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Sensing everyday activity: Parent perceptions and feasibility

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ABSTRACT

Mobile and wearable sensors provide a unique opportunity to capture the daily activities and interactions that shape developmental trajectories, with potential to revolutionize the study of development (de Barbaro, 2019). However, developmental research employing sensors is still in its infancy, and parents' comfort using these devices is uncertain. This exploratory report assesses parent willingness to participate in sensor studies via a nationally representative survey (N = 210) and live recruitment of a low-income, minority population for an ongoing study (N = 359). The survey allowed us to assess how protocol design influences acceptability, including various options for devices and datastream resolution, conditions of data sharing, and feedback. By contrast, our recruitment data provided insight into parents' true willingness to participate in a sensor study, with a protocol including 72 h of continuous audio, motion, and physiological data. Our results indicate that parents are relatively conservative when considering participation in sensing studies. However, nearly 41 % of surveyed parents reported that they would be at least somewhat willing to participate in studies with audio or video recordings, 26 % were willing or extremely willing, and 14 % reported being extremely willing. These results roughly paralleled our recruitment results, where 58 % of parents indicated interest, 29 % of parents scheduled to participate, and 10 % ultimately participated. Additionally, 70 % of caregivers stated their reason for not participating in the study was due to barriers unrelated to sensing while about 25 % noted barriers due to either privacy concerns or the physical sensors themselves. Parents' willingness to collect sensitive datastreams increased if data stayed within the household for individual use only, are shared anonymously with researchers, or if parents receive feedback from devices. Overall, our findings suggest that given the correct circumstances, mobile sensors are a feasible and promising tool for characterizing children's daily interactions and their role in development.

1. Introduction

Rapidly maturing technologies for sensing and activity recognition have the potential to provide unparalleled access into children's daily experiences and their role in development. Today, motion data, physiological activity, and samples of audio and video data can be logged by mobile and wearable sensors (Lazer, Brewer, Christakis, Fowler, & King, 2009). Machine learning algorithms can automatically process these signals into theoretically meaningful markers of developmentally-relevant activity, from children's motor

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activity (Nam & Park, 2013) and visual inputs (Bambach, Crandall, Smith, & Yu, 2018; Ye et al., 2012), to parents' affect and tone (Kim & Clements, 2015), including markers of depression (Alghowinem et al., 2013). Markers of parent and child behavior can be combined with physiological data, subjective reports of mood or parenting confidence, cognitive assessments, or even geo-coded location to provide rich detail on the dynamic contexts of behavior.

Such data have the potential to revolutionize research in infant development (de Barbaro, 2019). Traditional laboratory settings are known to restrict and distort natural behavior, meaning that researchers may draw inaccurate conclusions about the phenomena they are studying (Lee, Cole, Golenia, & Adolph, 2018). Even longitudinal studies typically only obtain snapshots of behavior that are often months apart because of the burdens of bringing families into the lab. For these reasons, there have been many recent calls to collect free-flowing data of children's behaviors and sensory inputs as they occur in natural settings, most notably in their homes (e.g. Franchak, 2020; Lee et al., 2018; Slone et al., 2018). For example, wearable cameras positioned to capture "what's in sight" for infants have been used to determine changes in infants' visual input throughout the first year, with implications for the development of face processing (Jayaraman, Fausey, & Smith, 2015) and object learning (Clerkin, Hart, Rehg, Yu, & Smith, 2017; Smith, Jayaraman, Clerkin, & Yu, 2018).

Sensors can also provide access to various dimensions of parent-child interactions as they unfold "in the wild". Perhaps most famously, the LENA (LanguageENvironment Analysis) is a wearable audio recording platform that automatically detects speech between parents and their young children (Zimmerman et al., 2009). Automatically detected markers of these "conversational turns" in natural home settings have been shown to predict children's later vocabulary (Weisleder & Fernald, 2013), and have been used to study processes of the infant vocal development (Warlaumont, Richards, Gilkerson, & Oller, 2014; Yoo, Bowman, & Oller, 2018). By analyzing other aspects of the recorded audio, researchers have also investigated contextual factors that affect the volume of these early interactions. For example, book reading increases the number of conversational turns (Gilkerson, Richards, & Topping, 2017), while television is associated with decreased conversational turns, in children ages 2–48 months (Christakis et al., 2009). By providing objective measures of such "ecological variability" between families, sensors can provide access to a novel set of drivers of individual differences in children's development.

Ambulatory sensors have also been used to characterize qualitative and affective aspects of caregiving interactions. For example, measures of maternal warmth and responsivity, as well as measures of family conflict have been manually annotated from audio sensor data (Berke, Choudhury, Ali, & Rabbi, 2011; Slatcher & Trentacosta, 2012; see also Hubbard & Van IJzendoorn, 1991). Capturing measures of caregiving quality in everyday settings is critical given that, for example, measures of sensitivity in laboratory free play do not appear to approximate measures of sensitivity in unstructured home activity (NICHD Early Child Care Research Network, 1997). Additionally, while the importance of caregiver responsiveness and sensitivity to distress and infant social-emotional development is well-established (e.g. Kopp, 1989; Leerkes, 2011; McElwain & Booth-LaForce, 2006), it is relatively rare to observe negative emotions in the free play sessions from which sensitivity is typically assessed (Fields-Olivieri, Cole, & Maggi, 2017). By virtue of the possibility to capture extended (24 h+) recordings of everyday activity, sensors can allow researchers to characterize these critical but seldom observed-in-laboratory aspects of parent-child interactions.

Existing studies only begin to scratch the surface of possibilities of how sensors could be used to gain insight into early development (for extended discussion see de Barbaro, 2019). Below, we provide a brief introduction to sensors and algorithms that could be used to capture and automatically detect aspects of parent and children's behavior and interaction in daily contexts. Future studies could combine these tools to provide new understanding of within- and between- family differences in child and parent behavior. For example, combining audio and physiological sensors could be used to examine whether dynamic markers of environmental chaos increase children's physiological stress moment-by-moment, or examining predictors of physiological co-regulation in parent-infant dyads (Smith et al., 2019). Data collected over longitudinal time could be used to understand how such interactions turn into established routines. For example, audio data capturing cycles of dyadic distress and soothing interactions over longitudinal time could be used to track developmental trajectories of self-regulation (de Barbaro, Khante, Maier, & Goodman, 2020; Granic & Patterson, 2006).

1.1. *Current study: motivation and goals*

While promising, the application of ambulatory sensors to study development is still in its infancy. Simply collecting these data involves many novel challenges, including but not limited to knowledge of what types of study designs will be acceptable and feasible for parents of infants and young children. There are a wide variety of options available when incorporating ambulatory sensing into a study, each with different implications for participant privacy as well as other burdens and benefits of participation. In turn, parent comfort and willingness surrounding these options has implications for the types of questions that are feasible to pursue, and the types of studies researchers can design. For example, parents may be willing to collect audio recordings of toddlers to study language development but unwilling to do so when data would be used to study parenting sensitivity or harshness, including automated detection of punitive reactions such as slaps or hits. Thus, the goal of the current study is to assess parents' willingness to collect and share parent-child interaction data from mobile sensor studies, to improve the design and success of future research.

1.2. *Sensor overview*

To provide background for our feasibility studies, we first review a subset of sensors and algorithms relevant for characterizing parent-child activity and interactions, focusing on those that are readily available for use with little to no engineering or computational experience. Researchers interested in a more thorough review of state-of-the-art possibilities should refer to de Barbaro (2019).

