Automated Vocal Analysis of Children With Hearing Loss and Their Typical and Atypical Peers

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Objectives: This study investigated automatic assessment of vocal development in children with hearing loss compared with children who are typically developing, have language delays, and have autism spectrum disorder. Statistical models are examined for performance in a classification model and to predict age within the four groups of children.

Design: The vocal analysis system analyzed 1913 whole-day, naturalistic acoustic recordings from 273 toddlers and preschoolers comprising children who were typically developing, hard of hearing, language delayed, or autistic.

Results: Samples from children who were hard of hearing patterned more similarly to those of typically developing children than to the language delayed or autistic samples. The statistical models were able to classify children from the four groups examined and estimate developmental age based on automated vocal analysis.

Conclusions: This work shows a broad similarity between children with hearing loss and typically developing children, although children with hearing loss show some delay in their production of speech. Automatic acoustic analysis can now be used to quantitatively compare vocal development in children with and without speech-related disorders. The work may serve to better distinguish among various developmental disorders and ultimately contribute to improved intervention.

Key words: Autism, Automatic speech processing, Automatic speech recognition, Hard of hearing, Language delay, Speech production, Vocal development.

(Ear & Hearing 2015;36;e146–e152)

INTRODUCTION

A number of recent reports have examined fully automated acoustic analyses of whole-day, naturalistic recordings of children's vocalizations and auditory environments (Christakis et al. 2009; Oller et al. 2010; Warren et al. 2010; Zimmerman et al. 2009; VanDam et al. 2012; Caskey & Vohr 2013; Ambrose et al. 2014b). Automated vocal analyses have been shown to differentiate children based on age and developmental status and may be useful in clinical, research, and educational settings. This study is the first to use automated acoustic analyses to examine vocal development in children who are hard of hearing (HH; those with mild-to-severe hearing loss [HL]), using a very large database (VLDB) of hundreds of whole-day recordings of families in naturalistic home environments. This study uses automated analyses to compare HH children with children who are typically developing (TD), autistic (autism spectrum disorders [ASD]), or language delayed (LD).

Automated speech processing (ASP) technology now allows researchers to automatically analyze very large data sets of naturalistically collected child speech (Richards et al. 2008). A recent report used an ASP system (LENA; LENA Research Foundation, Boulder, CO, USA) on a VLDB of naturalistic child audio recordings to examine vocal development in groups of children who are TD, ASD, and LD (Oller et al. 2010). Results showed that the ASP techniques were able to predict child age and distinguish TD from ASD and LD groups and to a lesser extent between ASD and LD groups, based on vocal development features associated with the linguistic infrastructure for syllabification. Oller and colleagues showed that the objective ASP techniques were able to accurately distinguish group membership based on acoustic features of the children's vocalizations.

Other studies have used the same ASP techniques to examine certain characteristics of the vocalizations of children who are TD (Gilkerson & Richards 2008), preterm infants (Caskey et al. 2011; Caskey & Vohr 2013), children with ASD (Warren et al. 2010; Dykstra et al. 2013), and children who are HH (VanDam et al. 2012; Aragon & Yoshinaga-Itano 2012; Ambrose et al. 2014b). In one study of HH children, both TD and HH 2-year olds were shown to engage in similar numbers of conversational turns. For the HH group, greater auditory ability was associated with more conversational turns (VanDam et al. 2012). Another study found that for children with HL, child vocalizations and conversational turns with adults were broadly similar in number when comparing between Spanish- and English-speaking households and when compared with TD children (Aragon & Yoshinaga-Itano 2012), but this study did not identify the nature or the degree of HL of the participants. Another study using the same ASP system looked at the rate of computed conversational turns between HH children and their caregivers, finding that greater numbers of conversational turns were associated with better language outcomes (Ambrose et al. 2014b). To date, however, automatic analysis strategies have not been used to directly examine vocal development in a large sample of HH children compared with their peers who are TD or have developmental disabilities. The present work uses ASP techniques to determine how the vocal development of HH children compares with other target groups and to test how well a model based on ASP classifies the respective groups.

