* increase in daily music exposure was associated with a decrease in PPVT SSs of $b =$ -5.7 points. One possible explanation for this is that background music effectively acts as noise which hinders language learning. It is also possible that some part of what was classified as music was actually TV, because N6 tends to classify children's TV programs as music (Hanvey & DeBold, 2015). Higher amounts of TV in children's homes have been associated with decreased quality of parent-child communication and decreased child language performance (Ambrose et al., 2014; Christakis et al., 2009).

The connection between the speech exposure metrics and PPVT SSs was less clear: In the best models, daily exposure to speech, speech in noise, and all speech appeared as predictors, but in various combinations (Table 5). This uncertainty was reflected in the small average coefficients. Thus, while the three speech scenes do seem to contribute to predicting PPVT SSs, their contribution is small, and they appear to be somewhat interchangeable. In part this might be due to the strong correlations between them (see Supplemental Digital Content, Figure S2). While there is no doubt that meaningful language input is crucial for language development (e.g., Hoff, 2006), it is possible that the N6 classifier's speech classes are not well aligned with those aspects of the language environment that drive language development. For example, N6 does not distinguish between language input and output, thus mixing environmental influences and their effects. Furthermore, sheer quantity of language input may not be as predictive as, for example, interactivity of parent-child communication (Ambrose et al., 2014; VanDam et al., 2012).

Separating own and external speech and adding information about the quality of spoken language interactions (e.g., their interactivity) could bring more clarity into these issues and improve the predictive power of data logs.

Additional uncertainty is introduced to the speech metrics because of varying accessory use. When accessories such as FM, telecoil, or wireless audio streaming are being used, the classifier is inactive, and all input is instead counted towards a dedicated accessory scene. Thus, it remains unclear how much speech the children have heard through accessories. However, the children in our sample barely used accessories: The median accessory use was just 0.01 hrs/day (Table 2). Similar to the results of Busch et al. (2017), accessory use differed between preschool and school-aged children. Of 30 data points taken before the age of six, only one indicated more than 5 min/day of accessory use, whereas 29 out of 43 data points from the 6–14 year old children did (median = 0.62 hrs/day, IQR = 1.05, range: 0–2.76). On the one hand, this means that the auditory scene classifier has categorized almost all auditory input that the children have received, and that the data logs provide a relatively complete picture of their auditory environments. On the other hand, the low accessory use is concerning, because accessories can support CI users in adverse listening conditions: in noisy classrooms, FM or similar remote microphone systems can help by directly streaming the teacher's voice to the child's hearing device (Bertachini et al., 2015; Davies et al., 2001; Iglehart, 2004; Razza, Zaccone, Meli, & Cristofari, 2017), and even at home, they can promote parent-child interactions by allowing spoken language communication in situations in which it would otherwise be difficult—for example in the car (Allen et al., 2017).

We also found no clear evidence of an association between daily exposure to noisy environments and the PPVT SS. Noise decreases speech understanding of CI users (Davies et al., 2001), increases listening effort (Pichora-Fuller et al., 2016), and interferes with language learning (Klatte et al., 2013; Kujala & Brattico, 2009; B. T. M. McMillan & Saffran, 2016; Vermeulen et al., 2012). Hence, chronic exposure to noise would be expected to interfere with cognitive and language development (Klatte et al., 2013; Kujala & Brattico, 2009). Perhaps, the association between daily noise exposure and language performance is too ambiguous: a noisy environment can be an obstacle for language learning or a sign of robust language skills and good integration in the mainstream. Moreover, the effects of background noise might be ameliorated by the sound processor's noise reduction (NR) features. Plasmans et al. (2016) have found that with NR, pediatric CI users were able to understand around 9.4% more words and 16.7% more sentences in noise. Mauger et al. (2014) have shown that NR helped adult N6 users to achieve 50% sentence understanding at SNRs as low as -7.6 dB (as opposed to -2.8 dB when NR was deactivated). Yet, the classifier already transitions from the speech environment to the speech in noise environment at around 15 dB, and from speech in noise to noise at around -5 dB SNR (see methods section). Thus, it is possible that a lot of what is classified as speech in noise by N6 can be understood well, due to NR (cf. Razza et al., 2017, who found no significant benefit of N6's NR on children's speech in noise performance). The association between exposure to noisy environments and language performance might be further weakened because some children have NR activated while others do not.

Although we found no clear association between the speech and noise metrics and receptive vocabulary, this does not preclude the existence of such associations for other language domains. While word learning certainly depends on language input (e.g., Hoff & Naigles 2002) and can be hampered by background noise (B. T. M. McMillan & Saffran, 2016), it is conceivable that vocabulary is more robust against environmental influences than other domains of language. Morphosyntax, for example, relies on subtle acoustical cues which are difficult to pick up with a CI to begin with (Markman et al., 2011), and might therefore benefit more from repetition and noise-free presentation. Similarly, more subtle language deficits might be revealed by more complex tasks like narrative production (Boons et al., 2013; Rinaldi, Baruffaldi, Burdo, & Caselli, 2013). Thus, associations between other language domains and data logs should be investigated.

Effects of Other Variables

We found that children in mainstream education had higher PPVT SSs than those in special education. Similar group differences have been reported by others (Boons et al., 2013; Geers, Nicholas, & Moog, 2007). It is possible that this reflects a beneficial effect of mainstream education on language development, or that it merely indicates that children with age appropriate language levels are more likely to be placed in mainstream education.

