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Investigating children's interactions in preschool classrooms: An overview of research using automated sensing technologies

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ABSTRACT

New technologies that combine digital sensors with automated processing algorithms are now being deployed to study preschool classrooms. This article provides an overview of these new sensing technologies, focusing on automated speaker classification, the analysis of children's and teachers' speech, and the detection and analysis of their movements over the course of the school day. Findings from recent studies utilizing these technologies are presented to illustrate the contribution of these sensing technologies to our understanding of classroom processes that predict children's language and social development. In particular, the potential to collect extended real-time data on the speech and movement of all children and teachers in a classroom provides a broader window on the variability of individual children's interactions with peers and teachers and their integration into classroom social networks. The article describes current challenges related to the use of sensing technologies in preschool settings, as well as advances that may overcome these challenges and allow for more in-depth investigations of children's early classroom experiences.

For young children who attend preschool, interactions with teachers and peers represent important opportunities for the development of language and social skills (Burchinal et al., 2008; Dickinson & Porche, 2011; Justice et al., 2011). Research in this area has typically relied on validated methods such as expert observations, peer nominations, and teacher reports of children's behaviors and characteristics (e.g., Chen et al., 2020a; Santos et al., 2014). Complementary methods that rely on new sensing technologies are now being deployed in the study of preschool classrooms. These technologies combine sensors that capture data from the environment and software algorithms that translate the data into usable outputs. As developmental researchers with backgrounds in social interaction, language development, and special education, we focus on sensing technologies that convert digital recordings of audio and physical location into measures of vocalization and social contact in preschool classrooms. These technologies show promise in documenting and localizing children's vocal exchanges with peers and teachers, describing children's classroom-level social networks and predicting children's language abilities.

The purpose of this article is to provide an overview of the use of sensing technologies—particularly continuous recording of children's vocal interactions and physical position within the classroom—in research on preschool children's language and social development. We begin with a brief description of research that underscores the importance of young children's interactions with caregivers, teachers, and peers. We then turn to the challenges in conducting observational research in preschool classrooms and the potential of sensing technologies to surmount these challenges and provide new perspectives on classroom interaction. In separate sections on automated measurement of speech, automated measurement of location, and synchronized measurement of both speech and location, we review key studies that have leveraged sensing technologies to advance our understanding of children's interactive experiences in preschool classrooms. Though the preponderance of research yielding statistically tested results in this area has used the Language ENvironmental Analysis (LENA) system (Gilkerson & Richards, 2020) for measuring speech, and the Ubisense system, https://ubisense.com/, for tracking movement and location, we also report on studies using other sensing technologies and discuss the strengths and weaknesses of different systems. In the discussion, we describe several promising directions in the use of sensing technologies as well as current challenges and applications to practice.

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1. The role of interactions in children's language and social development

The importance of conversational exchanges with teachers and peers in preschool settings is presaged by the role of children's exchanges with caregivers in the first years of life (Hart & Risley, 1995; Hoff, 2003; Masek et al., 2021; Rogers et al., 2015; Rowe, 2008; Rowe & Snow, 2020). A large body of research has demonstrated that conversational exchanges with caregivers are key drivers of growth in children's language skills (Masek et al., 2021; Rogers et al., 2015; Rowe & Snow, 2020). The wide variability in the amount and diversity of talk that parents direct to their toddlers is associated with variability in their language skills at age 3 (e.g., Hart & Risley, 1995; Hoff, 2003; Ramirez et al., 2020; Rowe 2008).

In preschool, children develop self-regulatory and social emotional skills that are crucial for their positive interactions with peers and teachers (McClelland et al., 2007; Russell et al., 2016). These skills contribute significantly to children's adjustment to and success in kindergarten (Justice et al., 2011; Klibanoff et al., 2006; Skibbe et al., 2011). Preschools providing dense exposure to complex vocabulary and syntax—from both teachers and students—positively impact children's language development over the course of the year (Huttenlocher et al., 2002; Justice et al., 2011) and reading skills in elementary school (Dickinson, 2011; Dickinson & Porche, 2011; Hjetland et al., 2019).

1.1. Methods for investigating children's interactions in preschool settings

Previous research utilizing validated observational coding systems has informed our understanding of the role of classroom engagement in children's academic achievement, the importance of peer interaction in language development, and the benefits of teacher sensitivity to children's emotional regulation (Bulotsky Shearer et al., 2020; Justice et al., 2018). Studies utilizing trained experts to code children's activity and speech (Chaparro-Moreno et al., 2019; Schaefer et al., 2010), whether *in vivo* or from video, have advanced the understanding of children's social interactions in preschool contexts. For example, preschool children who were regularly observed to be in close proximity reported sociometric preferences for one another whereas low proximity groups tended to reflect shared group goals in the absence of reciprocal dyadic ties (Santos et al., 2015).

