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Current, future and potential use of mobile and wearable technologies and social media data in the ABCD study to increase understanding of contributors to child health

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Abstract

Mobile and wearable technologies and novel methods of data collection are innovating health-related research. These technologies and methods allow for multi-system level capture of data across environmental, physiological, behavioral, and psychological domains. In the Adolescent Brain Cognitive Development (ABCD) Study, there is great potential for harnessing the acceptability, accessibility, and functionality of mobile and social technologies for in-vivo data capture to precisely measure factors, and interactions between factors, that contribute to childhood and adolescent neurodevelopment and psychosocial and health outcomes. Here we discuss advances in mobile and wearable technologies and methods of analysis of geospatial, ecologic, social network and behavioral data. Incorporating these technologies into the ABCD study will allow for interdisciplinary research on the effects of place, social interactions, environment, and substance use on health and developmental outcomes in children and adolescents.

Keywords

ABCD; Mobile technology; Wearable sensors; Social media; Child health; Child development

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1. Introduction

Mobile and wearable technologies, and new methods of data capture that leverage social media, are transforming the way we conduct health-related research. They support the capture of within-person intensive longitudinal high temporal resolution data on environmental, physiologic, behavioral, and psychological factors important to health. They allow deeper understanding of how individuals interact with one another and influence each other's wellbeing. Importantly, this can be accomplished on a multi-scale and multi-system level, including individual, interpersonal, family, school, and community-based influences on health. The complexities of these may be missed via in-lab assessments due to poor recall, diminished salience beyond the time of occurrence, or inability to measure secondary to subjective unaware-ness (e.g., sleep, air quality). New forms of data captured by mobile devices may lead to new insights into brain development and child health by assessing the multitude of real-time factors that contribute to developmental outcomes.

Mobile phone use is ubiquitous among adolescents. Nearly 75% of adolescents own or have regular access to smartphones, and over 90% of these adolescents access the Internet via smartphones. Seventy-six percent of adolescents use social media, with 71% of these adolescents using more than one social network site (Bagot et al., 2015). Further, minority adolescents are more likely to own smartphones and use apps (Bagot et al., 2015), providing the opportunity to understand factors, including family and culture, which contribute to development in populations that are underrepresented in research and health services. While there are fewer data on commercial wearable device use among children and adolescents, the extant literature suggests that pre-adolescent children find wearing wrist-worn devices such as activity trackers acceptable and are relatively compliant with use (Schaefer et al., 2014). Combined, these technologies and social media represent an enormous opportunity to improve how we understand the lives of children and adolescents.

This paper outlines mobile and social technologies and methods that are currently being used with children and families enrolled in the Adolescent Brain Cognitive Development (ABCD) study, and those that will be implemented during participants' early adolescence to augment data collection from other sources such as neuropsychological assessments, biospecimens, and structural and functional neuroimaging data. Linking mobile data with multi-level data that measures contextual place-based variables may provide synergy between traditionally more static, or less temporally dynamic data, and dynamic mobile data. Overall, the plans to capture data as described below will allow for: (a) more precise identification and monitoring of social, emotional, psychological, and behavioral trajectories, (b) in-vivo capture of contributors to substance use and mental health issues and outcomes, and (c) greater understanding of the impact of physical activity, sleep, and environmental exposures on development. Some of the methods outlined here are more established than others, and some may have been used infrequently (if at all) in child and adolescent populations. In addition, the underlying technologies are changing rapidly, and preferences for types of social media–in particular among adolescents–are difficult to predict. Thus, research in this area will require flexibility and adaptability, as there are many challenges in research keeping pace with the rate of change of mobile technologies (Patrick et al., 2016). If successful, we will contribute to the larger body of literature regarding use of these technologies to advance our understanding of contributors of healthy development, and psychosocial, behavioral, and health outcomes in childhood and adolescence.

1.1. Technology currently being used in ABCD

1.1.1. iPads—iPads are currently employed across sites in ABCD to capture clinical, neuropsychological, and self-report data. Parents use the iPads independently to provide historical information about their child, themselves, and their families, while youth use the iPads with the aid of research assistants (RAs). Baseline study sessions begin with RAs administering questions to the youth from the iPads. Surveys of the research assistants on youth and parent feedback, and observations of use by youth and parents suggest that youth are relatively technology-savvy and are able and eager to respond to questionnaires autonomously. Preliminary analyses of feedback data from 3621 youth across sites shows that 88.5% find iPads were easy to use and 82.4% find the iPad games fun. Similarly, parents have provided verbal feedback that the iPads are easy to use, iPad features and accessories such as the ability to zoom in, increase font size, and use an attached external keyboard and/or stylus to help input text are appreciated and increase usability. Overall, entering data into iPads, as opposed to traditional paper and pencil measures, allows for a streamlined data collection process and portability of data collection. Further, direct-data entry minimizes the likelihood of data entry errors, reduces the likelihood of missing data, and expedites the process by which the data are available for public release. These findings are consistent with previous literature that has demonstrated that electronic data capture via tablet is as accurate as traditional paper and pen questionnaires, and allows for immediate review and analysis of data (Walther et al., 2011). Further, there is an increased likelihood of participants reporting sensitive information, with automatic triggers for clinicians when concerning sensitive information is reported (Basch and Goldfarb, 2009).