Age was not an important predictor in the models without data-logging variables. This is no surprise, since PPVT SSs are normalized for age. A missing age effect also indicates that there was no evidence that the CI users, as a group, were developing at a significantly different pace than their NH peers in the test's normative sample. However, age became an important factor when data-logging variables were included in the models, often in an interaction with one of them (Tables 4 and 5). That is, age mostly helped to improve predictions when combined with data-logging variables, but not by itself. Such interactions might indicate that the effect of the data-logging variables on language performance changes with age. This is not surprising, given the age-related changes in the children's auditory environments that we found. For example, while it was normal for a 3-year old to have an average of around 4 hrs of exposure to speech per day, this would be rather low for a child above six years of age (Figure 1).

Besides educational placement and age, none of the other variables (i.e., gender, age at implantation, implantation mode, and etiology) had a clear effect on PPVT SSs, even though all of them were previously found to be important—for example, gender (Le Normand & Moreno-Torres, 2014), implantation mode (Boons et al., 2012; Sparreboom et al., 2015), age at implantation (Holt & Svirsky, 2008; Svirsky, Teoh, & Neuburger, 2004), and hearing age (Walker, Holte, et al., 2015). This discrepancy could be due to measurement error or due to the homogeneity of our sample with respect to these factors.

Complementarity of Data-logging Variables and Other Variables

It is conceivable that data-logging variables and other variables merely capture the same information in different form. For example, special schools in which sign language is used likely also provide less spoken language exposure. Here we found that data-logging variables explained more variance in PPVT SSs than other variables, and when both were combined, predictions improved further. This supports the notion that the data-logging variables captured information that was not contained in the other variables—at least not in the ones we have assessed. There is, however, a range of factors that we did not assess—or only coarsely. No information was available for some well-established predictors of language performance, like SES, pre-implant hearing experience, or residual hearing (Geers et al., 2007; Niparko et al., 2010). To some degree, these factors might have been reflected in the data logs: Low SES, for example, is associated with poorer language environments (Hart & Risley, 1995; Hoff, 2015; Huttenlocher, Waterfall, Vasilyeva, Vevea, & Hedges, 2010; Rowe, 2008; Vohr et al., 2010), more noisy environments (Evans, 2004; Pujol et al., 2012), and less hearing device use (Marnane & Ching, 2015; Walker, McCreery, et al., 2015; Walker et al., 2013). Similarly, complex family issues (e.g., death or divorce) are associated with decreased daily CI use (Archbold et al., 2009; Marnane & Ching, 2015). Thus, if we had been able to add these factors into the analysis, they might have explained additional variance and altered the estimates of the links between data logs and vocabulary.

Limitations

We explored a wide range of models for the association between data logs and language performance. While some argue that this approach to model selection is appropriate when exploration is the primary goal (Symonds & Moussalli, 2011), Burnham and Anderson (2002) warn that fitting too many candidate models can lead to spurious findings. In any case, the associations we found should be interpreted carefully and must be targeted more directly and rigorously in the future. Most importantly, the causal relation between environment and language performance remains unclear: It is possible that certain environments facilitate language development, or that children are placed in environments according to their skills, either because of self-selection or due to decisions made by their caregivers. After all, whether young children go to mainstream education, for example, is usually decided by their parents, teachers, and other caregivers based on their behavior and abilities.

Another limitation is our relatively homogenous sample. All children were prelingually deaf, early implanted, mainly communicating orally, and had no known severe cognitive or motor deficits. All these factors might affect the association between environment and language outcomes. This means, that it is not clear, whether the associations we found hold true for the broader pediatric CI population. In the future, it should be explored how the environment interacts with such child characteristics in shaping the language outcomes.

Another concern is that there is little information about the validity of N6's auditory scene classifier (Hanvey & DeBold, 2015; Mauger et al., 2014). The classifier has been trained on a large sample of labeled examples, so that it should generally agree with the categorization made by humans, and the 12-month windows we used should have made the averages robust against short-term and seasonal fluctuations. However, empirical evidence for the classifier's validity and reliability in real-world applications is needed.

Conclusion

We have shown, that CI data logs can be used to make comprehensive, naturalistic observations of children's daily CI use and aspects of their auditory environments, and that the information that data logs capture is associated with children's language performance. Specifically, children's receptive vocabulary scores were predicted by their average daily CI use and exposure to music. Higher amounts of daily CI use were associated with larger vocabularies, and children who were exposed to more music—as labeled by the N6 auditory scene classifier—had smaller vocabularies. Somewhat surprisingly, there were no clear associations between the data-logged daily exposure to speech and noise and children's language performance.

These findings are encouraging, because a child's daily CI use and environment can—at least in part—be changed through intervention, and data logs can be used to guide caregivers in making such changes. In fact, there already are intervention programs that use LENA in such a way, in order to help parents increase the quality of their child's language environment (Leffel & Suskind, 2013; Suskind et al., 2016). While LENA provides more detailed and accurate measurements of the child's auditory environment, CI data logs have the advantage that they are available for all N6 users, and that they can easily be collected over long time periods. Even outside of specific interventions, CI data logs can enrich the communication between clinicians and CI users (or their caregivers), and encourage the latter to take a more active role in the rehabilitation process (Chiauzzi, Rodarte, & DasMahapatra, 2015; McCurdy, 2016).

