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ORIGINAL PAPER

Exploring Classroom Behavioral Imaging: Moving Closer to Effective and Data-Based Early Childhood Inclusion Planning

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Abstract Combining digital sensor technologies offers vastly improved measurement of where adult and child speech occurs within the inclusive preschool classroom. Consensus in the literature indicates that the talk children hear is a driver of important school readiness outcomes, particularly for children with delays/disabilities. Advantages of sensors versus human observers in measuring speech include real-time recording of the frequency of adult and child talk, adult-child turns (reciprocal interactions) and peer talk over an entire day at preschool. We piloted the combining of two wearable sensor technologies in order to image classroom talk: the Language ENvironmental Analysis (LENA) and Ubisense Inc. The LENA is an automated recording and processing measure of adult, child and peer talk. Ubisense is a real-time indoor location system. The marrying of these novel technologies greatly enhances existing ecobehavioral assessment and in all likelihood our understanding of the degree that young children with disabilities can most effectively be included in mainstream classrooms. Findings include the distribution of time and speech captured in activity areas of the classroom in reference to a preschooler with a developmental delay and an illustration of adult talk displayed in heat map. These devices potential to inform future inclusion research are discussed.

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Introduction

The physical and social architecture of the early childhood classroom sets the stage for the interactions children have with teachers and peers (Ganz 2007; Twardosz and Risley 1982) that promote social and related language development (Bronfenbrenner and Morris 1998; Simpson et al. 2012). There is consensus and overall positive agreement that non-segregated, or inclusive, educational settings possess the design best suited to prepare young children with disabilities for kindergarten and that these children should be served in this setting whenever possible (Barton and Smith 2015; Garfinkle and Schwartz 2002; Odom 2000; U.S. Departments of Health and Human Services and Education 2015). Accordingly, it is no surprise that children aged 3–5 years with a disability served in inclusive preschools increased from 680,142 to 750,131 between 2003 and 2012, which represents a 10.3% increase (U.S. Department of Education 2014). When correctly implemented, inclusion is far more than simply placing students with disabilities in classrooms with their peers without disabilities (DeBoer 2009). In addition to physical access to the classroom, effective inclusion needs to be programmed to promote and support "full participation … in the social milieu of the regular classroom, particularly in preschool and elementary years" (Sailor and Wilson 1990, p. 2). There is evidence, however, that this standard is all too often unmet and the full participation of children with disabilities is ultimately not achieved (Kauffman and Hallahan 2005; Odom et al. 2006).

Consequently, children with disabilities in inclusive settings may experience isolation and their social and learning needs go unsupported (Burack et al. 1997). Without supports, young children with disabilities are notable for their learning challenges, including difficulty responding to standard early childhood core curricula and attaining normally projected early childhood program knowledge and skills via traditional methods (White et al. 2012). Additionally, social and communication deficits linked to disabilities can negatively impact a student's learning and instructional opportunities and create relational and social difficulties (Cotugno 2009; MacKay et al. 2007; Stichter and Conroy 2006). That many teachers lack critical foundational skills and knowledge (e.g., evidence-based practice) required to educate young children with disabilities contributes further to the often lackluster outcomes of young with disabilities (Barnhill et al. 2014; Cox et al. 2013; Simpson et al. 2011).

Juxtaposed with the aforementioned challenges and characteristics are questions and debates relating to strategies and procedures for effectively integrating young children with disabilities into mainstream classrooms (Simpson et al. 2003). The solution is to provide practitioners with: (a) more explicit guidelines for steering inclusion-focused practice (DeBoer 2009; Yell et al. 2003); and (b) valid, rich, and frequently available data that can be used to structure the classroom and create opportunities for strategically maximizing children's communication and interaction (Diamond et al. 2013). Without this readily available information, the question of how best to engineer classroom environments for maximally efficient and high-quality social interaction and social learning has typically had less to do with objectively-determined and data-based student characteristics and needs than with the values and preferences of adults who make educational decisions (Cook and Cameron 2010; Cook et al. 2000; Giangreco 2010).