1.2.1. Motion and physiological sensors

Sensors which detect physical motion and physiological data (e.g. heart rate or electrodermal activity) provide robust, easy to scale signals (Pellegrini & Smith, 1998). These sensors are most commonly used to detect markers of sleep and physical activity, both of which have clear consequences for children's development. Sleep predicts physical development and cognitive trajectories (Tham, Schneider, & Broekman, 2017), including measures of executive functioning and IQ (Bernier, Beauchamp, Bouvette-Turcot, Carlson, & Carrier, 2013; Pisch, Wiesemann, & Karmiloff-Smith, 2019). Infant and toddler sleep patterns are also associated with parental well-being and stress, which in turn affects overall family functioning (Middlemiss, 2004; Sinai & Tikotzky, 2012; Wolfson, Lacks, & Futterman, 1992). While studies of physical activity are less common, research indicates that children's quantity of motion is related to cognitive functioning (Junger & van Kampen, 2010) as well as social emotional and interpersonal functioning. For example, daily toddler motion is associated with an outgoing temperament (Buss, Block, & Block, 1980), and mothers of high-motion toddlers were rated as being more impatient and hostile with their children (Buss, 1981). Studies of hyperactivity in early childhood have found an increase in hyperactivity over time leads to higher levels of parenting stress (Beernink, Swinkels, Van der Gaag, & Buitelaar, 2012), which is associated with negative parenting behaviors (Anthony et al., 2005) and in turn, increased child hyperactivity (Carpenter & Mendez, 2013; Keown, 2012). Longitudinal motion data collected in a home setting may provide a unique opportunity to parse apart this complex set of associations.

1.2.2. Specialized algorithms for activity recognition

Machine learning algorithms can transform raw activity data into markers of other meaningful activities, similar to the way a smartwatch uses characteristic patterns of motion to identify "steps" or sleep episodes. This process, termed "activity recognition", is a focus of researchers in the field of ubiquitous computing. While current activity recognition research is mostly focused on adults, a number of algorithms of relevance to developmental scientists have been developed. These include algorithms to automatically detect stress, (Hovsepian et al., 2015), early motor experience, including crawling, toddling, and walking (Manu et al., 2020; Nam & Park, 2013), infant carrying and holding (Yao, Plötz, Johnson, & de Barbaro, 2019) and fuss versus cry detection (Syed, Schroeter, Sidorov, & Marshall, 2018; Turan & Erzin, 2018). However, researchers should be aware of the limitations of such automated models. Automated activity recognition has the potential for misclassification (Cristia et al., 2020; Kwon, Zavos, Nickele, Sugianto, & Albert, 2019), including for example, due to noise from caregiver activity (Worobey, Vetrini, & Rozo, 2009; Zhou, Schaefer, & Smith, 2019) or the presence of other children (Cristia, Ganesh, Casillas, & Ganapathy, 2018). These more specialized activity recognition algorithms are typically developed with small convenience samples in "clean" laboratory conditions, and thus need additional work to be validated for use in real-world scenarios (Lockhart & Weiss, 2014; de Barbaro, 2019). Researchers interested in these algorithms must thus carefully examine the contexts in which data was collected before incorporating them into their own studies (de Barbaro, 2019).

1.2.3. Audio and video sensors

Audio and video sensors provide a unique opportunity for accessing interactions in the home in that they provide high fidelity records of activity that can be richly interpreted (Adolph, 2016). While a limited number of algorithms exist that can robustly process naturalistic audio and video data (e.g. Zimmerman et al., 2009; Rehg et al., 2013), manual annotation is still necessary to characterize most behaviors of interest to developmental scientists. A wide variety of activities can be reliably annotated from these datastreams. For example, manual annotation of ambulatory audio data has been used to characterize various aspects of linguistic and affective activity (Mehl, 2017), as well as joint activities (Soderstrom & Wittebolle, 2013) and caregiving interactions, as noted above (Slatcher & Robles, 2012; Tobin et al., 2015). While time consuming, these annotations can provide critical context for interpretation and analysis of automated sensor outputs.

1.2.4. Location and communication sensors

Other devices that have shown promise for providing insight into developmental processes include location sensors, including GPS and physical proximity data, and communication logs, such as stored social media and chat data. Most relevantly in the context of early development, proximity data collected via Bluetooth ™ or radio signals can monitor the approximate distance between parent and child (Olguín et al., 2008; Salo et al., 2020). GPS data can detect markers of the caregiver's mental health or out-of-home activity (Saeb, Lattie, Schueller, Kording, & Mohr, 2016) and has been used to indicate likely activities via proximity to locations such as schools or liquor stores, with implications for parenting quality (Byrnes et al., 2017). Communication logs, such as texting frequency, can function as a marker of social interactions widely accessible from cell phones (Harari, Müller, Aung, & Rentfrow, 2017). Research indicates communication logs are associated with complex behavioral outcomes. For example, frequent texting may be associated with social support and connectedness (Pettigrew, 2009; Reid & Reid, 2010), but has also been associated with depression (Faurholt-Jepsen et al., 2016; see Rohani, Faurholt-Jepsen, Kessing, & Bardram, 2018 for a review).

Overall, developmental scientists have a wide variety of relevant and technologically feasible options to pursue when considering incorporating ambulatory sensors into their research paradigms. However, the relative novelty of these techniques within social science research means that parents may be apprehensive about these tools. Below, we review likely considerations of parents approached to participate in sensing research.

1.3. Factors affecting parent willingness

Parents may feel some discomfort around collecting and sharing sensor data capturing early interactions. Privacy is a primary concern in sensing studies (Kotz, Gunter, Kumar, & Weiner, 2016), which may be further amplified when collecting and sharing data in home settings (Choe, Consolvo, Jung, Harrison, & Kientz, 2011), the focal location for parent-child interactions. In particular, home activities can be highly personal and intimate in nature and individuals generally expect high levels of privacy at home (Shapiro, 1998). Additionally, recording children's activity in the home may present additional privacy concerns for parents, such as the desire to protect their children from harms related to breaches of sensitive data (Acquisti, Brandimarte, & Loewenstein, 2015).While the potential for such concerns has been acknowledged as an important issue for developmental science research (Cychosz et al., 2020), we know of no studies that have systematically examined parents' concerns and willingness to have their children participate in sensing research across a variety of sensors and privacy scenarios. We identified two previous studies regarding acceptability of the LENA, both with small samples of participants (N> = 5) who already provided consent to collect and share LENA data (Allen, Crawford, & Mulla, 2017; Choo, Dettman, Dowell, & Cowan, 2017), meaning that these studies don't speak to the acceptability of audio recording (or other sensors) in the general population. Additionally, given that a major functionality of LENA is to automatically detect speech, reported comfort may be very different than when the goal is to collect raw ambulatory audio data for human annotation. This current study seeks to address these gaps in knowledge by investigating parents' concerns with and barriers to participation in sensing studies with their children. Below we review several factors which may affect parents' comfort with collecting and sharing their children's ambulatory sensing data, drawing from the field of ubiquitous computing.