In summary, our results suggest that consistent daily CI use and a rich auditory environment play an important role in the language development of children with CIs, and that CI data logs are a valuable clinical tool, that can help to understand this role and support the auditory rehabilitation of children with CIs.

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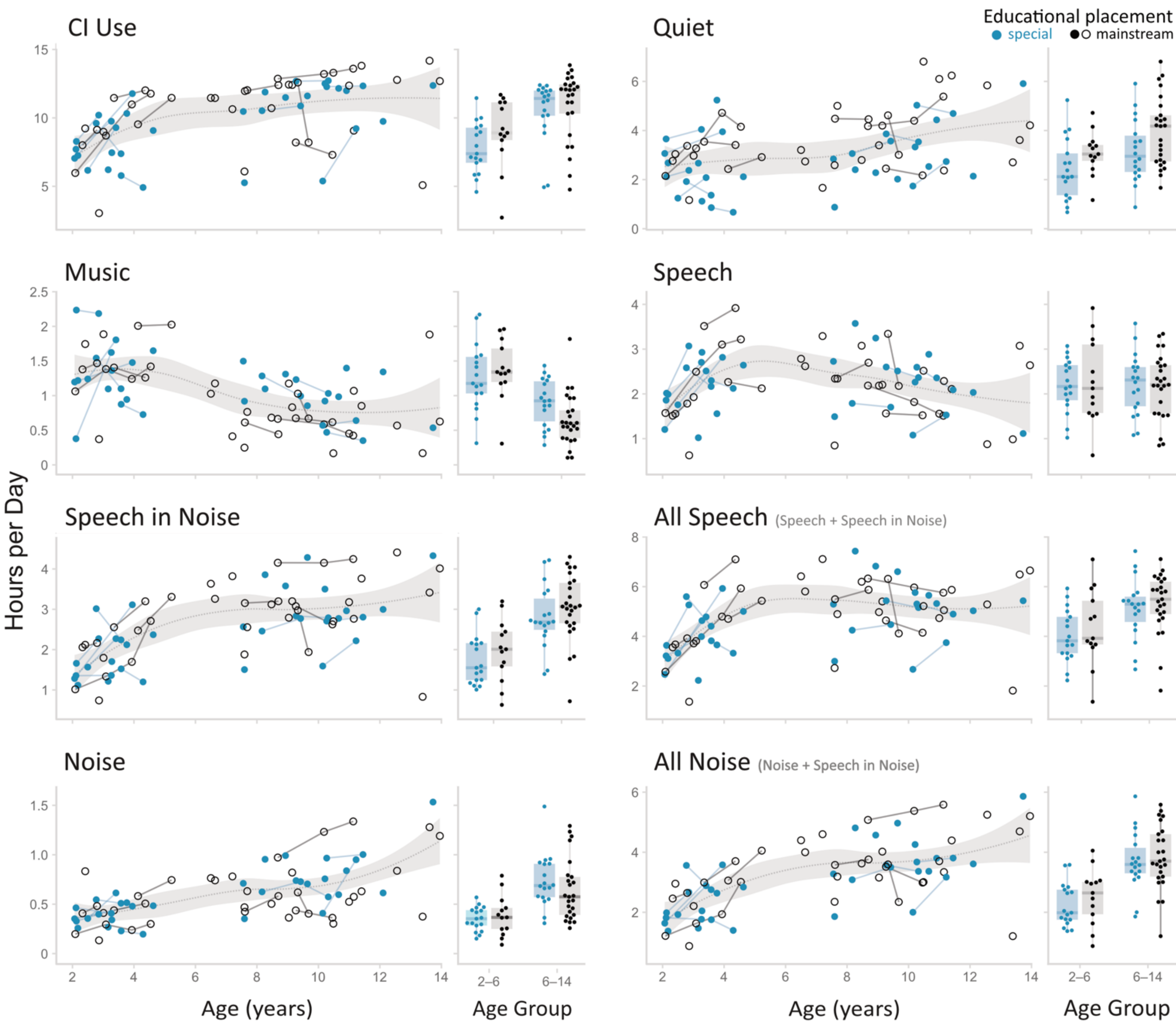

Figure 1. Aggregated data-logging variables for the 12-month time window before each PPVT test moment (n=73 test results from 52 subjects) by chronological age (scatter-plots), age group (boxplots), and educational placement (color). In the scatterplots, PPVT standard scores (SSs) from the same participant are connected by lines; the gray dotted lines and areas in the background show local polynomial regression (LOESS) fits and their 95% CIs.