A number of studies have addressed developmental characteristics of speech in children with HL. The general consensus is that children with HL have reduced consonant, vowel, and syllable inventories (Stoel-Gammon & Otomo 1986; Stoel-Gammon 1988; Moeller et al. 2007a), reduced articulation space

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(Kent et al. 1987; Uchanski & Geers 2003; Pratt & Tye-Murray 2008), atypical temporal and coordinative patterning (Uchanski & Geers 2003; Nathani et al. 2003; VanDam et al. 2008, 2011; VanDam 2010), delayed onset of or reduced place and manner of articulation inventories (von Hapsburg & Davis 2006; Moeller et al. 2007a), increased phonological errors (Elfenbein et al. 1994; Moeller et al. 2010), and lower scores on standardized speech production tests (Moeller et al. 2007a, 2010). In addition, a lack of difference has been observed between volubility measures of prelingual TD and HH children (Moeller et al. 2007a; Nathani et al. 2007). It is important to note, however, that the samples examined in the studies above characterize children with varying degrees of HL—some of whom are HH and some with severe, profound, or total HL—and varying intervention strategies. These and other features of the existing studies suggest caution in generalizing these results to all children with HL.

In addition to these considerations, certain challenges persist in studying the speech of HH children. First, due to difficulty in data collection, differences in research questions and goals, inconsistent definitions and groupings of variables, and varying levels of reporting, a generalized or comprehensive picture of speech and vocal development in HH children is challenging to assemble (Moeller et al. 2007a, 2007b). Large-scale studies with multiple comparisons such as those made possible by the procedures of the present work may begin to address these inconsistencies and contribute to a more comprehensive picture of speech and vocal development in HH children. Second, HH children are generally underrepresented in the literature (Wake et al. 2004), and research leading to a more complete description will advance understanding of this growing population (Tharpe & Bess 1999; Fitzpatrick et al. 2014), with the ultimate goal of improved service provision. Finally, the population of children with HL has undergone substantial change in recent years as a result of early detection through universal newborn hearing screening (UNHS; Yoshinaga-Itano et al. 1998; Moeller 2000; Yoshinaga-Itano 2003; Kennedy et al. 2006), improved assistive devices including hearing aids and cochlear implants (Tomblin et al. 1999; Niparko et al. 2010; Yoshinaga-Itano et al. 2010; McCreery et al. 2012), improved educational approaches (Bess et al. 1998; Lieu et al. 2012), and advantageous changes to public health policy (Johnson & Mitchell 2008; Houston et al. 2010). Of particular interest to the present work, one recent large-scale study looking at HH children suggested that the earliest-identified children were more likely to approximate the speech production accuracy (in terms of percent consonants correct) of their TD peers (Ambrose et al. 2014a). More research is needed on this group of HH children who experience early identification. If they are accruing the benefits of early identification, they should trend toward approximating the performance of the NH group. Similarly, if early intervention is a beneficial factor for a modern population of HH children, those HH children may differentiate themselves in performance from other groups, such as children with LD, ASD, or other disabilities. These transformative advances have changed the population so that the historical descriptions of children with HL in the literature may not accurately reflect the modern population (Wake et al. 2004; Marschark & Spencer 2006). Taken together, it is clear that a better description of HH children is needed to improve service delivery and to clarify the factors that influence the impact of HL on speech and vocal development.

This work explores the vocal development of HH children in their naturalistic, home environments in comparison with three other groups. The purpose of this work was to examine how vocal behaviors of toddlers and preschoolers who are HH are analyzed by an automated ASP vocal analysis system. Two specific research questions follow. First, to what degree can ASP procedures be used to classify children belonging to known TD, HH, LD, and ASD groups? Second, how accurately do the automated procedures predict a developmental vocal age in the HH group and how does the prediction of developmental age compare with other groups?