1.2. Technology currently being piloted in ABCD

1.2.1. Accelerometers—Insufficient or poor quality sleep is associated with alcohol, marijuana, tobacco, and other substance use in adolescents (Roane and Taylor, 2008; Fakier and Wild, 2011). Adolescents with large weekend-weekday differences in sleep duration are also at greater risk for heavy drinking and frequent intoxication (Sivertsen et al., 2015), higher alcohol and marijuana risk taking (O'Brien and Mindell, 2005), and increased marijuana and alcohol use (Pasch et al., 2010). Insomnia and short sleep duration have also been shown to predict depression, and suicidal ideation in adolescents with a > 8-fold increase in odds of depression for those with both insomnia and short sleep duration (Roane and Taylor, 2008; Sivertsen et al., 2015; Roberts et al., 2009). Depressive symptoms also predict insomnia in adolescents (Roberts and Duong, 2013). There is a similar reciprocal relationship between substance use and depression (Leve et al., 2012). However, the reciprocal interaction between sleep problems, substance use, and depression has not been prospectively evaluated in children and adolescents. Further, low levels of physical activity are independently associated with increased risk of mortality, obesity, type 2 diabetes, cardiovascular disease, and some cancers, and there is evidence that the global burden of non-communicable disease attributable to physical inactivity is similar to that of smoking (Lee et al., 2012).

The diversity of biological mechanisms contributing to physical activity and sleep, coupled with difficulties in precise measurement of these complex habitual behaviors, contribute to current challenges in assessing temporal trends and establishing dose-response relationships with physical and mental health. As such, valid measures of physical activity and sleep in-vivo are necessary to determine health outcomes.

Among the most valid and simple to use tools to measure physical activity and sleep are accelerometers (Corder et al., 2007; de Zambotti et al., 2015). These are most often worn on the waist or wrist and are capable of continuously measuring triaxial acceleration at varying frequencies. With the use of algorithms, accelerometers are able to measure the amount of time spent at various levels of activity intensity. Heart rate monitors are typically worn on the chest or wrist and measure direct physiological response of the heart to physical activity via a digitized electrocardiogram signal (chest) or an optical sensor that measures changes in blood volume (wrist). Limitations of accelerometers and heart rate monitors are overcome by combined sensing; heart rate monitors can accurately assess the high intensity physical activity that is the result of upper body movements (e.g., weight lifting) or cycling that accelerometers measure poorly, and accelerometers can accurately assess the low intensity physical activity (e.g. walking) that heart rate monitors measure poorly (Plasqui and Westerterp, 2007; Warren et al., 2010).

Recent advances in microtechnology, data processing, wireless communication, and battery capacity have resulted in the proliferation of low-cost, non-invasive, wrist-worn devices, such as the Fitbit Charge HR 2, Fitbit Surge, Microsoft Band, Apple Watch, etc. These devices include both accelerometers and heart rate monitors, and they are capable of continuously measuring and storing data at a 1 s sampling rate for up to 5 days before needing to be recharged. Wrist-worn devices that measure both acceleration and heart rate have recently been validated against direct observation and indirect calorimetry to provide an objective measure of physical activity (Diaz et al., 2015), and against polysomnography to provide an objective measure of wakefulness and sleep time (de Zambotti et al., 2015; Toon et al., 2016; Mantua et al., 2016; de Zambotti et al., 2016). Such devices infer wakefulness and sleep from the presence or absence of limb movement and an elevated heart rate, and they provide naturalistic measurements of sleep patterns in the home environment at a lower cost than polysomnography.

Because limited data are available about how well consumer-grade devices measure behavioral and physiological parameters in adolescents, a study validating the Fitbit Charge HR for use in children was conducted at University of California San Diego (UCSD) in anticipation of incorporation into ABCD. The validity of physical activity, heart rate and sleep from a consumer-level, multi-sensor, wrist-worn activity tracker in healthy children was assessed. Sixty boys and girls aged 9–10 years were recruited. Participants simultaneously wore a Fitbit Charge HR (contains a triaxial accelerometer, an optical heart rate monitor, an altimeter, and a vibration motor) and research-grade, wrist-worn triaxial accelerometer (ActiGraph Link, ActiGraph Inc.), portable three-lead electrocardiogram with built-in triaxial accelerometer (BioNomadix, BIOPAC Systems Inc.) and indirect calorimeter (K4b2, Cosmed Inc.) to measure steps, energy expenditure and intensity of physical activity, and heart rate while completing a series of sedentary/low intensity to high intensity activities. These activities included sitting while playing a game on a tablet, riding a stationary bike, walking and/or jogging on a treadmill, walking up and down stairs, walking outside on level and hilly ground, and completing a speed and agility course. Heart rate and the physical activity-related measurements from the gold standard measures were compared to Fitbit measurements. In addition, one night of sleep data was collected via polysomnography and the Fitbit Charge HR and these data were also compared. Fitbit measurements were comparable to those from research-grade, gold standard devices in this population (Wing et al., 2017).