Behavioral imaging is the use of digital sensing and computing technology to automate elements of observational measurement to better understand the relationship among human interactions and development (Rehg 2011; Rehg et al. 2014) and a path toward supporting effective inclusion in the early childhood classroom. For example, Rehg et al. (2014)) experimented with wearable glasses (e.g., Google Glass) to automatically detect and code joint attention (i.e., an intentional sharing of attention to objects or events external to communication partners), which is associated with children's language acquisition and is often stilted in children with autism spectrum disorder (ASD) (Warren and Yoder 2004). Other researchers have demonstrated successful use of wearable accelerometers along with pattern recognition algorithms to automatically identify sequences of children's stereotypic movements such as flapping and body rocking (e.g., Albinali et al. 2012), which may adversely affect social interactions (Loftin et al. 2008). Although there is an upward trend in automated observational measures for children with disabilities, much of this work has remained outside natural early childhood settings.

Ecobehavioral observational assessment is an often used instrument for capturing and understanding interactions in the early childhood inclusive classroom that has yet to move into the realm of behavioral imaging. This observational technique typically relies on three streams of information sampled by classroom observers on a momentary basis over time: focal child behavior, teacher/adult behavior, and classroom context (Watson et al. 2011). Contextual information focuses on the temporal relationship among variables, thus permitting not only assessment of the frequency of salient classroom events but also how these factors interact with teacher behaviors, environmental influences and, in turn, the overall inclusion of children with disabilities (Brown et al. 1999; Carta and Greenwood 1985; McConnell 2000). For young children with disabilities, ecobehavioral assessment has been used to identify activity areas (e.g., pretend-play vs. meal-time) in inclusive classrooms where specific types of adult and peer talk take place (Brown et al. 1999; Irvin et al. 2015a), as well as overall naturally effective instructional and socially supportive and responsive classroom environments (Greenwood et al. 1994a). In spite of its advantages, ecobehavioral assessment has not been widely adopted by practitioners, likely because this method is based on the use of complex event taxonomies, highly trained observers, and requires a significant time investment for collecting and analyzing data.

Automating elements of ecobehavioral assessment (speech and location) for the natural classroom setting could: (a) produce a data-based decision making tool for supporting children's social-communication opportunities; and (b) inform inclusive practice guidelines. Both of these outcomes may yield more effective inclusion practice and, in turn, improve child outcomes. In this paper, we report on a pilot investigation aimed at imaging central components of ecobehavioral assessment by marrying a wearable device for counting words/vocalizations of adults and children (the Language ENvironmental Analysis™ [LENA]), and a real-time indoor location system (RTLS) (Ubisense™). Specifically, we present the results of employing LENA and RTLS to capture the language environment of a preschool-aged child with a developmental delay. Imaging included the distribution of talk experienced across activity areas of an inclusive classroom over the course of a day in both a tabular and graphical (i.e., a heat map) format. Lastly, we discuss future applications of these sensors as a way forward in supporting more effective inclusion.

Method

Participant

In this pilot investigation, a preschooler with a language delay, male, and 5 years old, wore the LENA and Ubisense for approximately 6 h in the inclusive preschool classroom, post acquiring childcare director's and University IRB approval. The classroom this child attended operated within a full-day center-based inclusive program in a large urban community in the Midwest. The classroom was approximately 12 by 8 m in length, with extensions/cutouts for a small kitchen area and bathroom facilities.

Procedures

Before initiating our pilot investigation in an inclusive preschool classroom, a number of preliminary steps were completed. Because LENA is a well-known, research-corroborated wearable word/vocalization counting device for young children used in research (e.g., Irvin et al. 2013), it was a natural choice. Identifying a RTLS to use in a preschool classroom, however, was not as simple. First, a thorough literature search of commercially available indoor positioning instruments was conducted and discussions took place with researchers experienced in using this type of tool (Dr. William Kearns, personal communication, November 14, 2014) in order to evaluate the measurement properties and usability of various systems. After identifying an accurate and reliable indoor location and mapping system (i.e., Ubisense), the lead author visited the manufacturer's headquarters to meet with engineers and conduct an initial test to ensure that the LENA did not interfere with the transponder tag and sensor communications as well as determine whether the tool could potentially be utilized in the early childhood classroom setting. This test was accomplished by having the RTLS system and LENA operating in an average sized conference room and comparing audio and movement data over a 2-h period.