One limitation of standard observational methods is their inability to capture the totality of simultaneous interactions occurring in a preschool classroom. Manual coding of multiple children is possible if they engage in the same task (e.g., coding choral reading). However, it is difficult for an observer to code more than one child at a time when they are engaged in different activities. Similarly, video focused on a particular student or activity setting cannot capture the simultaneous interactions of all children and teachers present in the classroom. In addition, the resources required for an individual to learn a coding system, demonstrate reliability, and maintain reliable coding over time may be substantial (Bakeman & Gottman, 1986; Crowley-Koch & Van Houten, 2013).

Automated sensing technologies that use participant-worn audio recorders and location trackers can address several limitations of *in vivo* and video observations. First, these technologies can provide simultaneous real-time data on all the children and adults who are present in the classroom. Second, they can help to reduce the coding burden by applying machine-learning algorithms to yield automated measures of important variables of interest. Third, they offer the opportunity to do extended recording with consistent levels of accuracy of measurement over time.

1.2. Automated measurement of speech in preschool classrooms

Automated measures of children's interactions with speech partners were first developed to investigate the language-learning environments of typically developing infants and toddlers. The systems that generate these automated measures have two components. The first component is a digital audio recorder. The second component is software to identify speech in these recordings, determine who is speaking (e.g., the child wearing the recorder vs. a different child or an adult) and provide counts of key features of the recorded speech, e.g., the number of words or phonemes it contains.

The first widely available system to generate these measures was the LENA system (LENA.org; Gilkerson et al., 2017, 2018; Greenwood et al., 2018; Xu et al., 2009), which was introduced in 2009. LENA uses small audio recorders (LENA Digital Language Processers, or DLPs) worn by children in specially designed vests or shirts (see Fig. 1). Recordings are frequently processed by LENA software algorithms that distinguish speech by the child wearing the recorder, speech of other children, adult speech, and non-speech sounds. This allows researchers to obtain day-long child-focused audio recordings that are automatically analyzed to generate estimates of the number of adult words each child heard (adult word count), the amount of turn-taking that took place between the child and adults (child-adult turn-counts), and the number of vocalizations made by the child (child vocalization frequency).

LENA data in home contexts underline the importance of language input and turn-taking for the development of both typically developing children and those with developmental disabilities such as autism spectrum disorder (ASD). Donnelly and Kidd (2021), for example, found that adult word count, child vocalizations, and child-adult turn-count all increased between 9 and 24 months. Importantly, they demonstrated a bidirectional relationship between turn-counts and vocabulary growth, supporting claims for the contribution of social interaction to language development. In a study of infants at high familial likelihood for ASD, LENA measures of adult word count and child-adult turn-count collected at 9 and 15 months were associated with children's language skills at 24 months (Swanson et al., 2019). Automated measures derived from LENA have also been used to support speech-language interventions (Ganek & Eriks-Brophy, 2018), parent coaching (Ramirez et al., 2020), and public health initiatives (Beecher & Van Pay, 2021; Greenwood et al., 2017). Before turning to results obtained through LENA and other audio sensing systems in early childhood settings, we review the reliability of these systems.

1.3. Reliability of automated speech processing

The reliability of both automated classification of speakers and automated quantification of speech when compared to expert coders is a topic of ongoing research (Wang et al., 2020). Researchers have reported relatively large error rates in the LENA system of speaker classification, e.g., the identification of adult women's vs. children's vocalizations (Cristia et al., 2021; Lehet et al., 2021). Consequently, our team compared LENA classification of child versus adult vocalizations with

Fig. 1. Preschooler vest for wearable sensing technology.
Note: 1A. Front of vest with pocket for LENA Digital Language Recorder. 1B. Back of vest with pockets for left and right Ubisense (location tracking) tags. Photo courtesy Catalina Cepero.

those of trained coders. We found relatively high levels of agreement in recordings from preschool classrooms serving children with and without hearing loss (Perry et al., 2022) and those serving children with ASD or developmental delays (Fasano et al., 2021). In these studies, LENA and expert coder agreement on whether vocalizations were produced by an adult or child ranged from 86 to 89% Cohen's Kappa, which controls for chance agreement, ranged from .71 to .77. Other approaches to speaker classification are being developed. Hansen et al. (2019) for example, used LENA recorders coupled with a processing system developed by their research team. They reported accuracy of 86% in identifying adult speech and 77% in identifying child speech.

Researchers are also concerned with the reliability of automated measurements of the quantity of adult and child speech. Soderstrom and Wittebolle (2013) examined associations between LENA and expert measures of child vocalizations and adult word count in both the home and preschool. They found moderate to high correlations between LENA and expert coders in both contexts. In an analysis of five datasets from home settings, Cristia et al. (2021) found similar, moderately sized correlations between LENA and expert coders for child vocalizations (.76) and adult word counts (.76). However, Cristia et al. reported lower LENA-expert correlation (.57) for child-adult turn-counts, mirroring low turn-count reliability in 6–24-month-olds (Ferjan Ramirez et al., 2021).