In addition to validity of these devices, it is important to understand how feasible and acceptable it is for children and their parents to use them in research studies. Thus, a pilot study was performed to evaluate physical activity, sleep, and heart rate continuously over 21 days in 150 children 9–10 years of age using Fitbit Charge HR 2 at three sites (UCSD, SRI International and Virginia Commonwealth University). Participants wore the Fitbit continuously for three weeks, except when bathing or participating in water activities, and completed pre- and post-questionnaires querying self- and parent-perceived levels of physical activity, sleep, and eating behaviors and Fitbit likability, as well as use and ease of use. When a Fitbit was assigned to a child, the prequestionnaire was completed on an iPad and the Fitbit app was downloaded to either the parent or child’s cell phone. This allowed the data collected by the Fitbit to automatically sync and upload whenever the Fitbit was in close proximity to the associated phone. ABCD RAs monitored data syncing closely and families were contacted if a child’s Fitbit data had not been uploaded for four days, as after 6 days there is loss of granularity of data. Data were passively and securely streamed via wireless technology to the Fitbit website. It was then retrieved using software developed by Fitabase Inc (https://www.fitabase.com) and stored securely on their servers. After the designated three-week time period was complete, an RA contacted the family by phone to administer the post-questionnaire and remind the family to return the device by mail.

Across all three sites, only two Fitbit devices were lost (mail, swimming) and four damaged (one bicycle accident, three unknown). Preliminary data from approximately one-third of the projected sample show few differences in pre-post self-report of activity, sleep, and Fitbit ease of use. Data from the post-wear questionnaire demonstrate that 83% percent of children somewhat or strongly disagreed that the Fitbit was complicated to use, 92% somewhat or strongly agreed that they felt very confident using the Fitbit, and 92% enjoyed using the Fitbit a lot. The data also suggest that the parents enjoyed having their child use the Fitbit with 92% reporting that they would be willing to have their child continue to wear the Fitbit for longer if asked. Side effects reported have been minimal; the most common has been skin irritation on the wrist where the device is worn. Overall, use of the Fitbit has been well received. The plan is that the Fitbit will be available to be rolled out for use across all ABCD sites by the Year 2 follow-up, which would begin in September 2018. Incorporating wrist-worn devices such as Fitbit into ABCD will allow us to examine patterns of physical activity and sleep in free-living child populations and stability of these patterns over time. Additionally, this data, coupled with neuropsychological and biobehavioral assessments and imaging will enhance our understanding of the relationships between physical activity and sleep, and health in children and adolescents.

Finally, the mobile technology field changes rapidly, and research has yet to keep pace with advances in the field. We have experienced this in our attempt to integrate wearable devices into ABCD. By validation completion, and pilot study implementation, the Fitbit Charge HR 2 was released; an updated version of the Fitbit Charge HR device was validated for ABCD. The newer model does not differ in the manner in which it measures physical activity, including heart rate, and sleep, and it provides new features such as measurement of VO2 max. Additionally, we anticipate that updated versions of all technologies used in ABCD will be released during the lifespan of this longitudinal study. As such, learning how to monitor and adapt to shifts in the field is a component of the feasibility aspect of the pilot study. Other practical issues will be studied regarding use of wearable devices in children and adolescents as there is limited literature to date on issues such as rate of lost or damaged devices, completeness of data acquisition over time, and compliance with device charging and syncing.

1.3. Technology under consideration for implementation into the ABCD study at future follow-ups

The ABCD Mobile Technology Workgroup is currently reviewing several technologies for acceptability, reliability, and feasibility to potentially implement them into the ABCD study during future follow-up visits (Year 3, starting September 2019 and beyond).

1.3.1. Smartphones

1.3.1.1. Ecological momentary assessment, short message service (SMS) texting and continuous passive data collection.: Smartphones have been successfully used for assessment and intervention for substance use, mental health and other health behaviors in youth through ecological momentary assessment (EMA), Short Message Service (SMS) text, and continuous passive mobile sensing. (Ben-Zeev et al., 2015; Benarous et al., 2016; Wen et al., 2017; Mason et al., 2015; Jones et al., 2014; Belzer et al., 2014; Markowitz et al., 2014) EMA allows for study of dynamic interactions between individuals and their environments, and individuals' experiences of their environments through participant self-report during, or close in time to, an experience of interest. Youth 8–18 years of age in clinical (medical and psychiatric) and nonclinical populations have been shown to have compliance rates of approximately 78% regardless of duration of EMA period, study design (time vs. event based prompts) and technology (mobile alone vs. mobile + wearable device). Among clinical samples, compliance has shown to increase with increased number of prompts (6+), whereas nonclinical samples demonstrate better compliance with fewer prompts (2–3) (Wen et al., 2017). Interactive text-based programs have been designed alone, and with adjunctive internet-based programming, video messaging, and traditional clinician-guided treatment (Mason et al., 2015). Interventions for substance use in youth that use these approaches have been found to provide valid and reliable measures of risky behaviors. Further, there appears to be a positive relationship between number of texts and effect size (Mason et al., 2015). This is consistent with the literature that shows that adolescents age 13–17 send and receive a mean of 67 (standard deviation = 30) text messages per day (Bagot et al., 2015).