With a lead teacher's permission, the first and second authors set up and calibrated the Ubisense Research Kit in her preschool classroom. The RTLS package consisted of four sensors, mounting brackets and 10 Series 7000 Compact Tags. These two authors received training by an Ubisense engineer to establish proficiency in setting up and calibrating the system before final installation into the preschool classroom, which entailed the following: (a) placing sensors in the four corners of the space for maximum coverage; (b) networking sensors with the personal computer workstation; (c) minimizing electronic interference caused by other devices (i.e., Wi-Fi routers); and (d) precisely calibrating the RTLS to x, y laser rangefinder locations. The location accuracy estimates within this particular classroom space have been found to fall within the range of 1 ft (or +/−30 cm) of a transponder tag and are detailed in (Irvin et al. n.d.) under review. The final step in preparation for testing the system with children was to sew on an additional pocket for the RTLS transponder tag on the shoulder of customized T-shirts that held the LENA device (see Fig. 1).

The shoulder was chosen based on the recommendation of Ubisense engineers, because the system can lose accuracy if the transponder tag has to communicate with sensors through the body or metal.

Measures

Language ENvironmental Analysis System This speech recognition tool was originally developed to model Hart and Risley's (1995) measurement of home language environments. The Language ENvironmental Analysis (LENA) system consists of a digital language recorder (DLP) and speech processing software. The LENA DLP is a small, unobtrusive language recorder that can record up to 16 h of speech and is worn by the child in a specially designed t-shirt pocket. The LENA software analyzes and classifies the audio information collected by the DLP and automatically extracts frequencies of occurrence in terms of adult word count, conversational turns, and child and peer vocalizations. This provides valuable information about the audio environment, including labeling the audio stream into broad classes such as television and electronic sounds, noise, silence as well as the amount of meaningful data, defined as high-quality vocalizations and speech-related sounds captured during the recording. Using the LENA to better understand the language environments of school settings for children at-risk for and with documented disabilities is increasingly common (Burgess et al. 2013; Dykstra et al. 2012; Irvin et al. 2013; Soderstrom and Wittebolle 2013); however, the device is not sensitive to location.

Fig. 1 Position of the LENA and Ubisense location transponder tag in specially designed pockets on a preschooler's plain cotton t-shirt

Ubisense This RTLS uses an ultra-wideband radio to provide second-by-second, 3-D location simultaneously for up to 100 individuals in both outdoor and indoor environments. The analyzed RTLS data can yield location and movement features (e.g., patterns, direction). Ubisense relies on receivers (sensors) and transponder tags (small wearable units weighing 1 oz) to communicate (see Fig. 2).

Ubisense location coordinates are logged and processed by a tethered personal computer running the Ubisense Location Engine software packages. With proper calibration, the accuracy of Ubisense is +/− 15 cm under ideal measurement conditions, and +/− 30 cm in challenging measurement conditions (Phebey 2010), and these claims have been investigated and validated by independent researchers (e.g., Kearns et al. 2008; Woźniak et al. 2013). Ubisense has been used in a variety of research endeavors, such as improving indoor navigation among individuals with visual impairments (Riehle et al. 2008), examining functional recovery patterns in veterans with traumatic brain injury (Kearns et al. 2016) and, most recently, identifying stationary and atypical movement patterns in the preschool classroom (Irvin et al. n.d.).

Caregiver Report The caregiver completed a standard demographic form. This measure included questions about family structure (e.g., siblings), income as well as any medical diagnosis. The caregiver completed this measure before LENA and Ubisense data collection began.

Data Analyses

With the speech-location data on different metrics, we had to synchronize the two systems on the same rate. Ubisense was set to capture approximately 1 to 3 estimates per second (i.e., 1 Hz). The LENA audio can be placed on a second interval using Advanced Data Extractor (ADEX) software; however, this output is word/vocalization segments between speech pauses which can range in seconds. The lack of alignment among the data sources made synchronization a challenge. Using a series of Excel Marcos, we were able to create a datasheet that synchronizes speech-location estimates on a one-second metric. More specifically, this datasheet averages multiple location estimates in a given second and breaks word/vocalization segments down to a rate of words/vocalizations per second. Next, using a series of "if", "then" statements in SPSS, the collected synchronized location and talk (both spoken and heard) estimates were placed within specific activity areas using the known perimeter coordinates captured via the RTLS. Subsequently, the language environment the target child experienced across areas of the classroom were identified using descriptive statistics. Informally, we asked the lead teacher and target child about any difficulties encountered in wearing the devices over the course of school day and both stated there were none.