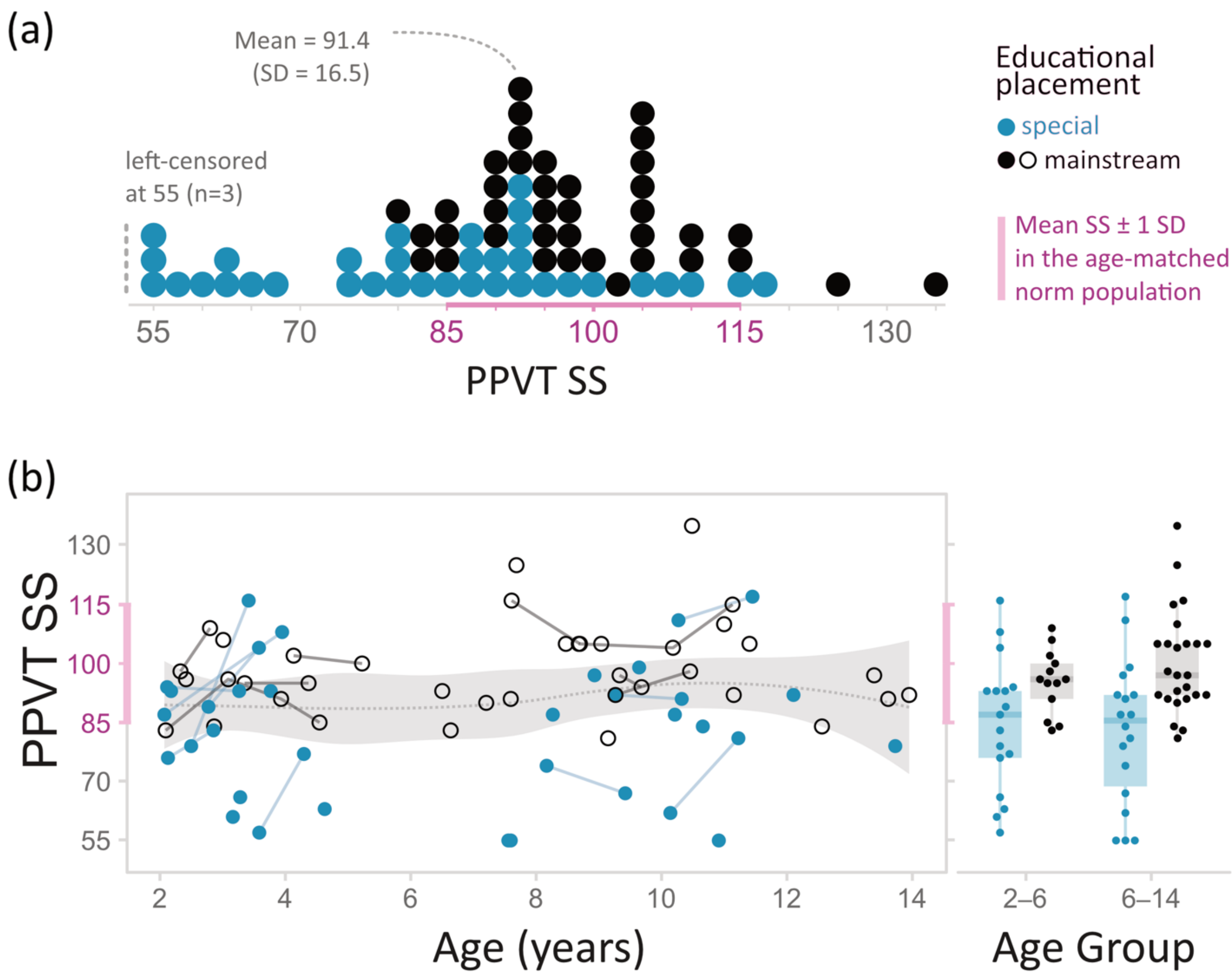

Figure 2. Distribution of the PPVT standard scores (SSs; *n*=73) by chronological age and educational placement. *(a)* Histogram of PPVT SSs. *(b)* Relation of SSs with age (scatterplot) and age group (boxplot). In the scatterplot, PPVT SSs from the same participant are connected by lines; the gray dotted line and area in the background show a local polynomial regression (LOESS) fit and its 95% CI.