Text messaging and EMA require additional privacy protections for users. Three safeguards are recommended to secure personal information: administrative, physical, and technological. To support these goals, studies should require participants to configure their phones to use built-in password and/or biometrics protection, disable pop-up and home screen previews of received messages, maintain physical control of their phones at all times, and install and use a free, cross-platform secure texting app. The secure texting app uses a cloud-based approach that prevents text messages from being saved, copied, or forwarded by the recipient and enables automatic message deletion from phones upon expiration, allowing an additional layer of privacy protection. Further code words can be used to represent sensitive health information when addressing issues like substance use, risky behaviors, and/or mental health conditions.

Advances in engineering, computer and data science, and communication technologies have led to rapid growth in mobile sensing capabilities as well (Bietz et al., 2016), and can be leveraged to passively collect health-relevant data. Data can be collected via sensors and integrated devices on smartphones including accelerometers, gyroscopes, compass, light and proximity sensors, microphone, global positioning system (GPS), and touch-based interactions (Lane et al., 2010). Data can also be extracted continuously from user interactions with phones including text messaging, phone calls, mobile web access, and apps (including apps used and duration of use). Wi-Fi and Bluetooth data can also be used to assist with location or communication patterns. Passive sensing can be supported by apps that are specifically designed for research such as Apple Research Kit (apple.com/researchkit) and Android Research Stack (researchstack.org). While this is a promising area of research, commercial capability has outpaced research in this domain. There are few studies to date using these technologies, and only in adult populations (Place et al., 2017). As such, validation of these models and platforms in large studies are needed. However, results are promising in regards to feasibility, acceptability and prediction of psychiatric symptoms via passively collected indicators of behavioral change (Place et al., 2017).

EMA, SMS, and continuous passive data collection allows for increased understanding of baseline psychosocial and behavioral status and real-time capture of perturbations to this when selected events of interest occur. In regards to EMA and text messaging, there remain issues with privacy and self-report; however compliance, reliability, and validity have all been demonstrated. For passive data collection, data from sensors in controlled, lab settings can be used to develop activity recognition algorithms (Bao, 2004; Wu et al., 2012) that can then be embedded within activity recognition apps to track physiological and behavioral states over time. Further, machine learning approaches allow for in-vivo data to be annotated by free-living individuals to provide “ground truth” of what is occurring (Scholkopf and Smola, 2001) decreasing the need for self-report and reducing concerns related to adherence. Increasingly accurate and highly individualized models are being created to support ongoing surveillance of health indicators of interest and provide real-time prompts via the phone or connected device to address such things as health behaviors “in the moment.” In ABCD, we will be able to identify and passively track behavioral, physiologic, and psychosocial trajectories, and determine changes in patterns relevant to developmental outcomes in youth.

1.3.1.2. Residence histories & geolocation.: There is increasing acknowledgement of the effects of place (i.e. neighborhood) on health, development and neurobiology (Glass and McAtee, 2006; Kawachi and Berkman, 2003; Fitzpatrick and LaGory, 2000). The most fundamental piece of information needed to put people in to place is the home or *residential address*, which is already being collected within the ABCD study. An address can be used to link data on individuals, families, or groups to a wide variety of ecological or place-based measures derived from social, policy, built and physical environmental data including: neighborhood deprivation, crime rates, alcohol outlet density, healthy food infrastructure, green spaces, clinics, schools, traffic density, marijuana use policies, education-related policy, air quality, temperature, precipitation, and elevation. By collecting residential history data (over years on a macro level) on the timing, sequence, and duration of residence, researchers can build more complex measures of place-based exposures across development and major life transitions (Wild, 2005).

We can also examine micro-level exposure over shorter time intervals via GPS data collection. Activity space research, an index of routine locations and all the accompanying psychological, social, and health-related experiences of these places, are important for addressing the spatial dimensions of children's lives (Matthews and Yang, 2013) and can be captured via GPS location data on smartphones. Youth, especially urban adolescents, spend their time in a variety of geographically dispersed activity spaces that are not delineated by conventional geographic boundaries, such as census tracts, ZIP codes, political wards, or even home neighborhood (Basta et al., 2010; Browning and Soller, 2014). Neighborhood characteristics are known to influence adolescents' perceptions of safety, risk, and exposure to violence and are associated with substance use and mental health outcomes (Graif and Matthews, 2017; Mason and Korpela, 2009), underscoring the importance of this construct for understanding urban youth. Research on activity spaces has also suggested that the places a person frequents outside the home, including schools, places of worship, grocery and non-food shopping and leisure activities, may expose him or her to a variety of psychological, social, and geographic factors that likely influence substance use, but that may not be observed within the home (Wong and Shaw, 2011).