Results

The close and clear vocalizations occurring within an approximately 3-ft radius of the target subject (i.e., meaningful speech) within classroom activity areas are presented in Table 1 as automatic scoring of Adult, Turns, Child, and Peer speech. The time the target child spent in 11 classroom activity locations ranged from 0 for Books to 178 min for Music (53%) of the total meaningful speech-location data. The frequency of occurrence of LENA-recorded speech events is shown in Table 1 and were generally greater given the more time spent in each location. More specifically, the correlation of speech to time within activity areas per minute was $r(10) = .78$, .56, .51, and .98 with AWC, Turns, Child, and Peer speech, respectively. While adult and peer speech were more frequently collinear with longer durations, turns and child speech were much less so. The rates of speech defined as frequency divided by time varied widely across the 11 activity locations. The mean speech-per-minute for meaningful speech was 11.5 for adults, 0.6 for adult-child conversational turns, 5.4 the target child and 2.6 peers. Conversational turns occurred less than 1 per minute (0.6) as compared to 11.5 adult words per minute. The Art activity area evoked the highest rates of talk across speakers: 33.9 for adults, 5.1 for the child,

Fig. 2 Illustration of Ubisense transponder tag (*left*) signal sent to sensor (*right*) in a preschool classroom

Table 1 Language environment of classroom activity areas

Activity	Min	Frequency AW	Turns	CV	Peer	Proportion Total min	Rate per minute AW/min	Turns/min	CV/min	Peer/min
Books	0	0	0	0	0	0%	0	0.0	0	0
Entryway	3	8	1	62	2	1%	2.7	0.3	20.7	0.7
Pre-academics	3	28	1	15	14	1%	9.3	0.3	5.0	4.7
Puzzles	6	57	0	30	19	2%	9.5	0.0	5.0	3.2
Pretend-play	7	51	3	56	13	2%	7.3	0.4	8.0	1.9
Art	13	441	23	66	66	4%	33.9	1.8	5.1	5.1
Sink/bathroom	17	332	14	51	64	5%	19.5	0.8	3.0	3.8
Snack/lunch	23	295	20	89	70	7%	12.8	0.9	3.9	3.0
Circle/large blocks	30	615	31	191	70	9%	20.5	1.0	6.4	2.3
Cubbies	55	330	19	102	69	16%	6.0	0.3	1.9	1.3
Music	178	805	26	126	446	53%	4.5	0.1	0.7	2.5
Total	335	2962	138	788	833	100%	-	-	-	-
Mean (Freq/min)	-	-	-	-	-	-	11.5	0.6	5.4	2.6

Notes. Abbreviations are as follows: *AW* adult words, *CV* child vocalizations, *Min* minutes

and 2.6 for peers, including conversational turns at 1.8 words per minute. Circle/large blocks also evoked relatively high rates in all speech indicators. Books, music, and cubbies were the least evocative of speech. Child talk was the highest in the Entryway to the classroom, followed by Pretend-play. Peer talk was highest in Pre-academics, Art, and Puzzles.

The heat map below was created using Excel Power Maps to display the AWC that the target child experienced, while accounting for the time spent within a given area. It provides information on the concentration of adult words at *x*, *y* coordinates and therefore more specifically locates the child within a given activity area (e.g., where the target child was sitting and receiving adult words at the snack table): *dark* represents more dense word count areas, while *light* areas indicate sites where adult words were more spread out. Art, Snack/lunch, Circle/large blocks had dense concentrations of word input relative to activity areas such as Music and Entryway, even though the child spent more time in the latter. This heat map represents the type of data visualization that could be provided to teachers in order to quickly convey where specific children are hearing more/less talk throughout the day (Fig. 3).

Discussion

In this pilot investigation, the participating child with a developmental delay wore a LENA and Ubisense tag for 335 min, yielding 20,160 1-s speech-location estimates within activity areas of an early childhood classroom. Although our results should be viewed with caution given our small sample size, there are some notable findings. Specifically, the more time the child spent in a location the more speech they experienced, and certain locations appeared to yield more peer talk than others (e.g., Art). These results align with over 30 years of previous studies using ecobehavioral assessment that have found that the talk young children at-risk or with disabilities receive from peers is related to activity areas of the classroom (e.g., File 1994; Irvin et al. 2015a; Carta and Greenwood 1985; Reszka et al. 2012).