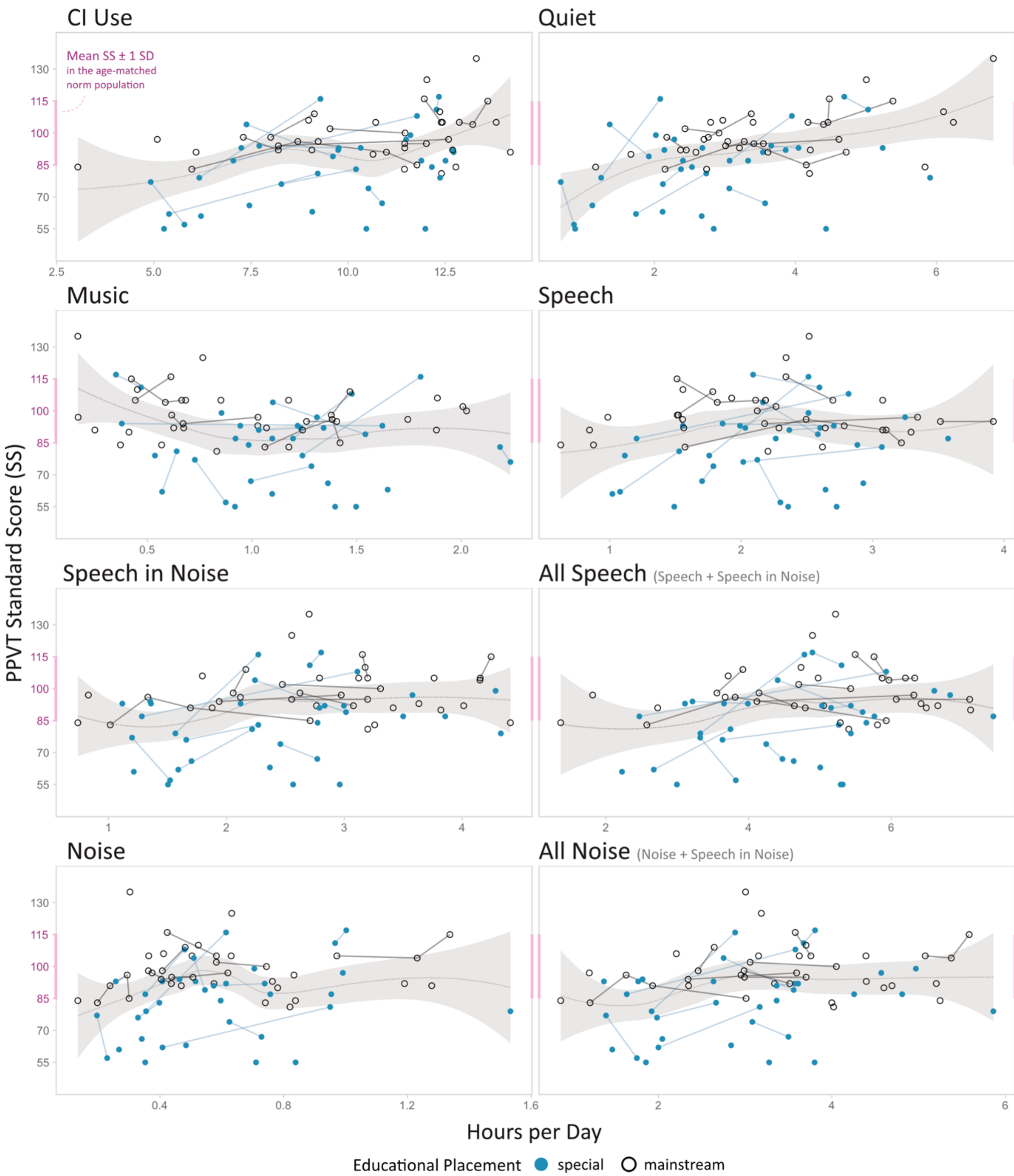

Figure 3. Relation between PPVT standard scores (SSs) and aggregated data-logging variables for the 12 months preceding the PPVT test moment. PPVT SSs from the same participant are connected by lines. The gray dotted lines and areas in the background show local polynomial regression (LOESS) fits and their 95% CIs.