Due to the ubiquity of GPS enabled devices such as smartphones and activity trackers, we anticipate incorporating into ABCD cross-sectional and dynamic (via residential histories and GPS 'movement' data on daily spatial behavior) measures of place, as well as social and environmental characteristics of neighborhoods and residential environments in which children and adolescents live. We will thus be able to capture a complete perspective on contextual exposure, examining exposure to multiple places across specified temporal (e.g. monthly, annually) and spatial (e.g., ZIP code, census tract) domains, and the impact on developmental outcomes over time.

1.3.1.3. Environmental measures.: Emerging research also demonstrates a relationship between environmental exposures and the human brain, cognition, and mental health. The impact of environmental exposures on neurodevelopmental outcomes appears especially important during critical periods of development, including both in utero and across childhood and adolescence, affecting intelligence (Edwards et al., 2010; Perera et al., 2012), mood, anxiety and behavioral dysregulation disorders (Perera et al., 2014; Liu et al., 2013;

Margolis et al., 2016), cognition (Chiu et al., 2013; Sunyer et al., 2015), and brain structure measured by MRI (Peterson et al., 2015). In particular, childhood exposure to heavy metals, including lead, has been associated with negative cognitive outcomes (Liu and Lewis, 2014). Moreover, growing data suggests that there is an increased risk for abnormal cognitive development at lower blood lead concentrations than the CDC's more recent standard for high blood lead levels in children (< 10 μg/dL). Recent data also shows that exposure to other air pollutants may result in cognitive impairments (Clifford et al., 2016). The ambient concentration of air pollutant in any given place depends on a number of factors such as the emission source (e.g. busy road, refineries), weather (i.e. temperature, wind speed/direction, precipitation) and land patterns (e.g. mountains, forestation) (Bell and Samet, 2016). Thus, beyond known regional differences in air pollution across ABCD sites (e.g. Los Angeles, CA versus Portland, OR), air quality also differs within a given city (Fruin et al., 2014), with lower socioeconomic status and minority communities exposed to higher levels of certain types of pollutants, such as particulate matter (Pratt et al., 2015).

With spatio-temporal land-use regression models, exposure to environmental exposures, including air pollution and metals, can be estimated from retrospective and prospective residential addresses, school locations, or both, while also taking into consideration additional patterns (Fruin et al., 2014; Urman et al., 2014). Further, recent developments in affordable, portable sensors that incorporate wireless sensor technology allow for high-resolution spatio-temporal data (Yi et al., 2015). For example, CitiSense provides micro-level detail on regional pollution via personal sensing in adults (Nikzad et al., 2010). Practical problems with traditional stationary monitoring devices relate to their large size and expense. Also, they are not individualized and only provide information about a region with little insight about any specific individual's journey through different areas. Mobile and portable sensors can address this problem because they can be low cost, and have been shown to be reliable and valid measures of air pollutants such as carbon monoxide, nitrogen dioxide, ozone and sulfur dioxide, and produce information in real-time (Yi et al., 2015). However, to date much of the research on mobile sensors for environmental exposures is early stage and thus may not be deployed in the ABCD study until the cohort matures in later years. Nonetheless, linking assessments of environmental exposures to other mobile and sensor data from smartphones allow for potential models of time allocation at any given location as well as dynamic travel patterns to increase the accuracy of toxic metal and air pollution exposure estimates (Liu et al., 2013; Dewulf et al., 2016). This will allow for evaluation of the impact of environmental exposures on developmental outcomes in adolescents, as well as the degree to which these exposures alter child health trajectories.

1.3.2. Biosensors—Video capture via smartphone allows for remote tracking of a variety of objective markers of substance use (i.e., exhaled carbon monoxide for cigarette smoking, alcohol breathalyzer for alcohol use, and buccal swabs for smoked marijuana use) (Alessi and Petry, 2013; Garrison et al., 2015; Alessi et al., 2017). There is current investigation into wearable biosensors for detection of opioid and cocaine use via measures of sympathetic nervous system (SNS) activity (Carreiro et al., 2015a; Carreiro et al., 2015b), and smoking via chest expansion and arm movements (Saleheen et al., 2015). Detection of alcohol metabolites in perspiration, reflecting recent alcohol consumption, has also been achieved in a wearable device (Selvam et al., 2016). A variety of additional wearable or portable technologies are being developed to more broadly assess markers of mood, stress, and anxiety states, as well as a variety of behavioral markers (Ben-Zeev et al., 2015), highlighting the opportunity to combine assessment of mental health and substance use. The state of the science is moving towards discreet, non-invasive, wearable devices that can measure and record concentrations of substances used and wirelessly transmit the data to a smartphone in real-time allowing for monitoring of progression of substance use longitudinally. To date, published studies report data collection in adults. However, researchers are increasingly using biosensors for measurement of substance use in adolescents, including alcohol use in adolescent females (Croff, 2017). Practical problems that researchers may encounter in incorporating biosensors into adolescent studies include: (a) expense of the devices, (b) reluctance to carry/wear these devices (e.g. wrist sensors for alcohol, cocaine [via SNS activity], and (c) burden of video capture (e.g. exhaled CO [nicotine], breathalyzer [alcohol], buccal swabs [cannabis]). Some of the these issues will eventually be mitigated as biosensors are incorporated into wearables that adolescents either already wear or would wear as a status symbol (e.g. Apple Watch; BACtrack) or discrete wearables that resemble something non-drug related (e.g., tattoos). As children enrolled in ABCD enter adolescence, we have the unique opportunity to capitalize on the increasing availability of biosensors to capture longitudinal progression through the substance use trajectory from initiation and experimentation through disordered use in an understudied population. Ultimately these approaches have has the potential to improve the accuracy and sensitivity of ongoing substance use detection, decrease participant and researcher burden through remote detection (as opposed to in-office toxicology screens) and potentially provide triggers for intervention in real-time.