Ecobehavioral assessment has been useful in understanding and informing the time children experience different classroom activities and also the specific classroom activity areas that fuel/hinder social, language and related development. These approaches, however, come with significant time requirements and human resource costs. For example, related to findings of arguably the most notable ecobehavioral study, Hart and Risley (1995) identified 30 million word disparity differences among low socio-economic families that were linked to early literacy outcomes (Torgesen 2002) and future school performance (Duncan et al. 2007). This investigation, however, took 6 years to transcribe, code and analyze 1318 1-h samples. That said, advances in portable electronic devices (see Greenwood et al. 1994b) and video coding software (e.g., Procoder; Tapp and Walden 2000) that capture interactions examined in ecobehavioral research have mitigated the need for transcription. However, the need for human observers will continue to restrict use of traditional ecobehavioral instruments and protocol. The behavioral imaging tools used in this study did not require human observers, covered a complete day and offer a promising way forward in capturing interactions that inform teacher practice and yield new knowledge on children's placement in inclusive classrooms.

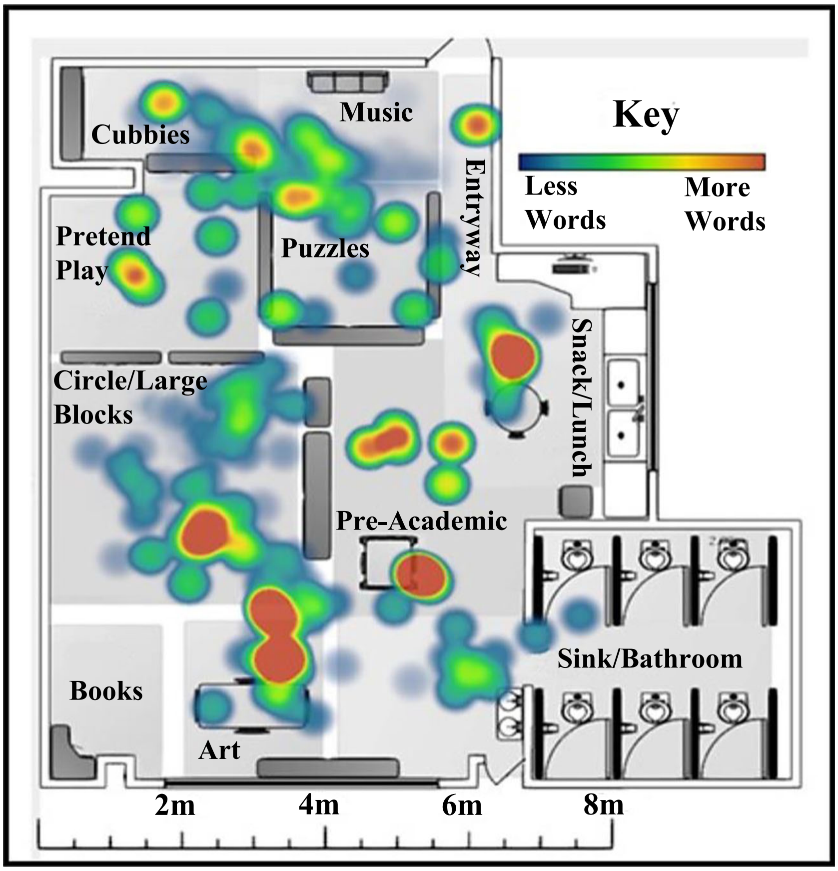

Fig. 3 Heat Map of word density from adults experienced by the target child in specific locations of activity areas

The strength of this investigation was examination of a novel technology for acquiring and interpreting ecobehavioral data that combined and synchronized two wearable sensors (LENA and Ubisense). It is a pioneering approach for natural classroom environment that automatically collects real-time speech and location data, factors that are malleable and at the crux of young children's development. Our work begins to address a considerable challenge early childhood educators encounter in preparing children with disabilities, namely: the lack of close to real-time data to inform daily practices and that lead to longer-term school readiness outcomes. Undoubtedly, behavioral imaging tools will become more common in research and practice that centers on young children's early childhood classroom experience. We predict these will yield compelling new insights on the effect of an early childhood inclusive experiences and desired child outcomes as well as inform the professional development of early educators.