1.3.1. Concerns due to datastream and device

Participants report varying levels of privacy concerns with sensors depending on the particular datastream. High fidelity datastreams, such as raw audio or video, can be easily interpreted without further processing and are typically more concerning than lower fidelity data, such as motion or physiological data (Klasnja, Consolvo, Choudhury, Beckwith, & Hightower, 2009). The collection of high fidelity datastreams may be more palatable for participants when privacy-preserving techniques are employed. Such techniques include subsampling, such as the collection of short (30–90 second) "snippets" of audio every hour (Lazer et al., 2009; Mehl, 2017), which can provide a rich and accurate reconstruction of daily activity (Mehl, 2017; Micheletti et al., 2020) while also reducing the ability to fully reconstruct potentially sensitive activities. Additionally, feature extraction techniques can process and store specific features of audio data, such as ambient volume or presence of speech. If done in real-time (i.e. on device or cloud), this can completely obviate the need to store raw audio, thus greatly increasing participant privacy (Wyatt, Choudhury, Bilmes, & Kitts, 2011). Similar data obscuring techniques have been created for location, video, and chat-log data (Chan, Liang, & Vasconcelos, 2008; Dong, Cheung Hui, & He, 2006; Narayanan, Thiagarajan, Lakhani, Hamburg, & Boneh, 2011). However, it is unclear the degree to which such techniques will affect parents' willingness to collect and share their children's data, a key question when considering possible avenues of collaboration with engineers and computer scientists developing these tools.

The popularity of products such as FitBit and JawBone (Choe, Lee, Lee, Pratt, & Kientz, 2014) have made self-tracking devices more familiar, providing known benefits with abstract risks (Nguyen, Kobsa, & Hayes, 2008). A 2019 national survey found that one in five American adults use a smart watch or fitness tracker (Vogels, 2020). As consumer devices utilizing audio and video recording become more commonplace (Hoy, 2018), people may become increasingly comfortable with this kind of tracking. Parents in particular may have substantial experience audio and video recording their own children through home and baby monitors, which may also increase their comfort with similar devices used by researchers.

1.3.2. Concerns due to use of data

The use and reach of data also likely affect parents' willingness to collect sensor data in the home. For example, participants reported being comfortable collecting data on home electricity use data, including real-time activity inference, when access was localized to the household and not shared with service providers (Choe et al., 2012). Comfort with sharing data can also depend on perceived trust. For example, a study of parents of children with disabilities found that parents were less willing to share information with children's care providers if they had prior negative experiences with the providers, such as observing sloppy confidentiality practices or witnessing gossip (Mikles, Haldar, Lin, Kientz, & Turner, 2018). Previous studies also suggest that individuals may be more willing to share personal data when it is used for scientific purposes and less willing to share with companies (Cheung, Bietz, Patrick, & Bloss, 2016). This may be due to relatively lower trust in companies, especially in light of recent scandals about data privacy breaches (Golden, 2018).

Individuals typically weigh the intrusiveness of monitoring and data sharing with its perceived benefits and are willing to sacrifice some privacy given sufficient benefits (Growth from Knowledge, 2017; Mahmoodi et al., 2018), such as using the data for personalized feedback. Researchers using mobile sensors have an opportunity to provide participants with reports of their daily activity data. Such summaries may enhance parental motivation to participate in mobile sensing studies. Parents often report a desire to monitor their children, for example, monitoring the types of television shows watched (Choe et al., 2012). Information that assists or enriches parenting responsibilities, such as exposure to toxins or deviant behaviors, or provides some feedback about their children may thus increase parent willingness to collect and share mobile-sensing information pertaining to their child.

1.3.3. Unique considerations within minority populations

Sensing research likely poses different challenges and opportunities across different social background. Across disciplines, low income and minority populations are historically harder to recruit for participation in research than white affluent populations and can be mistrustful of researchers (Arora, Yttri, & Nilsen, 2014; Scharff et al., 2010). Mobile sensing technology may be less familiar to low-income racial and ethnic minorities and could thereby increase mistrust in the technology itself as well as with the research group collecting the information (Berridge, 2016; Roy, 2017). At the same time, systemic barriers that minority populations face, and the stressors associated with poverty (Jovanovski & Cook, 2019; Towne, Probst, Hardin, Bell, & Glover, 2015) make low income and minority populations particularly high-risk for a range of maladaptive developmental outcomes (Gordon & Cui, 2018; Hair, Hanson, Wolfe, & Pollak, 2015; Tobler et al., 2013). Moreover, low income and minority children are less likely to be identified by current screening systems for a range of problems and risk factors (Moffitt, 2002; Yucel et al., 2019). Sensing technology could play a role in facilitating identification and mitigation of these risks (Leung, Hernandez, & Suskind, 2020). Thus, it is crucial to determine the applicability of mobile sensors with low-income ethnic minority populations in particular.

1.4. Current study: overview

Overall, there are many considerations that might affect parents' willingness to collect and share mobile sensor data of child and family activity at home. To assess the feasibility of leveraging sensors in developmental science research, we conducted two exploratory studies. In Study 1, we survey parents about their willingness to collect and share their children's mobile sensor data considering a variety of scenarios of likely interest to developmental scientists and practitioners.

In Study 2, we detail recent recruitment efforts for an ongoing mobile sensor study, including recruitment rates and barriers to participation. The sensor study involved families of infants and toddlers collecting up to 72 h of natural home activity with ambulatory sensors that have the potential to detect a wide range of theoretically-motivated parent and child activities. We recruited in-person, in a mixed-race low-income population with families that had not previously participated in studies in our lab.

The two exploratory studies reported here provide complementary insights into the acceptability and feasibility of mobile sensing in a developmental population. In particular, by comparing across many possible variations of potential technologies and study parameters, our survey provides valuable insight into the research designs that can make or break parents' interest in participating. By contrast, our recruitment data provides insight into parents' true willingness to participate in a specific mobile sensor study, given the opportunity to ask questions in a situation where their comfort, time, and effort are truly on the line, as well as to explain their concerns. As such, it provides a realistic measure of the acceptability of a research design that is technically feasible and of specific interest to developmental scientists. The complete research protocol for each study was approved by the Institutional Review Board (IRB) of the University of Texas at Austin.

2. Study 1: parent acceptability survey

In Study 1, we surveyed parents on their comfort with a variety of developmentally relevant sensors, privacy-preserving options, data-sharing options, and parent feedback options. Our survey also inquired about information that might influence parents' willingness to participate in sensing studies, including demographic information as well as current and desired ownership of commercially available sensors.

2.1. Methods

2.1.1. Survey design

We developed and administered an online survey through the Qualtrics Research Company Panel. The survey consisted of three blocks of Likert-scale questions measuring parents' willingness to collect and share their children's mobile sensor data. For each set of questions, parents indicated their willingness to participate on a seven-point Likert scale, ranging from 1 ("Extremely Unwilling" or "Much Less Willing") to 7 ("Extremely Willing" or "Much More Willing"). The order of the three main question blocks was randomized to avoid bias and category order effect.

The first block of questions surveyed parents about their comfort with different types of sensor data. We included five categories of

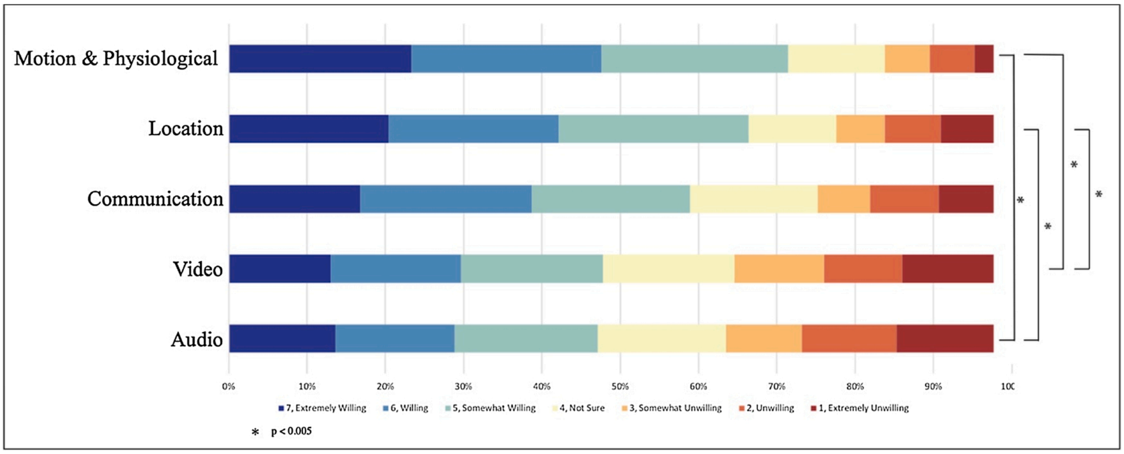

Fig. 1. Willingness to collect specific datastreams of interest.

sensor data: (1) location, (2) communication, (3) video, (4) audio, and (5) motion and physiological data. Within each category we also provided different privacy preserving options, for example recording 30-second "snippets" of audio data rather than continuous audio recordings (see Figs. 1 and 2).