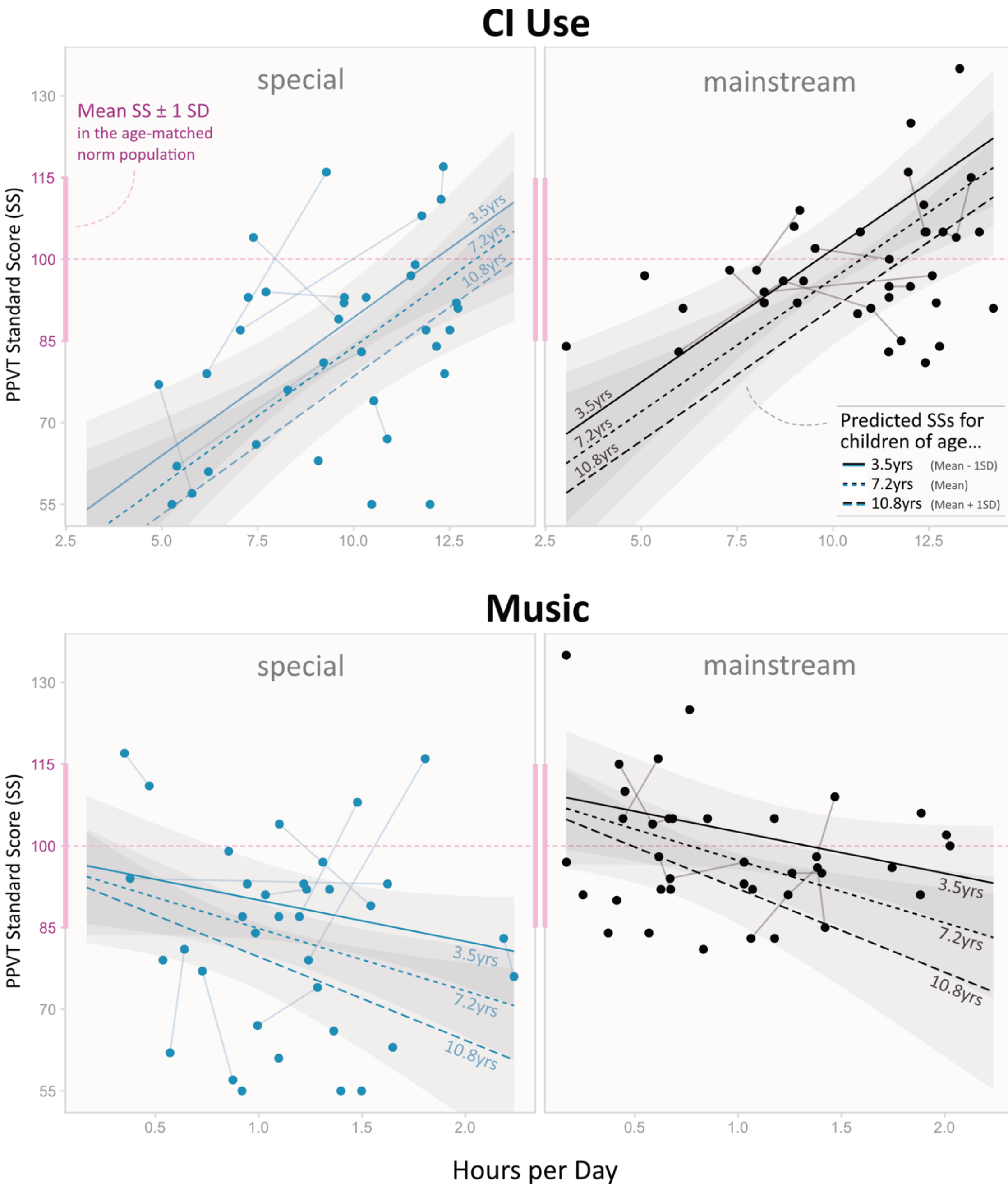

Figure 4. Raw data and predicted effect of daily CI use (*top*) and daily exposure to music (*bottom*) on PPVT standard scores (SSs), by educational placement and for three exemplary ages (corresponding to the sample's mean age ± 1*SD*). All other predictors are kept at the sample mean. Predictions are based on the model average of the models presented in Table 5. Gray areas show 95% CI

Table 1.
Sample characteristics, summary statistics for PPVT results and other variables by educational placement (*n=73* PPVT test results from *n=52* participants).

	Mainstream Education	Special Education‡	Total
N participants	27	25	52
Gender (n)			
Female	14	7	21
Male	13	18	31
Etiology (n)			
Genetic	10	15	25
Infection	6	3	9
Unknown	11	7	18
Age at CI in years, *M* (SD)	1.4 (0.5)	1.3 (0.5)	1.4 (0.5)
Implantation mode (n)			
Unilateral	6	10	16
Bilateral simultaneous†	11	6	17
Bilateral sequential	10	9	19
PPVT results§			
N test results	38	35	73
Age at test in years, *M* (SD)	7.6 (3.6)	6.7 (3.7)	7.2 (3.6)
Mean SS (SD)	98.6 (11.6)	83.5 (17.5)	91.4 (16.5)

Note: SS = PPVT standard score. † defined as <1 y time difference between implantations; § some participants contributed multiple PPVT test results. ‡ One child who had not entered school or daycare at 2.8 years of age was assigned to the special education group.

Table 2.
Summary statistics for distribution of data-logging variables in average hrs/day, aggregated over the 12-month time window before each PPVT test (n = 73).

	Mainstream Education					Special Education					Total				
			Percentile					Percentile					Percentile		
	M	SD	25%	50%	75%	*M*	SD	25%	50%	75%	*M*	SD	25%	50%	75%
CI Use	10.56	2.65	9.00	11.46	10.6	9.54	2.47	7.42	9.76	11.83	10.07	2.60	8.21	10.64	12.28
Speech	2.22	0.78	1.57	2.20	2.22	2.21	0.63	1.77	2.26	2.62	2.21	0.71	1.70	2.20	2.64
Speech in Noise	2.79	0.95	2.13	2.88	2.79	2.40	0.88	1.58	2.37	2.90	2.60	0.93	1.88	2.71	3.20
All Speech†	5.00	1.39	4.13	5.25	5.00	4.59	1.26	3.65	4.78	5.38	4.80	1.34	3.81	5.00	5.76
Noise	0.60	0.30	0.40	0.52	0.60	0.59	0.28	0.38	0.55	0.73	0.60	0.29	0.40	0.52	0.74
All Noise‡	3.39	1.19	2.72	3.43	3.39	2.99	1.12	1.95	3.08	3.60	3.20	1.17	2.34	3.19	3.80
Music	0.96	0.52	0.59	0.84	0.96	1.15	0.45	0.90	1.10	1.38	1.05	0.50	0.64	1.03	1.38
Quiet	3.65	1.31	2.75	3.39	3.65	2.81	1.30	2.05	2.67	3.61	3.24	1.36	2.37	3.04	4.18
Accessory Use§	0.42	0.58	0.00	0.03	0.42	0.46	0.74	0.00	0.00	0.86	0.44	0.66	0.00	0.01	0.81

Notes: Some participants contributed multiple data points to these summaries. †All Speech = Speech + Speech in Noise, ‡All Noise = Noise + Speech in Noise. § The time using accessories is not counted towards environmental scenes because the Nucleus 6 scene classifier does not categorize sound that is received through an accessory.

Table 3.
Most parsimonious models predicting PPVT standard scores (SSs) *without* data-logging variables (ΔAICc<2). Coefficients, model fit, and average coefficients (full average, with shrinkage).