METHODS

Participants

Children (n = 273) from four groups are represented: TD (n = 106), HH (n = 41), LD (n = 49), and ASD (n = 77). Demographic and recording details are reported by group in Tables 1 and 2. Socioeconomic status (SES) is the self-reported level of attained education by the mothers of children participating in the study. SES report was interpreted on an eight-point scale ranging from *no-high-school* to *graduate-degree*. Children in the TD, LD, and ASD groups were originally participants in a study by Oller et al. (2010); they were identified through extensive professional screening and diagnostic testing, and those data are further described in detail in that scientific report.

Participants in the HH group were recruited as part of a larger, multisite longitudinal study looking at a variety of outcome factors in children with mild-to-severe HL (Holte et al. 2012). Families of 41 HH children contributed multiple monthly recordings over about a year, with HH families contributing an average of 10.4 daily recordings each. The data reported here thus constitute a mixed longitudinal and cross-sectional data set. The average age at recording for the HH group was 29.7 months (range: 11–48 months; SD = 8.0 months) taking all 427 recordings into account. Families self-identified as white (34/41), black (3/41), multiracial (2/41), Asian (1/41), and other (1/41). Institutional review boards at participating institutions approved this study, and informed consent was obtained for all recordings.

Audiometric Evaluation

Hearing thresholds were measured by certified audiologists experienced in working with children, using developmentally appropriate behavioral methods, including visual reinforcement audiometry and conditioned play audiometry. Threshold frequencies at 500, 1000, 2000, and 4000 Hz were tested for both left and right ears (pure-tone average left [PTA-L] and pure-tone

TABLE 1. Demographic details by group

Group	Male (Proportion)	Mean SES (8-Point Scale)	Mean Child Age (mos)
TD	0.45	5.8 (0.3)	28.1 (1.7)
HH	0.42	6.4 (0.4)	29.7 (1.2)
LD	0.67	5.3 (0.2)	28.9 (1.0)
ASD	0.83	5.7 (0.3)	35.9 (0.8)
All	0.59	5.7 (0.3)	30.6 (1.2)

Standard error of the mean is given in parenthesis.
ASD, autism spectrum disorder; HH, hard of hearing; LD, language delayed; SES, Socioeconomic status; TD, typically developing.

TABLE 2. Recording details by group

Group	Individuals (n)	Recordings (days)	Duration (hr)	Total Child Utterances (millions)
TD	106	802	12,813	1.838
HH	41	427	5,194	1.168
ASD	77	351	5,586	0.694
LD	49	333	5,317	0.607
All	273	1,913	28,910	4.307

ASD, autism spectrum disorder; HH, hard of hearing; LD, language delayed; TD, typically developing.

average right [PTA-R], respectively), and better ear pure-tone averages (BEPTA) were computed. Insert earphones (Etymotic Research, ER-3A), supra-aural headphones (TDH-49P), or children's individual earmolds coupled with insert earphones were used to assess air conduction thresholds. In cases where the audiogram could not be completed at the study visit, the child's most recent audiogram was obtained from his or her clinical audiologist. Audioscan Verifit (v. 3.9, Dorchester, Ontario, Canada) software was used to calculate the aided speech intelligibility index (Aided SII) for each ear, using a standard male speech signal (carrot passage) at an input level of 65 dB SPL (ANSI S 3.5, 1977). All HH children received prompt intervention and were fitted with amplification at an average age of 7.62 months (SD = 6.56 months). For the HH group, 40 children were fitted with bilateral, air conduction hearing aids and one child was fitted with a bone conduction aid; 36 children were identified with HL at birth through UNHS, with the five other children identified at 1, 6, 12, 15, and 17 months of age. Group audiometric details are given in Table 3.

Hardware and Software

Day-long recordings were collected and processed using hardware and software developed by the LENA Research Foundation (Ford et al. 2008; Xu et al. 2008), supplemented by additional analyses of child vocalizations using procedures developed by the LENA Research Foundation and collaborating scientists. The system consists of a wearable recording device measuring about 1 × 5 × 8 cm and weighing about 70 g and includes associated ASP and output reporting software. The recording device is fitted into a pocket on the front of a custom shirt or vest worn by the child. The device is designed to be turned on in the morning and record continuous audio for up to 16 hours or until the device is turned off in the evening. Acoustic recordings are transferred to a computer and processed with the LENA software. The LENA software is capable of outputting the full audio (16 bit, 16 kHz sampling rate, pulse code modulation [PCM] WAV format) and summary reports of the ASP software.