1.4. Social media

Adolescents use social networking sites to list and connect to friends, socialize, express themselves, and share information and media. Social networks and online activities associated with them both reflect real life social networks and create new or unique social interactions that would not exist without the online social networking medium. Further, recent work suggests that important health behaviors and outcomes tend to spread through social networks (Christakis and Fowler, 2007; Shakya et al., 2012), and online social interactions affect mental health and well-being (Moreno et al., 2011; Burke et al., 2010) among youth 13–24 years of age (Best and Taylor, 2014). This work yields useful clinical data regarding the impact of social media on social and risky behaviors, communication, and mental health (e.g. depression, anxiety) (Best and Taylor, 2014; O'Keeffe and Clarke-Pearson, 2011). Because of the Children's Online Privacy Protection Act (COPPA), social media sites only allow participation by those aged 13 years and older, so younger children cannot be observed. For the ABCD Study, youth will be age 13 by the 3–4 year follow-up visit. Concerns of hacking or other threats to privacy need to be considered as well. However, use of social media sites that involve public posting in an open forum assumes loss of privacy as users typically agree to this in the terms and conditions of use for each social media platform. These terms also include clauses on whether and how data may be accessed and used by third parties including researchers (Lee, 2017; Moreno et al., 2013). This of course is not equal to informed consent in research, specifically as it relates to right to withdraw (which may be equated to deleting posts). In online social network studies, information about peers within a consented individuals' peer network is considered data about the social context of the consented individual (Moreno et al., 2013; Farina-Henry et al., 2015). There is precedent for this in traditional studies where researchers ask and record information (e.g., age, gender) about a consented minor's friends. Other than additional concerns related to all research with minors (i.e., parental consent, risk of harm and duty to report), analyzing these behaviors in adolescents and obtaining IRB approval are done in the same manner as for adult studies.

Increasingly robust community structure algorithms have been developed to measure the degree of connectedness and density of social networks (Mucha et al., 2010; Leicht and Newman, 2008) (and potentially the connectedness and density of social support), measure and model social dynamics and influence (Castellano et al., 2009; Pan et al., 2016). Online social networking sites enable greater depth of study of social behaviors in adolescents as online sites: (a) record and store nearly all information (including detailed time and behavior frequency information) that passes through the website, (b) possess complete information about the functionality of online social networks, and (c) enable observation of nearly complete and integrated social networks allowing for study of effect sizes out to several degrees of separation with fewer concerns about missing social network edges.

Examination of centrality, density, and communities enables investigation of connectedness or relationships between individuals. Centrality measures the interactions, or connections, of an individual in the network to others within the network. There are a number of methods to calculate centrality, and each has been shown to perform well in identifying important individuals in social and epidemiological networks (Freeman et al., 1991; Rothenberg et al., 1995). The first is the total number of friendship ties a person has; the *degree* to which that person is supported by others. Further refinement of this measure might generate scores based only on friendship nominations received (*in-de-gree centrality*) or sent (*out-degree centrality*). *Closeness and betweeness* centrality look beyond direct ties. *Closeness centrality* (Sabidussi, 1966) measures the social distance between any pair of individuals in the network by defining one's friends to be at distance 1, the friends of one's friends at distance 2, and so on. *Betweenness centrality* (Freeman, 1977) identifies the extent to which an individual in the network is critical for passing support from one individual to another.

Density, the observed connections a person has in a social network over all possible connections he/she could have, or relatedly, the *transitivity* of friendships within each person's network can also be measured. Previous work suggests that low density and high density are both negatively related to social engagement (Fowler, 2005).

Finally, communities and *community* structure (groups based on shared location, interests, schools etc.) in social networks can be detected via *modularity* (Fortunato, 2010). This method maximizes the total differences between in-group and out-group vertices, by examining the difference between the number of connections within a community and the expected number of connections within a community across all possible outcomes. By examining communities, we can study the spread of rumors or epidemics, and the effect of contagion among adolescents.

ABCD affords us the opportunity to extend existing research on social interactions by passively collecting social network data on Facebook, Twitter, and other social media sites (Ritter and Cameron, 2006), to study the impact of complete social networks on important areas of health (e.g. well-being, quality of life, mental health) affected by social connection and interaction.