Model	Int	Edu	Age	Gnd	k	AICc	ΔAICc	AICc-w	R_m^2
1	**82.4**	**16.3**			4	598.4	0	.57	.24
2	**82.4**	**15.9**	1.3		5	600.2	1.86	.22	.24
3	**84.1**	**15.7**		-2.4	5	600.3	1.96	.21	.25
Avg.	**82.8**	**16.1**	1.1	-0.5					
SE	3.2	3.9	1.1	2.1					
Imp.	-	1	.22	.21					

Notes: All models include a random effect for participant. Age was *z*-standardized. Coefficients larger than two times their *SE* are bold. Coefficients: Int = Intercept, Edu = educational placement (reference level: special), Gnd = gender (reference level: male). Model fit: k = number of parameters in the model, AICc = Akaike's information criterion, corrected for sample sizes, AICc-w = AICc-weights (indicate relative support for each model), R_m^2 = coefficient of determination for mixed models. Average Model: Avg. = average coefficient, SE = Standard Error, Imp. = relative importance.

Table 4.
Most parsimonious models predicting PPVT standard scores (*SSs*) with *only* data-logging variables (ΔAICc<2). Coefficients, model fit, and average coefficients (full average, with shrinkage).

Model	Int	Age	Use	Music	Age× Music	SpNs	Ns	AllSp	Quiet	Sp	Age× Use	Age ×Sp	Age× SpNs	k	AICc	ΔAICc	AICc-w	R_m^2
1	**89.1**	**-6.0**	**9.6**	**-6.9**	**-4.0**									7	595.4	0	.24	.32
2	**89.2**	-4.9	**13.2**	**-7.2**	**-3.8**	-5.0								8	595.5	0.12	.22	.34
3	**89.1**	-4.9	**10.7**	**-6.7**	**-3.9**		-2.8							8	596.5	1.19	.13	.33
4	**89.3**	**-6.0**	**12.4**	**-6.6**	**-3.6**			-3.2						8	596.7	1.37	.12	.33
5	**90.7**								**7.6**					4	597.1	1.76	.10	.21
6	**90.4**	**-6.2**	**11.3**	**-7.7**	**-5.4**					-1.0	-3.7	**5.1**		10	597.1	1.79	.10	.41
7	**90.1**	**-5.3**	**13.0**	**-7.3**	**-3.7**	-4.7							-1.4	9	597.3	1.98	.09	.34
Avg.	**89.5**	-5.0	**10.4**	**-6.3**	-3.6	-1.5	-0.4	-0.4	0.8	-0.1	-0.4	0.5	-0.1					
SE	2.1	2.9	4.5	2.9	2.0	2.9	1.3	1.5	2.4	0.8	1.3	1.6	0.6					
Imp.	-	.9	.9	.9	.9	.31	.13	.12	.1	.1	.1	.1	.09					

Notes: All models included a random effect for participant. All predictors were z-standardized. Coefficients larger than two times their *SE* are bold. *Coefficients:* Int = Intercept, SpNs = Speech in Noise, Sp = Speech, AllSp = All Speech. *Model fit:* k = number of parameters in the model, AICc = Akaike's information criterion, corrected for sample sizes, AICc-w = AICc-weights (indicate relative support for each model), R_m^2 = coefficient of determination for mixed models. *Average Model:* Avg. = average coefficient, SE = Standard Error, Imp. = relative importance.

Table 5.
Most parsimonious models predicting PPVT standard scores (SSs) with a combination of data-logging variables *and* other variables (ΔAICc<2). Coefficients, model fit, and average coefficients (full average, with shrinkage).

Model	Int	Age	Use	Music	Edu	SpNs	Age× Music	Edu× SpNs	AllSp	Edu× AllSp	Sp	Edu× Use	k	AICc	ΔAICc	AICc-w	R_m^2
1	**83.9**	**-5.3**	**12.8**	**-5.9**	**12.5**	-1.7	**-3.0**	**-7.0**					10	583.4	0	.24	.51
2	**84.1**	**-6.5**	**12.0**	**-5.5**	**11.9**		-2.6		0.4	**-7.0**			10	584.7	1.34	.12	.50
3	**83.9**	**-5.2**	**13.2**	**-6.2**	**12.4**		-2.7		-4.8	**-7.2**	4.9		11	584.8	1.37	.12	.51
4	**85.0**	**-4.9**	**13.0**	**-5.3**	**13.3**	-1.9		**-7.7**					9	584.8	1.42	.12	.48
5	**83.9**	**-5.2**	**13.1**	**-6.2**	**12.3**	-6.3	-2.8		4.4	**-7.3**			11	584.9	1.48	.11	.51
6	**85.0**	**-6.3**	**12.8**	**-4.9**	**12.5**				-0.2	**-7.7**			9	585.0	1.55	.11	.48
7	**84.9**	**-5.0**	**14.0**	**-5.5**	**13.0**				-5.1	**-8.0**	4.6		10	585.3	1.92	.09	.49
8	**83.9**	**-5.0**	**15.7**	**-5.8**	**12.3**	-5.5	-2.9					-5.5	10	585.3	1.95	.09	.49
Avg.	**84.3**	**-5.4**	**13.2**	**-5.7**	**12.5**	-1.8	-1.9	-2.6	-0.5	-4.1	1.0	-0.5					
SE	2.4	2.3	3.1	2.0	3.3	3.3	1.8	3.9	3.8	4.2	2.4	1.8					
Imp.	1	1	1	1	.68	.56	.56	.56	.35	.21	.09	1					

Notes: All models included a random effect for participant. Continuous predictors were z-standardized. Coefficients larger than two times their SE are bold. *Coefficients:* Int = Intercept, Edu = educational placement (reference level: special), SpNs = Speech in Noise, AllSp = All Speech, Sp = Speech. *Model fit:* k = number of parameters in the model, AICc = Akaike's information criterion, corrected for sample sizes, AICc-w = AICc-weights (indicate relative support for each model), R_m^2 = coefficient of determination for mixed models. *Average Model:* Avg. = average coefficient, SE = standard error, Imp. = relative importance.