The second block of questions measured parents' willingness to share data with various entities under four different conditions: (1) personal use only and not shared beyond the household, i.e. data is utilized within the household but not available for research purposes, as in an intervention study, (2) shared confidentially with researchers, i.e. data is stored separately from identifying information, (3) shared anonymously with researchers, i.e. data is impossible to link to identifying information, and (4) shared with technology companies according to their policies (see Fig. 3).

The third block of questions assessed whether various types of informational feedback impacts parents' willingness to collect and share data. We included nine unique types of informational feedback (see Fig. 4): ranging from exposure to toxins to parenting feedback. This group of questions asked parents how much more or less willing they would be to collect and share information if they received various types of information in return. Whereas the first two blocks surveyed parents' overall willingness to collect and share sensor data, this block of questions assessed whether user feedback *changes* their willingness.

2.1.2. Participants

To be considered for inclusion in the study, participants needed to endorse having a child under the age of five. We balanced parents' gender (50/50) and matched demographic characteristics to the U.S. population. Sixteen parents were removed and replaced for giving non-differentiated responses (i.e. identical responses to all questions) for a final sample of 210 respondents.

The main sample characteristics are described in Table 1. Parent gender was equally split with n = 105 males (i.e. fathers) and n = 105 females (i.e. mothers). Parents ages were between the ages of 18 and 24 (n = 21, 10.00 %), 25 and 34 (n = 120, 57.14 %), 35 and

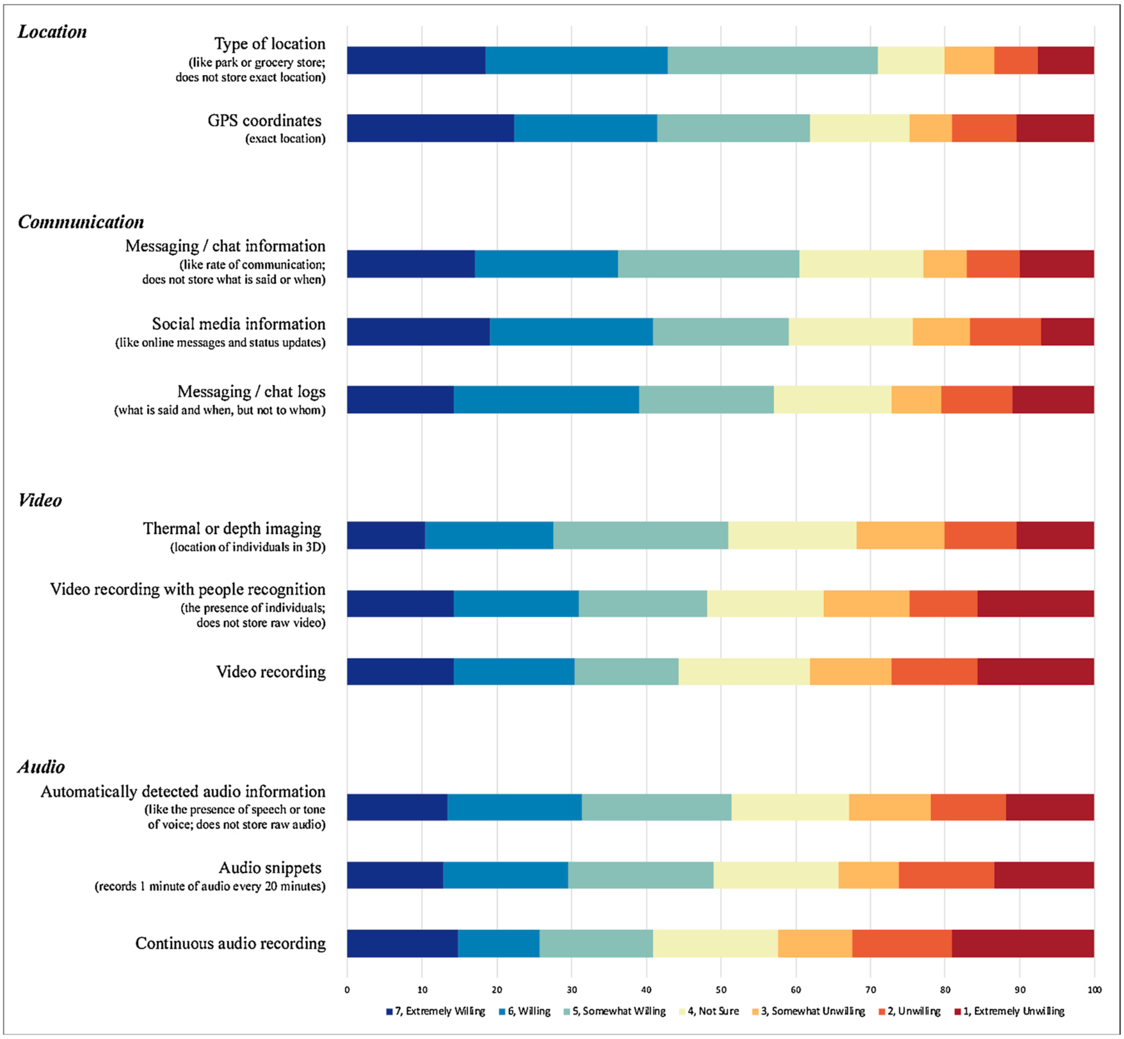

Fig. 2. Parents' willingness to participate given high versus reduced resolution options within each datastream. Italicized explanations of each datastream were included in participant questionnaires.

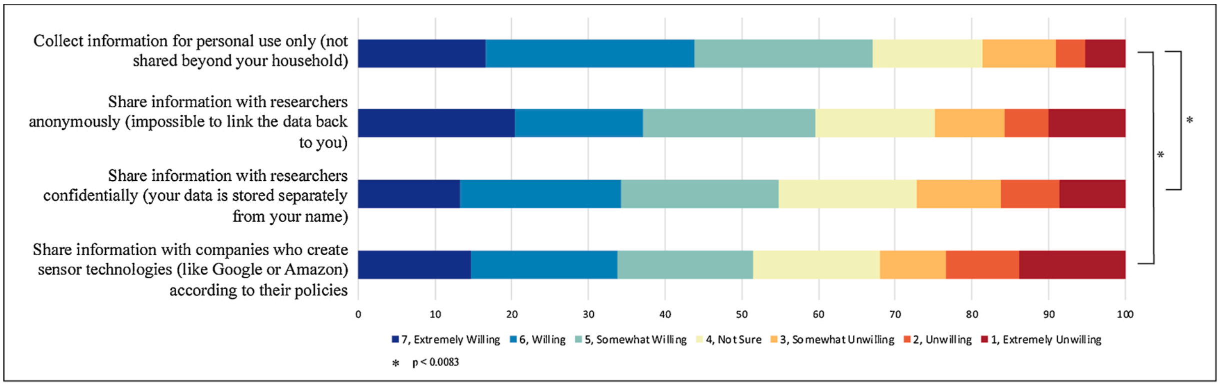

Fig. 3. Effects of data-sharing policies on parents' willingness to participate. Privacy policies were described as listed above.