Adding information about the location of children and their partners could improve the reliability of data obtained using automated vocalization technology. For example, location and orientation tracking could be used to identify time segments during which two children (and no teachers) are face-to-face, in proximity to one another. If this segment were identified by the automated system as containing adult speech, this would suggest an instance of misidentification of speakers and could be tagged for further analysis. Moreover, speech between two face-to-face children identified by objective methods could then be compared to human coded speech with the goal of more reliably identifying the participants in a vocal interaction. Examining the accuracy of tools to capture speech in specific contexts, as well as the methods used to determine accuracy, are essential for ongoing validation efforts (e.g., Gilkerson & Richards, 2020).

There are promising reliability reports for the quantification of speech using methods developed more recently than LENA. Using an open-source deep learning approach to the automated detection of vocalizations (ALICE), Räsänen et al. (2021) reported that ALICE counts of child and adult vocalizations more closely match those of expert coders than those of LENA (cf. Lavechin, et al., 2020). With respect to the more difficult task of quantifying children's speech in a classroom context, Lileikyte et al. (2020) and Dutta et al. (2022) reported that deep learning models trained on classroom speech correctly identified approximately one-third of specific child words. In a similar vein, automatic phoneme (language sounds) counts in teacher and child speech via software (Sphinx) showed high concordance with expert coders (Mitsven et al., 2022). Given both challenges and ongoing work addressing the reliability of automated identification and quantification of speech, it is important that researchers using sensing systems assess the reliability of those systems.

1.4. Associations with children's language abilities

Addressing predictive validity, LENA measures of child and adult vocalizations from multiple hours of recorded preschool activity can be used to examine associations with children's language outcomes. Meta-analytic results indicate a medium-sized association between children's assessed language abilities and LENA measures of child vocalizations and child-adult turn-counts, and a small to medium-size association between children's language abilities and adult word count (Wang et al., 2020). Results from individual studies show variability in the specific LENA measures associated with assessed language abilities. Dykstra et al. (2013) collected two LENA recordings from 40 preschool children with ASD in 15 self-contained preschool classrooms. Children's vocalizations and adult word count (but not child-adult turn- counts) were significantly associated with children's total language scores on the Preschool Language Scales (PLS-4; Zimmerman et al., 2002). However, a similar-sized study of 44 children observed over two days in 11 classrooms (Duncan et al., 2020) did not show associations between LENA measures of child vocalizations, adult word count, or child-adult turn-counts and vocabulary skills measured with the Peabody Picture Vocabulary Test-4 (PPVT-4; Dunn & Dunn, 2007). By contrast, a larger study involving 91 children in 23 preschool classrooms observed on three occasions showed this association (Duncan et al., 2023). Child-adult turn-counts were associated with children's vocabulary skills even when controlling for parent education levels and other demographic variables. Overall, automated measures of classroom audio suggest that children's vocalizations and child-adult turn-counts are often (but not always) associated with children's assessed language abilities.

Other measures extracted from classroom audio recordings have also shown associations with children's language abilities. For example, Sphinx (Walker et al., 2004, https://cmusphinx.github.io/), mentioned above, is software that identifies phonemes, the speech sounds of a language (Woynaroski et al., 2017; Xu et al., 2014). Using LENA recordings from classrooms serving children with and without hearing loss, Mitsven et al. (2022) complemented LENA measures of child and teacher vocalization rate with Sphinx measures of phonemic diversity. Children who were exposed to more phonemically diverse teacher speech tended to produce more phonemically diverse speech themselves. Crucially, the phonemic diversity of children's own vocalizations was a stronger predictor of children's end-of-year language abilities than vocalization rate. Moreover, the phonemic diversity of children's own vocalizations mediated an indirect relationship between the phonemic diversity of teacher vocalizations and children's language abilities. These findings held for all children in the classroom, underscoring the importance of high-quality, phonemically diverse classroom language in supporting the language development of children both with and without hearing loss.

Most studies utilizing sensing technologies in preschool classrooms collect a limited number of recordings (two to four) per classroom. Our group adopted a different strategy in an initial study of thirteen 2–3-year-old children with developmental delays in a single preschool classroom (Perry et al., 2018). Perry et al. collected weekly LENA recordings on up to seven children at a time over the course of a year. Children who received higher rates of vocal input from their peers and children who engaged in more conversational turns with teachers vocalized more themselves. Peer speech and child-adult turn-counts were also associated with children's gains in vocabulary over the course of the school year as assessed with the MacArthur-Bates Communicative Development Inventory (CDI; Fenson et al., 1993). Perry et al.'s results suggested the importance of LENA-identified peer vocalizations to children's language use. However, to identify which *specific* peers children are talking to, children must be located in space.