Supplemental Digital Content 1(Figure S1). Figure that shows the distributions of the data logging variables. pdf

Supplemental Digital Content 2 (Figure S2). Figure that shows the pairwise associations between the data logging variables

Figure S1. Distribution of Data Logging Variables, aggregated over 12 months before each PPVT test moment (*n*=73). Solid line and shaded area indicate the Median and central 50% of the data. Dashed line indicates the position of the Mean. Note that some participants contributed multiple data points.

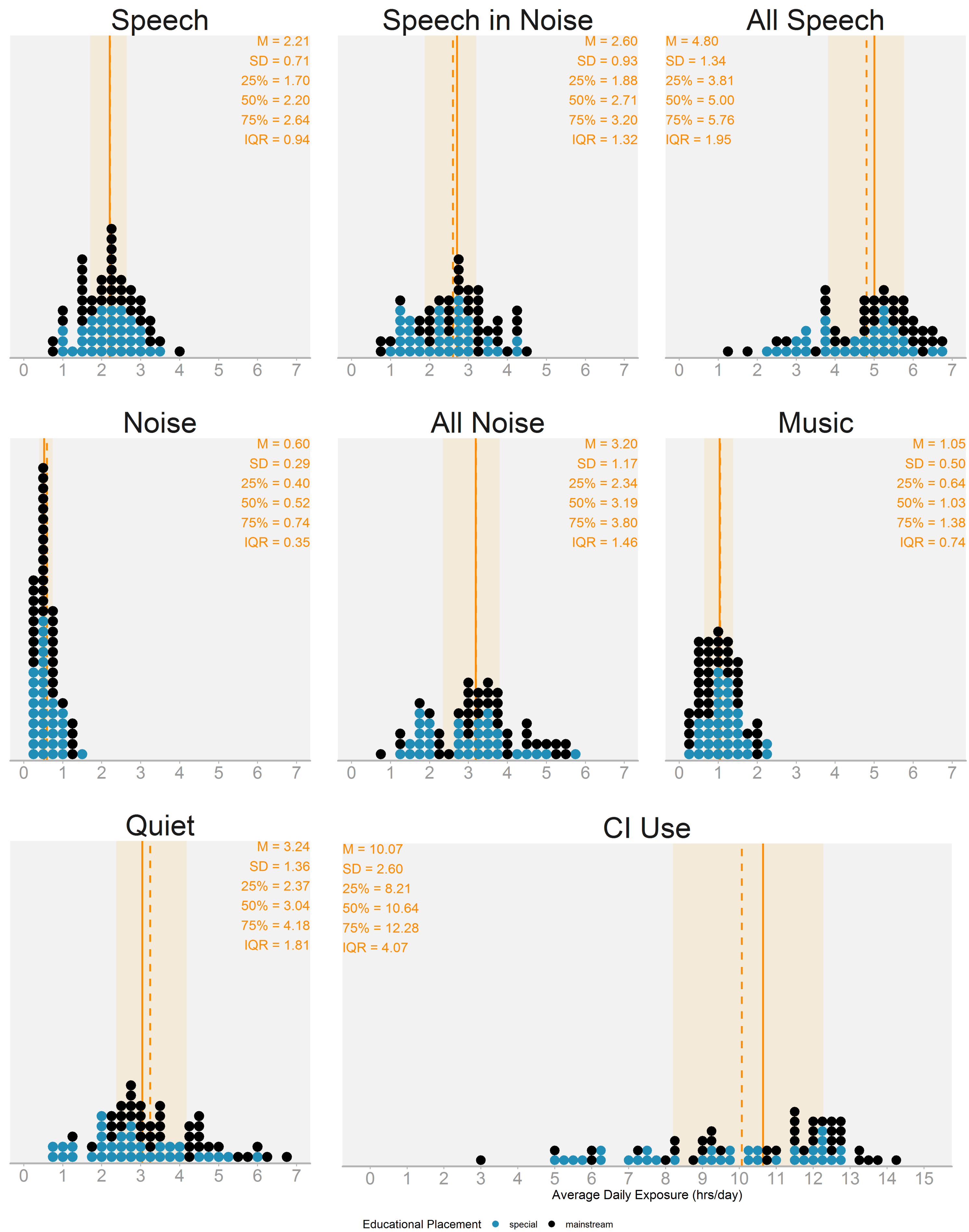

Figure S2. Pairwise Associations between Data Logging Variables, aggregated over 12 months before each PPVT (n=73 PPVT test results of 52 participants). Data points from the same subject are connected by lines. Lines and shaded areas in the background show the predictions and 95% CI from a simple regression with a random intercept for subject. The numbers in the top left corners indicate the corresponding standardized regression coefficients (β; pink: $p < .05$, grey: $p \geq .05$).