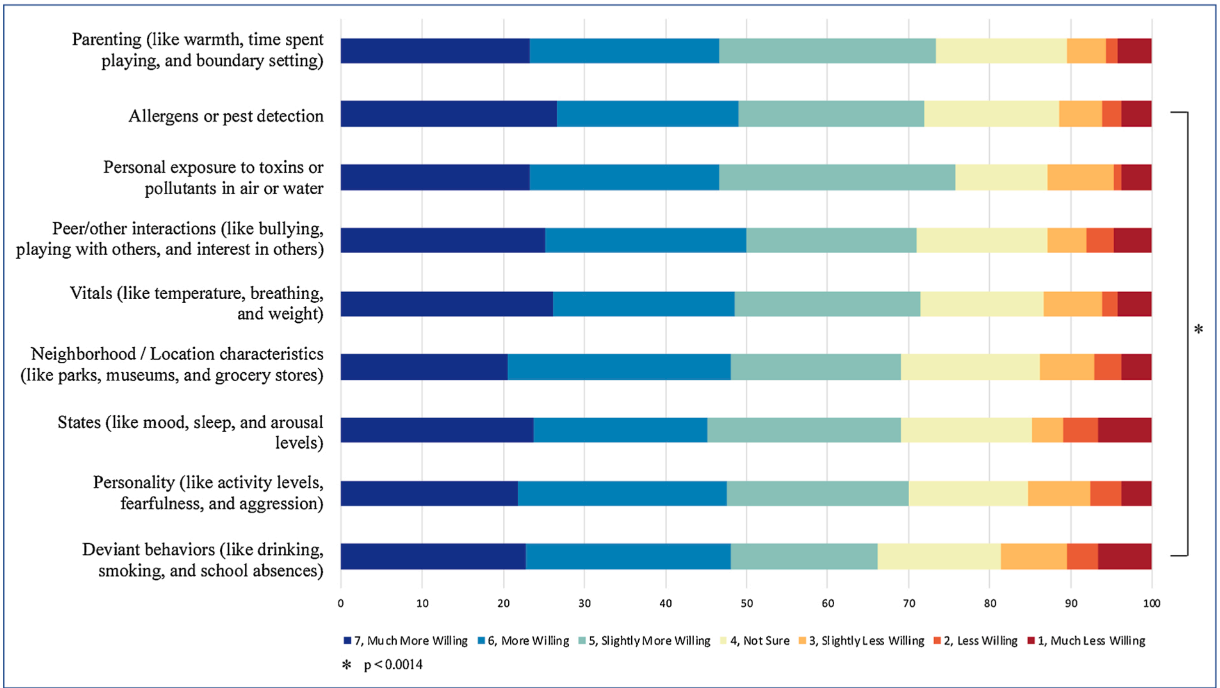

Fig. 4. Increases in willingness to participate given different types of possible feedback as described in questionnaires.

44 (n = 62, 29.54 %), and 45 or older (n = 7, 3.34 %). The majority of parents were married or in a domestic partnership (n = 167, 79.52 %), while other parents were single (n = 30, 14.29 %), divorced (n = 9, 4.29 %), separated (n = 2, 0.95 %), or widowed (n = 2, 0.95 %).

2.1.3. Data analysis

For each comparison, we provide descriptive reports of parents' willingness to participate in mobile sensing studies. Additionally, we used chi-square tests to identify statistically significant differences in parents' willingness between different study conditions. To do this we combined all positive responses into a single "willing" category (i.e. including "Somewhat Willing", "Willing", and "Extremely Willing") and all negative responses into a single "unwilling" category (i.e. "Somewhat Unwilling", "Unwilling", and "Extremely Unwilling"). To correct for multiple comparisons, we use the Bonferroni adjusted alpha level for a 0.05 significance level. For each significant chi-square analysis, we report the chi-square value, degrees of freedom, along with each within-block Bonferroni adjusted alpha level. The full chi-square results with the adjusted significance level are available in the Supplementary Material.

Table 1
Sample Characteristics (N = 210).

Category	Parameter	Number	Percentage (%)
Number of Children	1	77	36.67
	2	84	40.00
	3+	49	23.33
Age of Children	< 1 yr	49	13.39
	1–4 yrs	182	49.73
	5–7 yrs	52	14.21
	8–10 yrs	39	10.66
	11–13 yrs	25	6.83
	14+ yrs	19	5.18
Race	Black or African American	26	11.76
	Asian	9	4.07
	Native Hawaiian or Pacific Islander	4	1.81
	White	159	71.95
	American Indian/Native American	6	2.71
	Hispanic or Latino/Latina	17	7.69
	Other	0	0.00
Highest level of school completed	Less than HS diploma	11	5.23
	HS diploma or equivalent	38	18.10
	Some college credit, no degree	45	21.43
	Trade/technical/vocational training	13	6.19
	Associate's degree	17	8.10
	Bachelor's degree	49	23.33
	Advanced degree	37	17.662

2.2. Results

2.2.1. Parents' overall comfort with sensor datastreams

Our survey data indicated the proportion of parents' responses within five general categories of sensor datastreams (Fig. 1). These numbers were created by averaging parents' responses to corresponding subcategories (e.g. continuous audio recordings, audio snippets, and audio features were averaged into the audio category; see Fig. 2 for willingness within the complete list of surveyed datastreams). Survey results indicate that parents were most comfortable sharing their children's motion and physiological data, with 71.43 % of parents indicating they were at least somewhat willing to collect this data, and a mean rating of 5.11 (SD = 1.68), where five corresponds to Somewhat Willing and six corresponds to Willing. By contrast, parents were least comfortable with collecting audio data. However, up to 47.14 % indicated that they were at least somewhat willing to collect audio (M = 4.12, SD = 1.95). Under a Bonferroni correction for a 0.05 significance level, chi square analyses verified that parents were more willing to collect motion and physiological data than audio data and video data (M = 4.17, SD = 2.00), $\chi2(1) = 26.94$ and 24.55, $p < .005$. Parents were also more willing to collect location (M = 4.81, SD = 1.84) than either audio or video data, $\chi2(1) = 13.97$ and 12.23, $p < .005$. At the Bonferroni corrected significance level, there were no significant differences between willingness to collect audio and video data, communication and audio, communication and video, communication and location data, communication and motion and physiological data, or location and motion and physiological data. The full chi-square results are available in the Supplementary Information.

2.2.2. Effects of privacy-preserving techniques

Next, to investigate how different privacy preserving techniques might influence willingness to collect specific datastreams, we compared high vs low resolution sensing options within location, communication, audio and video datastreams (see Fig. 2). Parents' willingness to use mobile sensors given common privacy-preserving techniques showed small but largely insignificant increases in the expected direction. Differences ranged from an increase of 3.33 % willingness to share complete chat data (complete conversations) vs. chat logs (timing and count of texts to anonymized numbers; not significant under the Bonferroni corrected significance level) to a 10.48 % increase in willingness to record audio features relative to continuous audio data (not significant under the Bonferroni corrected level). Results indicated no significant differences in willingness to collect data at different levels of resolution for location, communication, video, or audio datastreams.