1.5. Automated measurement of location in preschool classrooms

Sociality may be inferred from children's spatial organization in physical spaces (Cristani et al., 2011). Both the distance between persons and their mutual orientation (e.g., two people facing one another) communicate socially relevant information such as engagement. Preschool-age children show individual consistency in their proxemic behavior (Eberts & Lepper, 1975), which may emerge early in development (Paulus, 2018).

1.6. Automated sensing of location

Radio Frequency Identification (RFID) is a generic term that refers to mobile tags that use radio transmissions to identify an individual. There are currently two main approaches to the automated detection of location and interpersonal proximity, both of which fall under the general RFID category. The first approach uses BlueTooth-based badge technologies that indicate when two children, or a child and a teacher, are in contact. Instances of contact are based on the strength of the BlueTooth signal, which is affected both by the proximity of the badges and their orientation, e.g., the degree to which the child and their partner are in a face-to-face orientation (Dai et al., 2022). BlueTooth RFID has been used to narratively compare social contact in classroom and playground settings (Dai et al., 2022). During playground time, Veiga et al. (2017) found that the mean duration of a child's contact with each of their peers was positively associated with teacher ratings of the child's social competence.

An advantage of BlueTooth-based RFID technology is that it is relatively low-cost and does not require calibration. ReelyActive, a commercial company, and Openbeacon, an open science organization, both offer access to BlueTooth-based badges and software for detecting social contact. However, BlueTooth-based badges are not designed to provide information on children's actual physical location in space. This difficulty can be overcome to some extent by attaching badges to physical locations in the classroom to detect when children are in or near those locations. Another approach to detecting location in playground spaces—and visualizing children's use of these spaces—is complementing BlueTooth-based badges with GPS sensors (Nasri, et al., 2022).

A second approach to studying child and teacher location and movement in preschool classrooms is ultrawideband radio frequency identification (UWB-RFID). UWB-RFID is a Real-Time Location System (RTLS). UWB-RFID tracks each individual's physical location over time (Kearns et al., 2008); as such, it can yield information not only on individuals' contact with others but also on where these instances of co-location occur. Our team and others have used a UWB-RFID RTLS produced by Ubisense in the classroom (Irvin et al, 2017; Messinger et al., 2019; 2022; Phebey, 2010) and on the preschool playground (Luo et al., 2020). Indoor set-up for the Ubisense system involves placing four sensors in the corners of a classroom and calibrating the sensors to ensure accurate measurement. The sensors are physically linked by a timing and a network cable to provide data to a dedicated laptop. Sensors track active lightweight UWB-RFID tags worn by children and teachers (see Fig. 2). Tags are located in XYZ space by means of triangulation (angle of arrival) and time differences in arrival. Comparing Ubisense to ground truth (e.g., laser tracked) location, Irvin et al. (2018) found the overall mean of UWB-RFID location coordinate estimates to be within 20 cm both when tags were static and moving. Likewise, in a challenging environment including tracking outside the areas circumscribed by the four sensors, Ubisense was accurate to within 40 centimeters (cm) in 95% of cases and accurate to within 20 cm in 50% of cases (Barbieri, et al., 2021). An alternate system featuring open-source components is produced by Sewio and marketed by Noldus, https://www.sewio.net/. Sewio requires less installation and calibration effort but as of this writing was reported to be less precise than Ubisense (Barbieri et al., 2021).

What information can tracking provide on classroom dynamics? Using Ubisense in a preschool classroom, Wallisch et al. (2022) noted that characteristics of children's movement paths (the distance travelled and straightness of the movement trajectories) showed potential to distinguish typically developing children and children with or at risk for developmental disabilities. Likewise, Banarjee et al. (2023) found that children with ASD, children with developmental disabilities or delays, and typically developing children in the same classrooms ($n = 77$) tended to approach children in the same group (e.g., ASD-ASD) at higher velocities (i.e., more quickly) than they approached other children. These results suggest that movement tracking can shed light on important aspects of children's experiences in preschool classrooms. But location or tracking data require further processing to determine when two children are in social contact.

Fig. 2. LENA Digital Language Processor and Ubisense tag.
Note: The LENA Digital Language Processor measures 2.2" x 3.4" x 0.5". The Ubisense tag measures 1" x 1" x 0.36". Photos courtesy Laura Vitale.

1.7. *Measuring social contact*

When using BlueTooth-based badges, social contact is determined by the Blue-Tooth signal strength using a cutoff point. By contrast, researchers using UWB-RFID location data are faced with the task of inferring when children are in social contact based on their co-location. One approach is to define an a priori distance within which two children are deemed to be in social contact. Studying a single classroom, Irvin et al. (2021) defined social contact as occurring when children were within 3 feet of one another. As classrooms differ in overall space, layout, and activity patterns (Butin & Woolums, 2009), our group has used a data-driven approach in defining social contact, which is specific to a given classroom in a given year (Fasano et al., 2021; Messinger et al., 2019; Perry et al., 2022). In each classroom, UWB-RFID measures of location are used to calculate the observed distance of each child from every other child over time. These observed distances are compared to those expected by chance, where chance is determined by children's cumulative location preferences over time without regard to the location of other children (Messinger et al., 2019, 2022). When two children, or a child and a teacher, are in closer proximity than would be expected by chance in their specific classroom context, those individuals are defined as being in social contact.