The LENA software determines segment boundaries and then assigns a label to each segment by proprietary algorithms that evaluate the audio signal using statistical likelihood techniques. Acoustic segments are labeled for non-speech events including noise, silence, and the presence of electronic media (e.g., TV, radio) and for human vocal activity including that of any adult female, adult male, the target child wearing the recorder, or other children in the environment. A final label designates "overlap" between any voice and any other category of sound. For target child vocalizations, the software subcategorizes segments as speech-like or cry/vegetative vocalizations. The present work is based on acoustic analyses (using the LENA ASP software) of speech-like segments produced by the target child. The LENA ASP system generates many acoustic variables and from these variables also generates an estimate of the child's vocal development age (see also Oller et al. 2010).

TABLE 3. Audiometric group characteristics of the HH group

	BEPTA (dB HL)	PTA-L (dB HL)	PTA-R (dB HL)	Aided SII
M	49.4	54.8	51.9	0.76
SD	12.6	16.2	13.2	0.13
Maximum	81.0	115.0	91.0	0.93
Minimum	24.0	27.0	24.0	0.31

BEPTA, better ear pure-tone average; PTA-L, pure-tone averages of left ear; PTA-R, pure-tone averages of right ear; SII, speech intelligibility index.

Data Analysis and Statistical Models

More than 4.3 million segments labeled as child utterances were automatically evaluated by the computer algorithms. The data were compared across groupings of the participant categories (TD, HH, LD, and ASD). Two models were used to evaluate the data. First, the acoustic variables (i.e., the data generated by the ASP software) are used in a linear discriminant analysis (LDA) model to examine their ability to classify group membership among TD, HH, LD, and ASD. Second, with these acoustic variables, a multiple linear regression (MLR) model was used to predict vocal development age separately for each group. This procedure is described in more detail in Oller et al (2010).

Procedures

All participant families contributed demographic and family information, and target children were administered a number of assessments, varying by group as appropriate. For example, only the children in the HH group were evaluated on better ear pure-tone average and speech intelligibility index. Acoustic recordings were collected on multiple days over the course of several weeks or months at regular intervals. The children in the HH group contributed more recordings per child (M = 10.4) and, on average, at more regular intervals than the other groups. Families were encouraged to pursue their normal daily activities during recording days, resulting in a wide variety of environmental settings, acoustic environments, participants, and events, yielding a realistic acoustic record of the observed days. Additional details are given in several reports in the literature examining other aspects of subsets of this data set (Gilkerson & Richards 2008; Zimmerman et al. 2009; Oller et al. 2010; Warren et al. 2010; VanDam et al. 2012). Oller et al. (2010) and this report include the exact subset of recordings for the TD, LD, and ASD groups.

RESULTS

Group Classification

The first research question explored the accuracy of ASP procedures in classifying children belonging to known TD, HH, LD, and ASD groups. To address this question, a distinct LDA model for each pair-wise group comparison (while

TABLE 4. Fit statistics of the linear regression for all groups of predicted age on known age

	m	CI_m	y	CI_y	r	CI_r	p
TD	1.43	1.34, 1.52	4.35	2.05, 6.70	0.762	0.731, 0.789	$<10^{-152}$
HH	1.60	1.44, 1.76	−3.44	−8.11, −1.27	0.654	0.586, 0.705	$<10^{-52}$
LD	1.39	1.19, 1.59	−7.18	−13.05, −1.34	0.593	0.519, 0.658	$<10^{-32}$
ASD	0.50	0.20, 0.80	14.66	4.44, 25.05	0.174	0.071, 0.274	$<10^{-2}$