2. Discussion

Mobile technologies allow for more complete data capture across domains of interest, greater fidelity of data captured, and measurement that is more precise. Further, they allow for dynamic measurement of the range and variability of diverse human states in real-time as well as environmental factors that may affect fluctuations in mood, behaviors, thoughts, and feelings. This provides new opportunities and greater precision in testing causal models and hypotheses regarding substance use and physical and mental health problems. In addition to enhancing research methodology, mobile technologies may also reduce participant response and engagement burden via passive data collection, and fewer in-person lab visits. Additionally, participants can be active in their assessment and treatment, and gain insight into their behaviors and physiological and psychological states. Finally, research shows that use of mobile technologies for assessment of health-related behaviors in adolescents is feasible, acceptable, and liked by users (Garcia et al., 2014), especially in early adolescence (Kauer et al., 2009).

Currently, ABCD is using iPads for assessment of clinical, neuropsychological and self-report data for parents and children, and is planning on incorporating wearable activity trackers into the overall study at the Year 2 follow-up starting September 2018. This will provide insight about fine-level fluctuations and patterns of activity and sleep that can be compared to self-report data and other physiologic data collected. Additionally, this may contribute to the literature regarding validity and reliability of data obtained from these devices and the feasibility of conducting studies of wearable devices in children.

In the future, ABCD investigators plan to incorporate use of direct, real-time measurement of alcohol, marijuana and other substances as nanoengineered biosensors become more refined and available. Biosensors allow for non-invasive, objective assessment and monitoring of substance use, and enable increased accuracy of measurement of substance use, and intensity of exposure, as it relates to adolescent brain development. Further, activity space data will increase our understanding of the influence of context and environment on substance use in youth.

While biological specimens and toxicology will be an important component for study of toxic environmental exposures, ABCD provides an exciting opportunity for novel examination of the effect of air pollution on neurodevelopment through collection of prenatal and postnatal residential and place-based histories and passive mobile and sensor data. We will be able to explore (a) relationships between air pollution and cognitive, mental, and brain function and structure, (b) the impact of changes in exposure on individual trajectories of cognitive, mental health, and neurodevelopment longitudinally, and (c) how air pollution exposure, directly or indirectly, interacts with other social and environmental factors to predict health behaviors and outcomes.

Longitudinal studies of exposure are particularly important as children move through different places as they age (e.g. new schools leading to new journeys through new or changing neighborhoods with use of different modes of transportation). GPS facilitates data collection on habitual journeys through communities and the linkage of these data to other sets of institutional and place-based characteristics; characteristics which may be different qualitatively and quantitatively from the same characteristics measured in their home neighborhood, allowing for a more dynamic conceptualization and measurement of mobility. These intensive, within-person longitudinal geospatial data can also be coupled with physical activity data (collected via activity trackers and accelerometers), and ecologic momentary assessment data on attitudes and behaviors (collected via smartphones) to link psychological health and well-being to physical activity at specific locations or contexts.

Research spanning social network analysis, computation and massive data analysis, health, human-computer interactions research, and psychology will allow us to study the relationship between online social behaviors and health outcomes, and the extent to which health outcomes alter the structure and function of online social networks. These data will inform the way we think about communication between adolescents and within groups of adolescents, and the impact on psychosocial development. It will also allow for study of mechanisms of groupthink and social contagion.

2.1. Practical issues in implementation

There are many practical issues involved in implementing these new research methods into a longitudinal study of children and adolescents. The first relates to both the age-appropriateness of any given technology and the age at which the exposure of interest occurs (e.g. initiation of substance or social media use). For example, the literature shows that 40% of those who have a lifetime history of substance use disorder and require treatment initiated substances prior to the age of 14 (10%–11 or younger, 30%–12–14 years of age) (SAMSHA Treatment Episode Data Sets, 2011). Thus, initiating monitoring of substance use by age 12 is important. Social media sites require users to be at least 13 years of age. Further, research demonstrates that by age 13–14 years, 57% of adolescents are on Facebook, 44% use Instagram, 31% use Snapchat and 23% use Twitter (Bagot et al., 2015). This suggests that beginning to monitor children as they enter early adolescence will be essential if we are to capture both the initiation of use behaviors, and trajectory of substance use. Also, because of COPPA, companies like Fitbit require users to enter a birthday with an age of 13 or older. As described above, we have been able to address this via participant assent and parent consent in our own study of 9 and 10 year olds (Wing et al., 2017). Research also demonstrates that the age in which youth typically have their first smartphone is age 12 (Bagot, 2017), yet there is little published evidence to date on how to fully leverage this device as a platform for data collection in studies like ABCD.

Finally, with respect to issues of cost and burden, while some of these devices are financially costly, they decrease the cost of research personnel and space and potentially the cost for families to participate in research (e.g. time off from work, transportation costs). Further, they may reduce participant burden such as time spent answering research questions at home or in the lab vs. simple passive data collection in the background with subsequent wireless transmission of data to research databases. However, these approaches do require more front-end effort on the part of research staff to set up systems for data collection and their associated algorithms and databases. Additionally, some institutional review groups may have concerns related to the need to monitor these data for events of concern such as harm to self or others.