Using the data-driven approach described above, our group defined social contact as occurring within a range of approximately 1 m (3 feet) during free-play periods (Messinger et al., 2019). There was high variability in the distribution of children's social contact with peers. A child's social contact with those peers with whom they had the most contact was hundreds of times greater than contact with their least contacted peers. Thus, tracking technology helped to quantify patterns of peer preference in the classroom (Martin et al., 2013; Schaefer et al., 2010).

Social contact as defined solely by proximity (as in Messinger et al., 2019) could, however, misidentify co-located individuals as interacting, for example, if two individuals were sitting back-to-back (see Healey & Battersby, 2009; Lu & Brimijoin, 2022; Setti et al., 2015). In subsequent studies, described below, we applied a second parameter related to body orientation (Fasano et al., 2021; Perry et al., 2022). Social contact between two children was defined as occurring when two conditions were met: (1) proximity greater than expected by chance (.2–2 m in these classrooms) and (2) body orientation within 45 degrees of face-to-face. Using these parameters, Banarjee et al. (2023) found that in inclusive classrooms serving children with ASD, children with developmental disabilities/delays, and typically developing (TD) children, children spent more time in social contact with children in the same group (e.g., TD-TD) than did children in different groups. Thus, objective measures of social contact can detect homophily (a preference for similar individuals) in children's interactions with peers.

1.8. *Combining measures of speech and location*

Measurements of preschool children's social contact and vocalizations are each important in their own right. However, synergies are created when location data and vocalization data are combined by temporally synchronizing location and audio data. This synchronization is a step forward in the use of automated sensing technologies in classroom spaces. A key premise is that periods of social contact are fertile spaces for vocal interaction, such that the ability to identify the likely participants in a child's vocal interactions enhances the field's tool kit for understanding communication in the preschool classroom.

Irvin et al. (2017)—a case study of one child with a developmental delay in an inclusive preschool classroom— was the first published research to combine position tracking (via UWB-RFID) and vocalization detection (via LENA). The research was motivated by an ecobehavioral perspective on where children spend time and where they hear and produce speech (Carta & Greenwood, 1985). Descriptive analysis of the synchronized LENA and Ubisense data indicated differences across areas in terms of the amount of speech produced by the child as well as the amount of speech heard by the child. For example, child vocalizations were highest in the entryway to the classroom, followed by the pretend-play area. A follow-up study of a focal child at-risk for a disability and the child's peers found that the child's engagement with peers differed by activity area (Irvin et al., 2021). Hansen et al. (2019) combined a deep learning approach to identifying child and adult speech with Ubisense to estimate the amount of verbal interaction that took place in different activity areas. Teachers' speech was more frequent in certain activity areas (e.g., books, science, lunch table) and less frequent in others (blocks and manipulatives).

1.9. Peer vocal interaction

The integration of location and audio data for all participating children and teachers in a classroom allows researchers to potentially identify each child's or teacher's vocal interaction with every other child or teacher in the classroom (see Fig. 3). The actual proportion of children recorded, which typically hovers around 95% in our team's research highlighted below (Fasano et al., 2021; Mitsven et al., 2022; Perry et al., 2018, 2022), depends on parental consent to participation and children's tolerance of lightweight wearable recording devices.

Using the output of synchronized audio and location data streams and applying the social contact parameters described above, Perry et al. (2022) investigated children's vocalizations in social contact with peers in a classroom that included children both with and without hearing loss. Over 600 h of data were collected from 29 children belonging to three different classroom cohorts. Results indicated that when a child heard more vocalizations from a specific peer on a given observation occasion, they tended to produce more vocalizations to that specific peer on the following observation. That is, a given child's level of speech to a specific classmate predicted that classmate's level of speech to the child in the next observation. This pattern of dyadic speech held even when controlling for the classmate's speech to the child during the most recent previous observation. The pattern also held in classrooms that included children with ASD and children with other developmental delays or disabilities (Fasano et al., 2021). Notably, no differences were found in the strength of the effect of peer vocalizations between children with or without developmental delays or disabilities, suggesting the same reciprocal pattern of dyadic vocalization among all children in these classrooms.

To further examine the role of this reciprocal pattern on language development, mediation analyses were used to predict children's end-of-year expressive and receptive language abilities from their peer vocal input during earlier observations and their own vocalizations to peers during later observations (Perry et al., 2022). Peer vocal input had an indirect association with children's end-of-year language abilities, mediated by children's own vocalizations to peers. The results underscore the importance of children's own speech to peers, which may play a special role in supporting children's language development (cf. Hirsch-Pasek et al., 2015; Ribot et al., 2018). The use of sensing technology to measure children's vocal interactions with individual peers suggests a mechanism for such effects. Speech *from* peers seems to be a platform for increasing children's subsequent vocalizations to those same peers. This may provide children with an opportunity to consolidate developing language abilities.