2.2.3. Effects of technology ownership

We observed a number of significant differences, based on the Bonferroni corrected significance level, in parent willingness to participate in mobile sensor studies according to the sensors and devices they currently own or use. Parents who have a smartphone with location services always on (34.8 %) were significantly more willing to collect communication data and video data than those who do not, $\chi2(1) = 16.66$ and 17.98, $p < .005$. Parents who own a voice-controlled speaker (23.3 % of parents) were significantly more willing to collect video data than those who do not own a voice-controlled speaker, $\chi2(1) = 8.47$, $p < .005$. Parents who own a baby monitor, wearable motion sensor, or have social media accounts were no more or less willing to collect and share any type of sensor data than parents who do not own or have those technologies.

2.2.4. Effects of data-sharing policies

Parents were most willing to collect data in a personal-use scenario, i.e. when it would not be shared beyond their household (M = 4.95, SD = 1.63). 67.14 % of parents were at least somewhat willing to collect data in this scenario, relative to 54.76 % (M = 4.50, SD = 1.79) when data was shared confidentially with researchers, 59.52 % (M = 4.67, SD = 1.88) when data was shared anonymously with researchers, and 51.43 % (M = 4.31, SD = 1.98) when data was shared with technology companies. With the Bonferroni corrected significance level, chi square analyses indicated that personal use scenarios were significantly more comfortable to parents than sharing confidentially with researchers (with protection of personally identifying data), or with technology companies, $\chi2(1) = 5.84$ and 11.70, $p < .0083$ (Fig. 3). No differences in parents' willingness emerged between anonymous and confidential data sharing with researchers or between anonymous sharing with researchers and technology companies or confidential sharing with researchers and technology companies. There was also no significant difference between personal use scenarios and sharing anonymously with researchers.

2.2.5. Effects of providing feedback to families

Between 66–76 % of parents reported that they would be at least somewhat more willing to share data if provided feedback in any domain; between 20–27 % reported that they would be much more willing to participate (Fig. 4). We observed minimal differences in parents' interest in different categories of feedback: the only significant difference to emerge when using the Bonferroni corrected level of significance indicates that parents were significantly more willing to collect data if it provides information on allergens (M = 5.26; SD = 1.56) than information on deviant behaviors (M = 5.01; SD = 1.75), $\chi2(1) = 4.04$, $p < .0014$.

3. Study 2: Recruitment for live mobile sensing study

In Study 2, we analyze recruitment data collected as part of a larger study seeking to use ambulatory sensors to characterize everyday mother-infant interactions related to maternal depression in a low-income, predominately Latinx population. Broadly, the study involved a 1.5 -h introductory session at the university and the collection of 72 h of sensor data over the course of a week. The sensors used collected continuous raw audio data from a device worn by the child, motion and physiological data collected from the mother and the child, as well as six daily surveys assessing mothers' subjective mood and recent experiences. These sensors were selected for their potential to detect a wide range of theoretically motivated parent and child activities, including child distress, maternal sensitivity and responsiveness, physiological synchrony, sleep, and mental health symptoms. Caregivers were eligible for participation if they spoke English or Spanish, if they were the primary caregiver, and if their baby was between the ages of 4 weeks and 9 months or 16 months to 36 months.

3.1. Methods

3.1.1. Procedure

To recruit for the sensing study, trained research assistants were stationed in the waiting area of a local federally qualified health center (i.e. a community clinic) serving primarily Latinx, low-income families in the area. Specifically, the center's patient demographics are 66.7 % Latinx and 53.7 % at or below 200 % Federal Poverty Level (CommUnity Care Health Centers). A research assistant approached caregivers who appeared to be eligible and invited them to participate in the study using a standardized script to ensure consistency. Caregivers who were interested in participating provided their contact information and were later contacted by phone to schedule a session. If caregivers were uninterested in talking to the research assistant or participating in the study, the research assistant recorded their stated barrier for participation. The barriers were collected through a form completed by the research assistant on the iPad. The barriers were either recorded via open-ended responses or a predetermined list including limited time to talk or participate, believing the baby is too young, sensor concerns, privacy or security concerns, or objections of another household member. All information was recorded at the clinic on an iPad during contact and promptly uploaded to secure lab servers. The research assistants were trained to address common concerns by educating the caregivers on our confidentiality and protection practices (see Supplementary Material for detailed script).

3.1.2. Qualitative analysis

The open-ended responses by the research assistants detailing the barriers for participation were qualitatively analyzed using descriptive thematic analysis (Braun & Clarke, 2006). Patterns within the data were identified and then grouped together by similarity of content and meaning. Qualitative analysis of the research assistants' open-ended responses was conducted by the first author with confirmation of the analysis performed by the second and third author. Thematic analysis of the comments yielded three new categories of barriers: logistical constraints, being uncomfortable and unfamiliar with research in general, and wanting more information or time to think about whether to participate. After identifying the three categories, two coders independently coded all open-ended responses to assess reliability of the coding scheme. The average Cohen's kappa coefficient was 0.85 (ranging from 0.846 to 0.860), indicating a good level of agreement between the two raters. The new categories were analyzed alongside the predetermined barriers, which we report below.

3.2. Results

3.2.1. Recruitment rate in applied setting

Research assistants approached 359 caregivers at the community clinic. Some caregivers had been previously approached (n = 20), were ineligible to participate (e.g. not the primary caregiver or their child was too old, n = 15), or unwilling (n = 21) or unavailable (e.g. called for their appointment; n = 22) to talk. This resulted in 281 eligible caregivers who were willing to talk to the research assistant. Due to various constraints, research assistants were unable to complete the recruitment logs for 60 participants, who were removed from subsequent analyses. Of the remaining 221 eligible caregivers who were willing to talk, 129 (58.37 %) caregivers were still interested in participating after learning about the study and provided contact information for scheduling. 64 (28.96 %) eligible approached caregivers were scheduled to participate in the study, with the remaining being uninterested at the follow-up call (n = 21), not possible to reach (n = 35), or unable to schedule for other reasons (n = 9). Ultimately, 21 (10 %) of caregivers participated in the study.

3.2.2. Barriers to participation in applied setting

92 of 221 eligible caregivers were uninterested in participating after hearing about the study at the clinic. We obtained data on barriers to participation from 74 of the 92 uninterested caregivers. Table 2 summarizes all recorded barriers to participation. Caregivers reported an average of 1.59 (SD = 0.94) barriers to participation, with 46 caregivers stating one barrier, 17 caregivers stating two barriers, and 11 caregivers stating three or more barriers. Below we describe the barriers to participation and include example notes from the research assistants describing their encounter with the caregiver and the barrier as explained by the caregiver. Nearly 70 % (n = 49, 66.22 %) of the uninterested caregivers cited one or more barriers to study participation that did not appear to be specific to sensing. These included: limited time to discuss or participate in a research study (n = 30, 40.54 %), logistical constraints such as lack of transportation (n = 16, 21.62 %), or discomfort or unfamiliarity with research in general (n = 7, 9.46 %; some caregivers stated multiple responses). Next, although all children in this sample were eligible for participation, over one fifth of caregivers (n = 17, 22.97 %) described that they did not want to participate because they believed their child was too young to participate in the study.