Limitations

This pilot investigation has several limitations. First, the analyses produced by the LENA software indicated that the preschool classroom was, perhaps unsurprisingly, a noisy environment with 15% of the auditory input detected as meaningful speech. Although this is indeed a challenge, advances in speech algorithms (described below) will in all likelihood boost the meaningful speech gathered via the device. Second, unexpectedly, the child participating in this study spent large amounts of time in music and cubbies. The informal conversation with the teacher at the end of data collection offers some explanation for this occurrence. Specifically, the she stated the child's sleeping cot was set-up in the music area for an approximately 2-h nap and the teacher took off the shirt with the LENA and Ubisense transponder tag and placed in cubbies while the child was on the playground. Lastly, this study is based on one participating preschooler on one school day and therefore the results of the work should not be generalized. That said, we thought it necessary to attempt this approach with a single child before replicating it in larger studies with more young children.

Future Directions

Speech Activity Detection and Speaker Diarization

For naturalistic audio in locations such as classrooms, the background noise and potential reverberation can be quite variable and presents both significant research and practice-oriented challenges (Sangwan et al. 2012). Recent work with

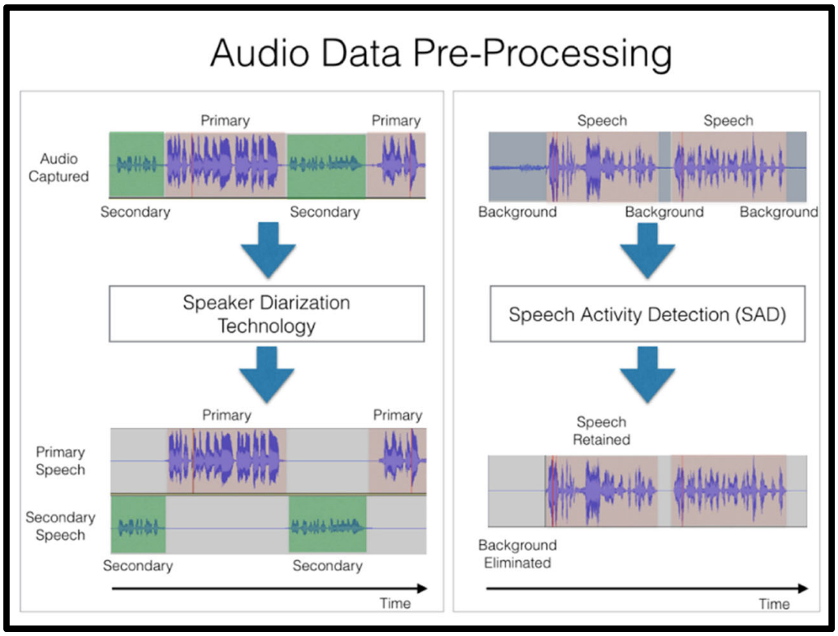

Fig. 4 Audio pre-processing system utilizes speech activity detection (SAD) and speaker diarization

LENA recording technology for the Prof-Life-Log study has resulted in the identification of challenges and speech signal processing algorithm advancements to address overlap speech conditions, which include speech activity detection (Shokouhi et al. 2015; Ziaei et al. 2015) and speaker diarization (Hansen and Hasan 2015) (see Fig. 4). Speech activity detection algorithms help separate speech from acoustic background. By eliminating acoustic background, speech activity detection helps downstream applications to focus on the speech signal, which helps in reducing the error rates of the overall speech/language system. Speaker diarization algorithms help identity and separate individual speakers in a single audio track from other speakers. The technical properties of the speech advancements to address the challenges of collecting and quantifying speech in the early childhood classroom are detailed in Sangwan et al. (2015).