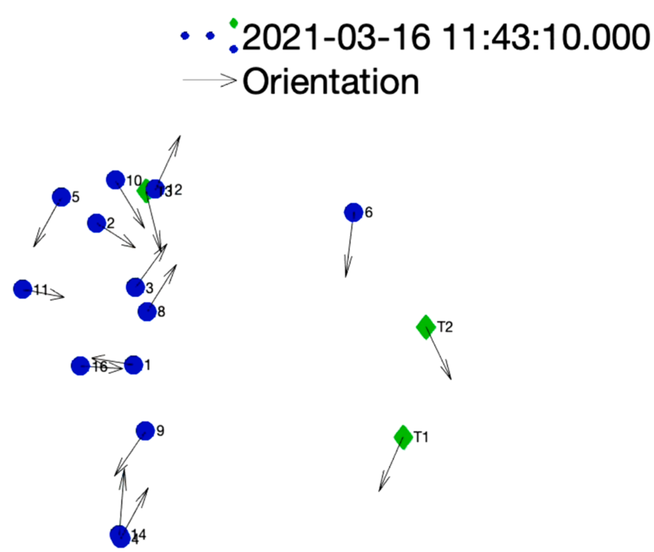

Fig. 3. Visual representation of children and teachers in a preschool classroom. *Note:* This still-frame illustration shows the location and orientation of each person in the classroom space at the moment indicated by the timestamp. There are three teachers, indicated by diamond shapes and labeled T1 (partially covered by a circle), T2, and T3. There are 12 children, indicated by circles. The arrows coming out of each shape indicate front-facing body orientation. Child 1 and Child 16 are considered to be in social contact in that (a) they are proximal to one another *and* (b) they are oriented towards one another. Photo courtesy Hugo Gonzalez Villasanti.

1.10. Social networks

Zooming out from the perspective of an individual child's peer interactions to the totality of peer interactions across all child dyads is possible by constructing a network map of social connections within a classroom. Within the classroom social network, children are connected to multiple peers through their interactions with them. The strength of these connections depends on their frequency or duration. Children with more, or stronger, connections are considered more central to the network, while those with fewer or weaker connections are more peripheral.

Previous research suggests that children with developmental disabilities and language delays are more peripheral to classroom social networks than their peers without disabilities (Chen et al., 2019, 2020a; Locke et al., 2013). Specifically, Chen and colleagues (2019) found that children with disabilities had smaller play networks than children without disabilities (see also Lin et al., 2019). Consistent with this finding, Chen et al. (2020a) found that children with and without disabilities both benefited from peer interaction, but children with disabilities experienced fewer such interactions than children without disabilities. The networks reported in these studies were based on data from child or teacher ratings of friendships or teacher judgments of interaction frequency. Interpretation of data based on these methods is tempered by lack of strong concordance between children's ratings and those of adults (Chen, et al., 2020b). Shin et al. (2014), for example, found only modest concordance between preschool teachers' identification of their students' dyadic relationships as "friendships" and children's own nominations of classmates as friends. Data from synchronized multimodal sensing technologies can provide a complementary, objective view of classroom social networks. There is evidence that objective measurements of children's vocalizations to one another are associated with sociometric indices of peer relationships and observational measures of classroom engagement. Pairs of children who engaged in more time vocalizing in social contact tended to be rated as friends by their teachers (Altman et al., 2020).

In our group, Fasano et al. (2021) used measures of vocalization in social contact, obtained over multiple days of observation, to construct classroom networks for 56 preschoolers in five inclusive classrooms that included children with ASD as well as children with other developmental delays or disabilities. Within each class network, nodes (children) were connected by edges weighted by the vocal interaction between the two children (the sum of the rate of the vocalizations made by each child to the other across observations). Children with ASD exhibited lower modularity (within-group cohesiveness) than children with developmental delays or children without any delay or disability. These findings suggest that even in classrooms designed to foster interaction between children with and without developmental delays or disabilities, children with ASD can be isolated from other children's conversations. To understand the effects of such isolation, Fasano et al. examined the association between degree centrality (the sum of child vocalization rate to and from peers in social contact) and assessed end-of-year language abilities. Even when accounting for group differences in language abilities, degree centrality was positively associated with assessed language abilities, underscoring the importance of peer vocal interaction to children's language abilities.

The social preferences revealed by Fasano et al.'s (2021) analyses of social networks in inclusive classrooms align with the decades of research on the social challenges of inclusion (e.g., Diamond et al., 1993; Chen et al., 2019) and reinforce the need for teachers to implement specific strategies aimed at facilitating social interactions between children with and without disabilities (e.g., Hong et al., 2020). Results of these types of investigations highlight the ability of continuous, multimodal sensing technologies, deployed across multiple classroom actors, to reveal factors that support (or possibly limit) children's access to peer language resources.