Caregivers also stated that they declined to participate because they anticipated that another household member would not approve of the study (n = 12, 16.22 %), or because they wanted more information or to talk more before committing (but were simultaneously unwilling to provide contact information for follow up; n = 12, 16.22 %). Finally, about 25 % (n = 19, 25.68 %) of caregivers noted privacy or security concerns (n = 12, 16.22 %) or general concerns about the sensors (n = 11, 14.86 %). Below we provide select notes from the research assistants describing their encounters with caregivers with these latter concerns. While caregivers may not have explicitly stated that they had privacy and security concerns, their comments suggested that they were not comfortable with the abilities of these devices. For example, one caregiver described that they "*did not want to be videotaped.*" Other caregivers indicated more general concern about recording data. For example, one research assistant noted that an approached caregiver was "i*nterested and engaged but as soon as I said 'recording device' mom was completely uninterested. I tried to tell her [that the] information will be kept under a safe program but [she] showed strong disinterest*" In this case, the promise of confidential data storage did not alleviate the concerns of the caregiver.

Other caregivers expressed concerns about the sensor's physical placement on their children. One research assistant noted that a caregiver "*was uncomfortable with the idea of sensors being on either of her kids- she had both an infant and a toddler. I tried explaining that the sensors were harmless but she was still not convinced.*" Another caregiver "w*as concerned about baby taking sensor off*" and did not want her child to be troubled by wearing the sensors.

4. General discussion

In this paper we examine parents' willingness to use wearable and mobile sensors to record and share data about their children's daily experiences via a nationally representative survey (N = 210) and recruitment efforts for an ongoing mobile sensor study with parent-infant dyads (N = 359). Our survey results indicated that the type of sensor, sharing policies, receiving feedback, and current sensor ownership were associated with willingness to participate. However, typical privacy preserving techniques of collecting lower-resolution data showed small and inconsistent relationships with willingness to participate, suggesting that such techniques are not as readily appreciated by parents. Reported willingness to collect highly sensitive data both parallels and indicates some key differences from the results of our in-person recruitment. In sum, our results suggesting that willingness to participate in sensing research is high in

Table 2
Barriers to participation (N = 74).

Reason	Number	Percentage (%)
Did not have time to talk or participate	30	40.54
Baby is too young	17	22.97
Logistical constraints (e.g. transportation)	16	21.62
Wanted more information or to talk later	12	16.22
Household member's concern	12	16.22
Privacy or security concerns	12	16.22
General sensor concerns	11	14.86
Uncomfortable/unfamiliar with research in general	7	9.46

low-income Latinx populations, but that logistical barriers need to be addressed. Below, we review our results in more detail and consider their implications for research design.

4.1. Willingness to participate

Surprisingly, parents being recruited indicated substantially more interest in participating in-person relative to our survey data. After learning about the study from research assistants, 58 % of eligible approached caregivers provided contact information to be scheduled for a later date, relative to 41 % of surveyed parents reporting that they were at least “somewhat willing” to participate in studies that included audio sensing data, or 26 % reporting that they were “willing” or “extremely willing”. This discrepancy may reflect that parents are more comfortable with sensing studies when they have the opportunity to learn more about the study’s privacy practices, such as the data storage and security options. This is consistent with previous studies which highlight the importance of a dynamic consent conversation, particularly when recruiting minority populations (Winter et al., 2018). Alternatively, given that our in-person recruitment population was lower income and more minority relative to our surveyed population (53.7 % are 51–200 % Federal Poverty Level and 66.7 % Latinx; [(CommUnity Care Health Centers)]; 7.69 % Latinx and 28.05 % non-white), the high rate of interest in participating may also reflect an increased draw of financial compensation for this population (Pandya & Desai, 2013). Finally, the increased interest in participating assessed through in-person methods relative to online may be due to social desirability, or the desire to present themselves favorably, which is typically stronger face-to-face than online (Heerwegh, 2009).

Next, 29 % of approached parents were scheduled for the session, typically via follow-up calls. This is lower than the 41 % of surveyed parents reporting that they were at least “somewhat willing” to participate in studies that included audio sensing data. This may be due to drop out of those people who just wanted to be socially desirable, and may therefore reflect a more accurate metric of comfort with sensors and desire to commit to a research protocol. Intriguingly, it resembles the roughly 26 % of surveyed parents who reported that they were “willing” or “extremely willing” to participate in sensing studies. Additionally, we note that our scheduling rate was roughly similar to rates of in-person recruitment consistently seen in low-income minority populations (e.g. Baucom et al., 2018).

Unfortunately, only about 10 % of approached caregivers ultimately participated in the study. This may reflect the 14 % of caregivers who reported being “extremely willing” to participate in sensing studies. However, this failure to retain scheduled participants is substantially higher than in our past efforts and thus may not be an accurate reflection of willingness per se, but rather reflect challenges specific to a low-income minority population.

In particular, in a recent recruitment effort for the same sensing study described here, only one of 66 scheduled families ultimately did not participate in the study (unpublished data, i.e. a retention rate of 98.5 %, relative to 33 % reported in the current manuscript). In contrast with the recruitment efforts described in the current manuscript, in this prior recruitment effort we made no effort to recruit low income or minority populations. This resulted in a much whiter, more educated sample (54 % white and 50 % had a household income over $75k, relative to 66.7 % Latinx and 53.7 % at or below 200 % Federal Poverty Level in the current study; [(CommUnity Care Health Centers)]) similar to those which traditionally comprise the bulk of participants in infancy studies, for better or for worse (Henrich, Heine, & Norenzayan, 2010; Nielsen, Haun, Kärtner, & Legare, 2017).

Thus, our data suggests that low-income minority populations, while willing and interested in participating in sensing studies, may face many challenges that prevent them from actually participating in these studies. This conclusion is also supported by our analysis of stated barriers to participation in Study 2, in which nearly 70 % of uninterested participants reported logistical constraints to participation. Other, non-sensing studies have also found high withdrawal rates in minority populations, ranging from 32 % to 86 % (Baxter et al., 2012; Pappas, Werch, & Carlson, 1998), as well as that logistical constraints pose a greater barrier for minority populations relative to white, non-Hispanic populations (Chandra & Paul, 2003; Giuliano et al., 2000). However, the dramatically poor rates of retention in our low-income minority sample suggest that sensing studies may pose a particular set of challenges to participation. For example, the week-long nature of the sensing protocol in Study 2 may be perceived as an extreme time commitment to participants relative to traditional, one-time laboratory studies. In future studies, researchers could anticipate this concern and carefully describe to participants the actual amount of effort required rather than simply the study duration.

4.2. Factors that do and do not affect parent willingness

The results from the survey along with the barriers to participation from our in-person recruitment efforts indicate the variables that do and do not impact caregiver willingness to participate in sensing studies. Below, we review our results in more detail and consider their implications for researchers interested in using mobile sensors.

4.2.1. Sensor type

Survey results indicated that parents’ comfort with sensors generally conformed to previous research on personal recordings (Klasnja et al., 2009; Krishnan & Cook, 2014). That is, parents were most comfortable recording their children’s motion and physiological data and least comfortable with collecting audio and video. The popularity of consumer heart rate and activity trackers may increase parents’ comfort with these types of sensors. Also, the fact that raw motion signals are generally not interpretable may cause parents to feel that these types of sensors are less intrusive than sensors that collect data that is immediately interpretable, such as audio and video data. Our recruitment efforts indicated it was valuable to carefully craft a standard response to concerns about audio data in order to educate the caregivers on our privacy and confidentiality practices. Parents’ comfort with activity monitoring may decrease if they are alerted to the types of activities that can or will be detected with motion data, thus, it is important to share such plans with parents at the consent stage. Additionally, given that caregivers in Study 2 expressed concerns regarding the physical impact of the sensors on their child, recruitment efforts should describe the safety and comfort of the devices themselves.