Key Word/Phrase Spotting

While speech activity detection and speaker diarization systems can likely improve quantitative metrics of talk (such as word count or turn taking) in the early childhood classroom, automatic speech recognition (ASR) and keyword spotting (KWS) technology have the potential to measure more qualitative aspects of communication (Kaushik et al. 2015). ASR coverts speech to transcripts and KWS detects presence of "high-value" terms. A combination of ASR and KWS could potentially be used to track words and phrases associated with the quality of inclusive classrooms such as labeling emotions (e.g., "Are you feeling tired?") and helping children understand peers' intentions (e.g., "I think your friend wants to play with you"), to name a few. At higher levels, collected data for subjects can be split into conversations, which can be compared to investigate patterns of similarity. Analysis of these conversation collections could also reveal the range of communication (type, style, duration, etc.). We anticipate that research into conversations using ASR and KWS could yield more useful metrics for capturing the nature of interaction within inclusive classrooms. Recent advancements in machine learning (particularly, deep learning) have led to significant improvements in speech recognition accuracy, albeit at a high cost relative to both data requirements and computer-based training resources. A combination of high performance computing with advancements in model training has produced ASR systems that can provide 40% or lower word error rate (WER) in extremely practical settings, such as those seen in corpora like Prof-Life-Log, UT-Opinion, and so forth. Research in information retrieval has shown that speech data can be mined for knowledge discovery once WERs are at or below 40% and this makes the ASR performance useful, even though it is far from perfect. However, much of ASR and KWS research has focused on adult speech in adult-communication environments. Investigations of the current state-of-art systems in children-dominant communication environments is necessary to better understand performance and challenges and to plan and execute research advancements which will contribute to an improved scientific understanding of language and social environments children with disabilities experience within inclusive classrooms.

Advancing the Measurement of Inclusion

Applying advanced speech processing and key word/phase spotting algorithms to our LENA-Ubisense measurement system has a number of implications for measuring inclusion in early childhood classrooms. For example, educators have long relied on peers to model and prompt appropriate social initiations, responses, and other age- and setting- appropriate behaviors of young children with disabilities (Brown et al. 2001; Chan et al. 2009; Kohler et al. 2007) because they facilitate skill maintenance and generalization (Zhang and Wheeler 2011). Without question, peer-mediated strategies are evidence-based methods whose underpinning is the long-acknowledged finding that peers are uniquely and naturally equipped to effectively instruct children with disabilities in acceptable social behaviors and skills within natural settings. A salient underpinning of peer-mediated methods and activities, relative to development of social skills, facilitation of pro-social peer interactions, and support of peer relationships, is that these methods frequently operate relatively independently of direct teacher and staff supervision and direction, subsequent to initial peer training (Theimann and Kamps 2008). We are in general agreement with the *National Standards Report* (Green et al. 2009) that "peer training" is an "established treatment," and that this method has demonstrated capacity to produce positive outcomes. However, clearly measuring the effectiveness of this type of intervention has been out of reach. Moreover, fully harnessing the potential of classroom peer supports within inclusionary programs requires objective and data-based decisions. That teachers and program staff have historically lacked reliable, efficient and functional means for making maximally effective decisions has clearly contributed to hit-or-miss inclusion programming. The LENA with RTLS coupled with speaker diarization and key word/phrase spotting are potentially utilitarian tools that could be used as both progress-monitoring and data-based planning instruments to capitalize on the potential of peer-mediated programs.

Teacher talk directed to young children with disabilities and their peers aimed at supporting peer relations is thought to affect their subsequent interactions (e.g., Brown et al. 2008). For example, recent work indicates a strong association ($r = 0.716$, $p = <.0001$) between the supporting peer relations talk adults provide young children with ASD and subsequent positive social bids toward peers (Irvin et al. 2015b). However, there is also ample evidence that teachers struggle with determining when and where to provide supporting peer relations types of talk to young children (e.g., Boyd et al. 2008). This uncertainty could potentially explain why the talk teachers provide to young children aimed at supporting peer relations is minimal (e.g., "Ask Kelly if she wants to play cars and trucks") (Kontos and Keyes 1999; Reszka et al. 2012). Leveraging LENA with Ubisense and the advanced speech processing algorithms described above could provide teachers with information about where child-peer interactions are taking place so that they may be better able to discern when to provide support.

Relatedly, the positive child-peer interactions that take place in the classroom lay the foundation for friendships between children with disabilities and their typically developing counterparts. Young children's friendships are important because they fuel essential developmental outcomes (e.g., social-emotional competence, language skills) linked to school readiness (Buysse et al. 2008). Traditionally, young children's friendships have been measured using teacher/parent report and/or direct observation. All of these measurement approaches have certain types of unwanted measurement error and some come with additional administration challenges (e.g., learning complex taxonomies for direct observation). Our speech-location measurement system would provide teachers and allied health service providers (e.g., occupational therapists, speech language pathologists) a way to monitor fundamental components of children's friendships (i.e., proximity to and talk directed at their friends). Additionally, this system could advance our knowledge of the types of child-peer and teacher-child dyad talk that supports children's friendships as well as how this talk changes over the course of the school year.

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