1.11. Promising extensions of automated measurement in preschool classrooms

Automated sensing technologies are evolving at a rapid pace. Gonzalez Villasanti et al. (2020) used head-mounted video cameras, for example, to capture children's first-person perspectives on their classroom experiences. In this study, children's interaction partners were identified from video using Amazon Rekognition software, https://aws.amazon.com/rekognition/, and the presence of vocalizations in the audio recordings was identified by Amazon Transcribe, https://aws.amazon.com/pm/transcribe/. Trained coders indicated whether the identified vocalizations were spoken by a teacher, a focal child, or a peer. The integration of automated video and audio coding via Amazon software yielded promising levels of accuracy in comparison to human expert coding of interaction. Substantively, this dataset provided information on children's experiences in the classroom (Chaparro-Moreno et al., 2019). In particular, the number of utterances, the number of words, and the number of sentences directed to children by teachers was greater than the corresponding numbers of utterances, words, and sentences directed to children by their peers. Further advances in automated speaker classification and transcription hold promise for conducting even finer-grained analyses of the language experienced by children in preschool classrooms.

In Gonzalez Villasanti et al. (2020) and Chaparro-Moreno et al. (2019), expert identification of speakers was complemented by information from automated video analysis, which identified the person to whom the speech was being addressed. Another example of such complementarity is research conducted by Custode et al. (2023) who complemented LENA measures of teacher and child vocalization counts with expert coding of interaction quality (positive, negative, or neutral). Pairs of children with higher levels of vocalizing were more likely to engage in positive interactions. Measures derived from automated speech processing can also be complemented with human coding of complex linguistic features. For example, automated counts of child vocalizations during shared reading could provide complementary information on the association between the frequency of teachers' inferential questions and the length or complexity of children's responses (Zucker et al., 2010).

The coding of activity context in preschool classrooms is another important example of this type of complementarity. Dutta et al. (2022) manually identified classroom areas that were typically used for different activities; Ubisense was used to identify when children and teachers were in these activity areas. The authors then reported on the percentages of automatically identified verbs and *wh*-words spoken by different children in those contact areas. Dutta et al.'s results rest on technologies being developed to automatically recognize the content of recorded speech. While this technology is fairly robust for adults in relatively quiet situations, child speech and classroom noise remain challenges. Lileikyte et al. (2020) used LENA devices to record child speech in a noisy childcare learning center. They used data augmentation and an array of machine learning methods to test an automated speech recognition (ASR) system. They then investigated the extent to which the resulting ASR yielded child word counts that may be sensitive enough to identify children in need of further evaluation for potential language delays. Identifying such differences could lead to a more thoughtful configuration of learning spaces to encourage greater adult-child conversational engagement (Kothalkar et al., 2021).

The configuration of learning spaces rests on findings that certain activity settings are more highly associated with language interactions—with either peers or adults—than other activity settings (Hong et al., 2020; Irvin et al., 2017; Nores et al., 2022). Multiple studies have shown that adult speech to children differs by activity setting, both in the home and in child-care and preschool settings (Hadley et al., 2021; Tamis-LeMonda et al., 2017, 2019). Studies using observational methods indicate that preschool teachers interact with children more frequently during structured activities than they do during free-play activities (Booren et al., 2012; Fuligni et al., 2012; Perry et al., 2018; Vitiello et al., 2012).

2. Discussion

2.1. Challenges associated with the use of automated sensing technologies

Researchers intending to adopt automated sensing technologies face several challenges. These include investment in hardware and software (Altman et al., 2020) and the need for trained individuals on the research team to set up and maintain the equipment. In addition, technical skills are needed to manage and integrate data streams from sensing technologies and to turn these measures into analyzable datasets (for further discussion, see de Barbaro, 2019). These include the need to temporally synchronize sensors such as audio recorders and location trackers to a common time clock. Another challenge relates to the framing of future research questions. Some forms of data generated by automated sensing technologies, such as adult word counts, map onto established coding systems designed to capture children's language input in the classroom. Other data generated by sensing technologies, such as time spent by a child in proximity to each classmate over the course of an entire school day, suggest new avenues of investigation to better understand features of children's experience that are associated with their language and social development. Researchers using new technologies have an opportunity to expand theory and produce evidence concerning the role of both established measures (e.g., child vocalization rate) and newly available measures (e.g., time in proximity to specific peers) in explaining children's interactions and development in the preschool context.

Additionally, all sensing technologies have limitations with respect to the behaviors they can measure. Of note, we are not aware of extant technologies for capturing child gaze and gesture in the classroom. These modalities are especially relevant to children who are nonverbal or minimally verbal. Nor has there been research, thus far, using sensing systems to process audio data from assistive devices employed by children with special needs. Moreover, despite the research reviewed in this article, we are not aware of any automated systems that can yield large-scale, accurate transcriptions of young children's speech in noisy environments.