4.2.2. Privacy preserving techniques

In general, common privacy preserving techniques did not appear to influence surveyed parents' willingness to participate in sensing studies. Similar results have been found in other studies (e.g. Neustaedter, Greenberg, & Boyle, 2006). Resolution of the data did not impact willingness for any of the sensor types surveyed (audio, video, location, communication data). However, the percentage of parents willing to collect low resolution data was higher than the percentage of parents willing to collect high resolution data. This suggests that while parents appreciate some benefit to obscuring raw data, the magnitude of these benefits are relatively low.

These findings may be counter-intuitive given a recent emphasis on privacy-preserving techniques in the sensor development literature (e.g. Chou et al., 2018). One possibility is that individuals do not truly understand the differences between high and low-resolution data, and that additional education will lead to greater differences in willingness between these data. However, even if our results are due to the lack of understanding about these techniques, lay participants are unlikely to have any more knowledge than our sample, meaning that advertising privacy-preserving techniques will likely have minimal effects on participant recruitment.

Overall, our survey results suggest that reducing data resolution with subsampling or feature extraction techniques is unlikely to provide a benefit in attracting more participants or increasing their comfort with participating in sensing studies. At the same time, our experience with in-person recruitment indicated that privacy and security concerns were a common reason reported for not participating. Thus, privacy appears to play an important role in a parent's willingness to participate in mobile sensing studies and should be carefully considered by researchers.

4.2.3. Data-sharing policy

Surveyed parents had a clear preference about data sharing, namely, they were more willing to collect data if it stayed within the household for individual use only, as opposed to being shared with researchers or companies. Parents' willingness to participate in studies did not significantly differ between anonymous or confidential data sharing with researchers. Generally, though, 54 % of parents reported a willingness to share data confidentially with researchers. These patterns are consistent with previous studies and our current results from in-person recruitment (Choe et al., 2012; Critchley, 2008; Markos, Milne, & Peltier, 2017): parents care about who has access to their data. Caregivers from a minority population may be even less willing to share data with researchers due to the historical treatment of these populations by researchers (Scharff et al., 2010). A small portion of the caregivers who provided a barrier for participation indicated that they are uncomfortable or unfamiliar with research in general (9.46 %). Thus, we recommend that researchers inform parents about data sharing and, in particular, whether it will be shared with third parties. To enhance recruitment rates, parents should be provided multiple options when consenting which include options to share deidentified data with third-party researchers but do not require them to do so in order to participate and gain compensation, as was the case in our in-person recruitment.

4.2.4. Feedback

Our results suggest that feedback could be a strong motivator for parents' use of these devices. Within our survey data, 66–76 % percent of parents indicated that they would be more willing to share sensitive data (such as audio or video data) if provided feedback. A previous study with LENA also found that parents enjoyed the visual feedback and it contributed to their positive experience with the sensor (Choo et al., 2017). The particulars of the type of feedback did not show many statistically significant or apparently meaningful differences, suggesting that regardless of the type of information provided, feedback is of interest. Future studies should investigate the impact of feedback amount and format on parent willingness to participate in sensing studies.

We also note that 10–19 % of surveyed parents indicated they would be less willing to use a device if it provided feedback. This may be due to a lack of awareness or discomfort with the fact that devices can be used to infer such complex aspects of behavior. In turn, these data speak to the need to educate potential participants on the types of information that can be inferred from sensors, in particular those which are perceived as less sensitive (e.g. physical motion, i.e. accelerometry data), as this information may lead them to be less willing to participate. As activity recognition algorithms become more sophisticated and we can recognize more types of activities, educating the participants will become key for providing informed consent.

4.2.5. Current ownership

Our survey indicated that parents who own technologies that can be used for health or entertainment (i.e. voice-controlled speakers or use their smartphone with the location always on) were more comfortable collecting sensitive sensor data, while parents who own technologies for security purposes (i.e. baby monitors or home security cameras) were no more willing to collect data. While we were unable to collect this information from the caregivers in Study 2, a survey conducted by Pew Research Center found that Latinx and low-income populations are less likely to own smartphones but own voice-controlled speakers at about the same rates as white, high-income populations (Auxier, 2019; Pew Research Center, 2019). The similarity in ownership rates of voice-controlled speakers may contribute to relatively similar rates of willingness between our representative sample and minority population sample. Growing rates of voice-controlled speaker ownership mean that increasingly more parents may be comfortable using these devices for research or personal interest in the future. It is important for researchers to consider the limitations that will occur due to people who own technologies being more likely to participate in sensing studies. Because people who own sensing technologies tend to be wealthier, sample characteristics may not represent the general population.

4.3. Limitations and future directions

We note some limitations to our work. First, privacy is dependent on time and place, and thus it is plausible that parents' willingness to collect and share information may change over time, as news of privacy breaches emerges, or new technology becomes more ubiquitous. The current climate of major security breaches may mean our parents were more conservative; similarly, the fact that the speech and voice recognition market (e.g. Amazon Eco and Google Home) is projected to grow from USD 7.5 billion in 2018 to USD 21.5 billion by 2024 means that future participants may be more likely to own and record with these devices (Research & Market. ltd., 2019). Additionally, the current political climate may continue to increase existing privacy concerns for immigrant and minority populations specifically. Thus, our results may shift in response to future effects.

The studies reported here address the gap in knowledge surrounding caregiver willingness to participate in sensor studies and provided insight into barriers to participation. Future studies should investigate strategies to overcome these barriers, such as how to minimize the logistical and practical constraints as well as how to best present feedback to caregivers. Additionally, researchers should determine methods for educating participants of various backgrounds on the benefits of using sensors for research. It is important to continue to improve recruitment and retention rates of minority populations so that research findings are inclusive and can be used to effectively develop interventions.

5. Conclusion

Mobile and wearable sensors hold promise for providing a new lens into the great mysteries of development: how and why individuals become who they are (de Barbaro, 2019). At the same time, by providing access to objective markers of activity and interactions in intimate and personal contexts, sensors also open critical questions about privacy and participant comfort. Based on the two studies presented here, many parents are apprehensive to collect and share their children's mobile sensing data. They are relatively conservative about the benefits of potential privacy-enhancing solutions. However, over 40 % of surveyed parents were at least somewhat willing to collect and share high-fidelity data (i.e. continuous video and audio data) and 14 % of parents were extremely willing to collect and share high-fidelity data. These rates mirrored interest in participating in an ongoing study in a low-income, minority population. Thus, overall, our data suggest that it is feasible to undertake mobile sensor studies in parent-child samples, even in historically hard-to-recruit populations. Our results indicate that future studies would have higher rates of participation if they incorporated more feedback, were able to retain data in-home or otherwise not shared with third parties, and reduced the logistical demands of participation. Additionally, rates of participation may be higher in wealthier populations, given that device ownership is higher in these populations (Pew Research Center, 2020) and this was positively related to increased willingness to participate. While parents are aware of the privacy implications of these emerging techniques, there are clear opportunities for researchers interested in incorporating mobile sensors into their own work.

CRediT authorship contribution statement

Hannah I. Levin: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization, Project administration. **Dominique Egger:** Writing - review & editing. **Lara Andres:** Writing - review & editing. **Mckensey Johnson:** Methodology, Data curation. **Sarah Kate Bearman:** Conceptualization, Methodology, Supervision, Funding acquisition. **Kaya de Barbaro:** Conceptualization, Methodology, Resources, Writing - original draft, Writing - review & editing, Supervision, Funding acquisition.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.infbeh.2020.101511.

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