ASD, autism spectrum disorder; HH, hard of hearing; LD, language delayed; TD, typically developing.

still including all data in the model) was used to determine the equal correct classification rate (ECCR)—in which the expected ECCR for four groups by chance alone is 25%—along with the corresponding posterior probability threshold (PPT) that the correct group classification was achieved. The PPT is the empirically determined threshold for defining classification success at the ECCR. The pair-wise classification performance of the LDA between the TD group (as the standard reference) and each of the other three groups was relatively robust, performing well above chance for every comparison. For the HH group, the ECCR was 76.4% and the PPT was 44%; for the ASD group, the ECCR was 85.7% and the PPT was 24%; for the LD group, the ECCR was 73.0% and the PPT was 38%. A relatively high ECCR indicates good performance of the model. Lower PPT scores are an indication of better model fit, with percentage values <50% indicating good performance of the model (or better fit of the model from a statistical perspective). Because only the TD group has a standardized value, only group-by-TD relationships may be assessed.

ASP Used to Predict Age

The second research question considered how accurately the automated procedures predict a developmental vocal age in the HH group in comparison with the other groups. To address this question, the relationships between the ASP-predicted developmental age and the known age of the children were compared. The MLR model was run to assess the relationship between actual age and predicted age based on vocal development. A model for vocal development age was constructed by regressing the known age of the TD group on the output performance of age estimated by the model to achieve a normative standard with which to compare the observed samples of the HH, LD, and ASD groups. Bootstrapped (10^4 iterations of resampling with replacement) estimates of slope (m), y-intercept, Pearson correlation coefficient (r), 95% confidence interval (CI), and probability (p) of obtaining a significant correlation by chance are reported for each group in Table 4. The fit of the linear regression was relatively good for the TD, HH, and LD groups explaining 76%, 65%, and 59% of the variance, respectively, but was notably poorer for the ASD group, explaining only 17% of the variance. Analysis of confidence intervals indicates significant differences among all four groups for correlation coefficients, between the ASD group and each of the other three groups for slope, between TD and HH, TD and LD, ASD and HH, and ASD and LD for y-intercept. Overall, these group comparisons suggest that the patterns shown by each group are distinct. Individual observations and fitted least-squares linear regression lines are shown in Figure 1 for all groups.

DISCUSSION

This study examined how an automated acoustic analysis system differentiated four groups of children: TD, HH, LD, and ASD. Discrimination between the TD group and the three other groups was relatively good, greater than 72% ECCR for all comparisons. Age estimates modeled on child vocal characteristics were unique for each of the four groups, with the HH group patterning most similarly to the TD group, followed by the LD and ASD groups, respectively.

The present work provides evidence that automated analysis of all-day, naturalistic recordings in children's homes or schools is a new, objective tool for monitoring vocal development in children, including children who are HH. Such analysis previously has been possible only at very small scale, but now it is possible to examine and compare VLDBs comprised of completely naturalistic recordings, using automated tools modeled on many years of speech development research. Using this approach, we were able to provide new quantitative data illustrating that 11- to 48-month-old HH children demonstrate vocal behaviors that share much in common with TD children. The HH children show patterns across real and predicted age estimates that appear more similar to TD children's patterns than to those of children with other disorders, namely LD or ASD (see, e.g., Fig. 1). This similarity between TD and HH groups—and the presumed gains by a modern population compared with an earlier generation of HH children—may support the practice of early identification through UNHS and subsequent interventions. At the same time, the developmental patterns of HH and TD children are not identical, and even in this first attempt to make automated comparisons of TD and HH samples, we find that the HH children were distinguishable within the statistical model. Further work is needed to clarify the parameters that contribute to both similarities and differences among the groups.