Nevertheless, we envision that the availability and rapidly increasing accessibility of sensing technologies will open up new avenues of research. These technologies may be particularly useful in future studies exploring variation in the individual experiences of children within the same classroom (cf. Burchinal et al., 2021; Chaparro-Moreno et al., 2019). The ability to capture variation in individual children's experiences of proximity to, and communication with, teachers and peers can support future work on the variability of developmental pathways in early childhood (Cantor et al., 2019; de Barbaro, 2019; Rose et al., 2013).

2.2. Applications to practice

The general principle of teachers leveraging data from their own classrooms to modify classroom practice or individualize instruction is supported by the practice recommendations of U.S. professional organizations including the Division for Early Childhood (Division for Early Childhood, 2014), as well as research demonstrating the social validity and efficacy of data-driven decision making for classroom teachers (e.g., Buzhardt et al., 2020).

Initiatives are under way to explore the utility of data generated by sensing technologies to inform instruction. Datla et al. (2022) used computational processing (python scripts) of manually coded transcriptions of speech recorded with LENA devices in two preschool classrooms to generate visual representations, known as chord diagrams, of the amount of time that each child spent in interaction with other children and teachers over the course of a school day. Saquib et al. (2018) used a distributed sensor network to investigate the spatial movement of teachers and children in three Montessori-based early childhood classrooms. The researchers developed visual displays of key outputs of their Sensing Educational Interaction (Sensei) system, to enable teachers to visualize both pairwise and classroom-wide patterns of co-location over the course of a school day. The data enabled teachers to better track how, in which classroom areas, and with which other children or teachers the students were spending their classroom time.

We foresee additional opportunities to utilize the data produced by automated sensing technologies to improve practice. For example, Allen et al. (2017) have investigated the use of LENA technology and the system's associated data visualizations, provided in LENA Grow's Child Report, with parents of deaf children. Similar visualizations could be provided to teachers as feedback on critical features of their interactions with individual children, such as the number of turn-counts experienced by individual children in the course of a school day. These visualizations might alert teachers to children who require more opportunities for extended back-and-forth interaction. The examination of social network maps could also allow teachers to identify children who are experiencing low social interaction with peers and take appropriate action.

The practical applications described above may be particularly relevant to preschool classrooms that include children with a range of abilities and developmental needs (Irvin et al., 2021). As underscored in the joint policy statement of the Division for Early Childhood and the National Association for the Education of Young Children (DEC/NAEYC, 2009), the goal of inclusion is not simply access to typical settings but full participation and engagement in those settings with appropriate supports. Data generated from automated measures may assist teachers to monitor the progress of all students, particularly those with developmental challenges, in terms of their integration into the social fabric of the classroom as well as the intensity of their linguistic interactions with teachers and peers. For children receiving special education services, measures over time of the rate of a child's vocalizations to peers could be of use in identifying whether a child is attaining the short-term objectives identified on the child's Individualized Education Program (IEP). Data on a child's place in the social network of the classroom could inform conversations concerning the child's social and behavioral goals. If and when the available automated data suggest that included children are not making sufficient progress towards meeting their social or language-related IEP goals, this information would allow teachers to consider implementing more targeted naturalistic instructional interventions within the classroom context (Snyder et al., 2015).

3. Conclusion

Research on children's experiences in preschool classrooms has been constrained by methods requiring time-consuming human observation and coding. Newer approaches using multimodal sensors and machine-learning-based algorithms can overcome some of the limitations of previous methods and also provide new perspectives on children's behavior in interactive spaces. In this article, we have described how speech and location sensing technologies, used both separately and in concert with one another, can generate measures of social contact and language use that predict children's later social development and language abilities. Advances in the reliability of automated measures, such as those of contact with peers or conversational turn-taking, will improve our ability to test hypotheses about the processes underlying these aspects of children's development.

Challenges remain, however. The use of sensing technologies that require a high level of technical skill will be limited to teams that have such expertise. At the same time, conducting research with a single sensing technology simplifies the requirements for conducting relevant research in the classroom. In fact, relatively large studies using either automated speech processing or location tracking have begun to enrich the literature. Multimodal studies involving two or more types of sensing technologies are currently somewhat smaller in scope but are beginning to shed light on children's experiences and language development in early childhood settings. Finally. advances in location tracking, speech recognition, natural language processing, and video analysis (computer vision) continue at an unprecedented pace. These advances are likely to create new insights into interaction and development in preschools. It is our hope that technological advances will also yield tools that are more widely accessible, paving the way for innovations in research and practice that hold promise for improving children's developmental and educational outcomes.

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CRediT authorship contribution statement

Batya Elbaum: Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Lynn K. Perry:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Daniel S. Messinger:** Conceptualization, Writing – original draft, Writing – review & editing, Funding acquisition.

Data availability

Data will be made available on request.

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