2.2. Privacy and ethical issues related to mHealth

Data derived from, and activities inferred by, mhealth and related technologies raise several important ethical issues for researchers. For example, GPS data that indicate locations frequented, patterns or routines of travel and precise location at any given time, may be difficult to anonymize. However, while GPS data points do reveal where a person has been, in and of themselves, they do not identify any specific person (except when they ‘stay at” or “return’ to their home generating data clusters around one ‘home’ location). By contrast a ‘home’ address – from another survey instrument – explicitly identifies a person (or group of people/co-residents). A day’s worth of GPS point collected a minute apart (or more frequently) can be used to generate a spatial ‘footprint’ that captures the mobility of a person across 24 h. In turn, the derived activity space boundary can be used to generate contextual attributes of the social, built and physical environment (e.g., crime rates, fast food restaurant density, land-use mix, elevation variation) devoid of locational or individually identifiable information. Similarly, GPS data can be analyzed to derive more nuanced metrics related to the temporal dimensions of exposure to specific places (e.g., the timing, sequence and duration of visits to specific places), also resulting in de-identified data.

Data recorded and collected on a smartphone, and wirelessly transmitted, may lead to incidental, accidental or legal discovery by third parties and/or may capture illegal activities that are reportable or could be subpoenaed. This risk may be reduced by limiting locations in which data are uploaded to secure locations such as a private Wi-fi network, or selectively uploading data via physical means such as linking to hard drive via a physical cord. Additionally, monitoring data secured through a third party app (e.g. social media apps) has risks. Participants may not understand the meaning and impact of terms and policies in service contracts even if they voluntarily set up an account and are signed up for the service. Importantly, app-specific contracts may conflict with federal guidelines for human research participants, in particular for those under the age of 14 years. Also, the presence of a non-commercial research and/or health app on a smartphone may belie one’s enrollment in a study or disease condition.

If in reviewing data, researchers identify concerning patterns of behaviors or activities that may imply current or impending medical and psychological harm to the participant or others, there are no clear guidelines on reporting this potentially clinical meaningful data to minors and/or parents. In non-intervention research, individualized clinical feedback may alter study course, and may be inappropriate given non-clinically trained staff reviewing data.

Another issue is that depending on the type of data collected, the medium on which it is collected and where it is collected, bystander rights may also be an issue. Those who may interact with a consented individual while data are being collected may have their (bystander) data or personally identifiable information collected via audio, photographs or video, as well as interactions via social media, text message or phone. There are no standard guidelines in place for addressing these issue, however it has been suggested that consented individuals should disclose their participation in research and the potential for bystander data to be collected.

As these technologies yield large amounts of potentially personally identifiable data, secure data management strategies and guidelines are critical but remain unstandardized. Consent and assent must be obtained from parents and minors respectively prior to data collection and all the aforementioned privacy and ethical issues must be discussed. The inherently identifiable nature of individual level mobile technology-derived data present privacy and confidentiality concerns, as well as ethical concerns. Study participants and their families may not understand what types of data will be collected, or the potential meaning of that data, and how it will be stored and analyzed. Every effort must be taken to explain the potential benefits and risks of these types of data, and what may be inferred. Further, discussion of the steps researchers are taking to safeguard participants' data must be occur during consent and assent. This may include storage of data on secure servers, encrypting data, including audio and visual data, or de-identifying data prior to storage. For example, home address and the massive volume of 'digital footsteps' generated by GPS would require that all data and processing be handled in a HIPAA secure geodatabase environment. Data are considered de-identified in accordance with the HIPAA Privacy Rule if the data do not 'identify an individual and if the covered entity has no reasonable basis to believe it can be used to identify an individual (HIPAA, 2012).'A recent review suggests two main approaches for de-identifying geographic information using HIPAA Privacy Rule guidelines: (1) remove or aggregate geographic identifiers to large population area-based units, and (2) apply statistical or scientific principles to render information not individually identifiable ("geomasking"); (Haley et al., 2016) a series of analytical approaches to mask geographic identifiers have been suggested (Armstrong et al., 1999; Allshouse et al., 2010; Hampton et al., 2010; Wieland et al., 2008). A recent study of GPS data also explores the balance between privacy and spatial pattern resulting from two methods of obfuscation, grid masking and random perturbation (Seidl et al., 2016).

To address the many and rapidly changing ethical and legal issues involved mHealth research initiatives are emerging that aim to help mHealth researchers learn about, understand and share best practices. One important current example of this is an initiative supported by the Robert Wood Johnson Foundation called the Connected and Open Research Ethics project (thecore.ucsd.edu). As of the date of this paper over 500 researchers and related organizations have joined this network.

3. Conclusion

Advances in mobile and wearable technologies coupled with improved methods of analysis of geospatial, ecologic, social network, and behavioral data allow for unprecedented opportunities for interdisciplinary research on the effects of place, social interactions, environment, and substance use on child health and developmental outcomes. In ABCD, we will capitalize on these novel methods and technologies to examine the myriad of social, environmental, and behavioral factors and the interactions that take place between these elements. We thus have the opportunity to greatly enhance our understanding of adolescent neurodevelopmental and mental and physical health outcomes in youth.

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