ASP Performance of the HH Group Compared With TD, LD, and ASD Groups

With the TD group as reference, the HH group was distinct but demonstrated an overall developmental trajectory that was similar to the TD group. The model's ability to discriminate by group was relatively high, with the best discriminability between the TD and ASD groups (>85%). Discrimination between TD and HH and between TD and LD was somewhat lower, but pairwise classification remained greater than 72% in all cases. This model performance may be useful in identifying constituents of groups through the application of automated ASP in a variety of settings. Supplemental to currently available technology that reliably characterizes, HL advances in automated techniques such as those reported here may alert providers to the need to test for cases of progressive, undiagnosed, or acquired HL, and

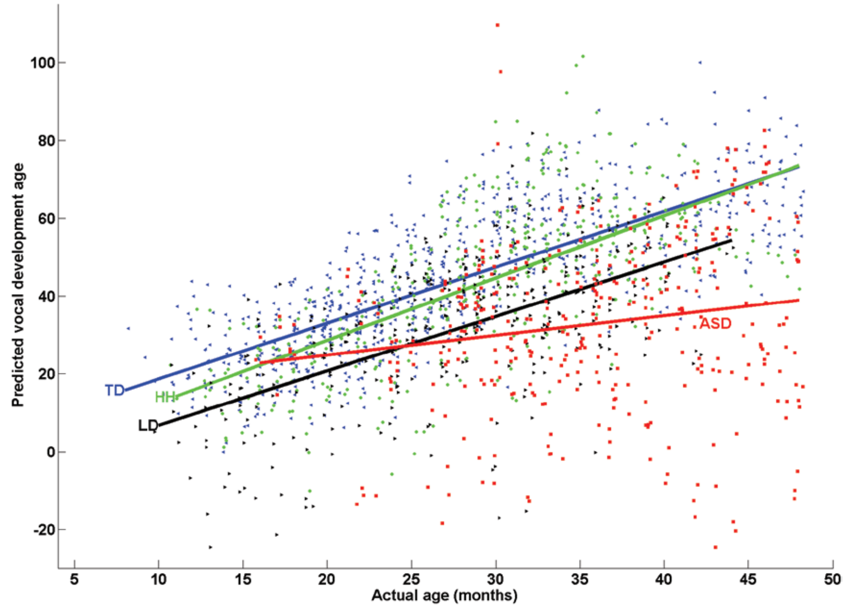

Fig. 1. Multiple linear regression (MLR) model predictions for individual observations (i.e., individual recordings). Regression lines and markers are shown in left-triangle for the typically developing (TD) group, circle for the hard of hearing (HH) group, right-triangle for the language delayed (LD) group, and square for the autism spectrum disorder (ASD) group.

to identify children who have HL accompanied by comorbid conditions.

The similarity between TD and HH groups may increase at older child ages, suggesting a more efficient predictive model at relatively older ages. The steeper slope for the HH group compared with the TD group (1.60 and 1.43, respectively) suggests that the model's performance at older ages of the HH group was more similar to the TD group. The slope of the LD group was similar and slightly shallower than the TD group, and the ASD group did not appear to have a developmental trajectory similar to any of the other groups. These findings may be useful in distinguishing a child with HL alone from a child with HL and comorbid disorders or from a child with certain disorders that present similarly to HL.

The LD group was further distinct from both the TD and the HH groups and also patterned similarly in terms of overall developmental slope trajectory. The appearance of the LD group below the TD and HH groups lends support to the possibility of delayed but parallel development. The HH group was more similar to the TD reference, suggesting greater similarity between HH and TD groups than between LD and TD groups. For both comparisons with the TD reference group, the differences were consistent with developmental delay rather than difference in the mechanism. The ASD group, however, showed differences from all other groups in terms of both the time course of development (the shallower slope of the developmental trajectory) and the observed performance (the relatively lesser *y*-intercept of the developmental trajectory). This developmental difference suggests not only delay but also the possibility of varying mechanisms responsible for the observed difference. For more discussion on LENA ASP technology with ASD populations, see Warren et al. (2010) and Oller et al. (2010).

ASP and Model Specification

The present work also considered the classification performance of the ASP model, finding good overall performance of the model. Further examination of the specific determiners within the ASP algorithms or details in the acoustic signal itself may reveal underlying mechanisms of both human and machine classification and decision processes. That is, given the successes of the classification procedures of the model reported here and elsewhere, a next reasonable step is to investigate the specific acoustic and participant parameters that drive the performance of the model. We know, for example, that certain acoustic parameters related to the infrastructure for syllabification play a key role in the early development of speech (Oller 2000; Oller et al. 2010), but a detailed acoustic investigation of the parameters for children with HL has not yet been reported in the literature. Furthermore, it is of interest to explore how audiological variables of the HH children affect the fully automated methods described here. If certain parameters alone or in combination are found to be associated with specific groups or individuals according to hearing or audiological variables, the technology could be used to track or assess children's development on those parameters.

Better understanding of these mechanisms may lead not only to the ability to improve identification of disorders and subsequent intervention, but also to improvements in machine classification capabilities. Improvements in machine performance may lead to faster, potentially real-time, outcomes or allow for more parsimonious analysis to the growing number of VLDBs.

ASP Performance for Children Who Are Hard of Hearing

The performance of the ASP algorithms predicting developmental age in the HH group was quite high overall, with model performance falling lower than for the TD group but higher than the LD and ASD groups. This suggests that developmental age estimates from the LENA software analyses are able to identify and evaluate children in the HH group similarly to extant procedures used in the ASP initially developed for use with TD samples. From a practical standpoint, the present work illustrates the possibility of adding a convenient, unobtrusive, and fully objective evaluation tool to the battery of tests that are currently used to monitor the early development of children who are HH.

Limitations

The present work was limited by a number of design features. First, associations were assessed via correlational statistics, which might overestimate the influence of one or more of the actual parameters examined. Variables may be moderated or mediated by additional variables not directly considered here. Correlational analyses do not consider the source of influence, if any, which is of interest for practical implementation. Second, although reliability of LENA ASP techniques (i.e., the assignment of labels) has been examined in the groups considered here (Christakis et al. 2009; Oller et al. 2010; Warren et al. 2010; VanDam & Silbert 2013), systematic errors in label assignment are certainly present in the data. Given the highly structured VLDB, automatic analysis techniques are required, and certain artifactual or epiphenomenal results may unwittingly influence the data. Third, individual variability has not been systematically accounted for in the present work, although certain consideration of known or expected individual variability could be explicitly modeled. Human speech is inherently variable and interpreted through contextual variables not considered here or in any acoustic model. As a result, the products of automated procedures must be cautiously, judiciously interpreted. Fourth, it is unknown how demographic or other variables not assessed here may influence spoken language in the homes of families. For example, on average the families in the HH cohort are of relatively higher SES than other families examined here. It is unknown what role SES plays in the output of the LENA ASP procedures, but SES has been shown to influence speech and language behavior in several studies using LENA technology (Gilkerson & Richards 2008; Oller et al. 2010; Warren et al. 2010).

ACKNOWLEDGMENTS

We are grateful for the assistance of Lisa Burton, Rick Arenas, Jake Oleson, Stephanie Nielsen, Aneesha Pretto, and Jaimie Horning. We are grateful to the many families and children who contributed to this project. This project was supported by Washington State University Spokane Seed Grant Program and the Hearing Oral Program of Excellence (HOPE) School of Spokane.

This work was supported by National Institutes of Health Grants/NIDCD R01-DC009560 (co-principal investigators, J. Bruce Tomblin, University of Iowa, and M.P.M., Boys Town National Research Hospital) and (LENA Supplement) R01-DC009560-01S1. The role of D.K.O. in the paper was supported by Grant R01-DC011027 from the National Institute on Deafness and Other Communication Disorders and by the Plough Foundation. J.A.R., D.X., and J.G. are employees of the LENA Research Foundation. S.G. is a former employee of the LENA Research Foundation. D.K.O. is an unpaid member of the Scientific Advisory Board of the LENA Research Foundation. The content of this project is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute on Deafness and Other Communication Disorders or the National Institutes of Health.

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Received May 21, 2014; accepted November 24, 2014.

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