Building the Next Generation of Early Warning Systems in Education

Tyler Burleigh, PhD  The HUMAN Project
Paul Glimcher, PhD  The HUMAN Project

Abstract
For centuries our educational systems have been built on the idea that both feedback and intervention are critical to success. Students have been evaluated by teachers, and these evaluations have guided families, classrooms, schools and districts in their interventions for centuries. As our technologies for gathering new classes of data at faster timescales have burgeoned, however, the measurements used by parents, teachers and administrators have hardly changed. We still rely principally on grades, attendance and standardized test scores. But by the time a student shows unambiguously failing grades and failed attendance, it is often too late. Once children have stopped passing tests and stopped coming to school, intervention is costly and often ineffective. At the HUMAN Project we imagine a different future in which students never get all the way to defeat. We imagine low-cost easy-to-use tools that not only tell parents, teachers and schools that a specific student is at risk six months before grades and attendance drop, but can pinpoint the specific causal life changes that are putting that student risk. In this white paper we describe a proposed Early Warning System for educators that can identify students at risk of failing to complete high school and failing to successfully prepare for college, and can identify the specific sources of that risk, before it is too late.

This is not the first proposed early warning system for education, and existing systems are without a doubt hugely valuable. What sets this system apart is that is the first to use a synoptic large-scale representative dataset built from smartphones, administrative records and IoT tools to generate an Early Warning System that relies on a smartphone-based deployment. New Data we are in the process of gathering will provide the insights that drive and continuously improve this system. New Tools we have already developed allow us to deploy these insights into the community for pennies a student.

Over the last two years we have built low-cost automated data collection systems that allow us to measure literally every property of a student’s life in real-time. We are now in the process of deploying those tools in a first cohort of 3000 New York City students (and with their 7000 co-resident family members). At over 200Gb per student per year, the dataset we are building will be the largest and deepest profile of the social-educational world ever attempted and one now ready for deployment in other cities. It offers a unique opportunity to examine how casual factors ranging from real-time interfamily distances to peer interactions to detailed health affect, each affect student accomplishment. We believe that this database will be the ultimate tool for identifying the causal factors that achieve, or break, connections between students and schools in a way that harnesses the individual differences between students. In this white paper, we describe one of many education-related applications of this database and our toolkit. We describe how our proposed Early Warning System would work, where we are in its development, and how we would propose to deploy it.

Introduction
Higher education is the great equalizer (Pascarella and Terenzini, 2005). Yet the pathway to a high school diploma or a college degree is much harder for some people than for others. Education is one of the critical paths to a better life on nearly every dimension, but many children struggle
to obtain adequate or appropriate support. An estimated 750,000 children will drop out of high school this year (Brown, 2015)—that’s one child every 45 seconds. For this reason, a key goal for education researchers has become identifying the life-course challenges – and the interventions that mitigate those challenges – particularly in underserved communities and populations. Nearly everyone’s goal, at some level, has been to figure out how to prevent children from dropping out of a system that too often fails to provide them with the support they needed to become successful, confident, and motivated learners.

At the HUMAN Project we believe that families, classrooms, schools and districts are in a position to enhance their support systems by adopting a new kind of proactive and preventative approach to addressing problems in school. Consider an analogy with cutting edge health care: the approach known as preventative medicine (Swan, 2012; Dogan et al., 2017; Hood and Galas, 2008). Researchers have long recognized that diseases develop gradually over time and display numerous warning signs. With recent low-cost advances in mobile-digital technologies, health care providers are beginning to build systems that can monitor individuals for warning signs, and predict when they’re at risk of becoming ill, allowing treatment before things get out of control. (In fact, the HUMAN Project is playing a role in this revolution; Burleigh et al. (2017)). Rather than wait until individuals become seriously ill, individuals and health care providers are beginning to be able to identify early warning signs of impending health issues and can intervene when action is both less costly and most likely to be impactful. Episodes of acute depression, which are difficult and expensive to treat, can be predicted weeks or months in advance by monitoring social network data, activity data and sleep data. This allows early interventions which are more effective and less costly. Like the individual who becomes depressed, the student who falls behind in school, who loses focus, who becomes frustrated, does not do so suddenly and without warning. And as in depression, we believe it is the prevention of acute failure, rather than trying to deal with acute failure after it happens, which is likely to be most effective.

Many groups have begun to recognize the importance of this approach in education. Early warning systems are a promising new technology in this area, and many schools have already begun to use simple versions of these tools with some notable successes (Bruce et al., 2011; Frazelle et al., 2015; Pinkus, 2008)—indeed according to a recent estimate, more than half of all high schools (52%) have implemented some form of early warning system (U.S. Department of Education, 2016). It is worth noting, however, that the current generation of systems are quite simple, even old-fashioned. These systems monitor the “ABC” indicators of Attendance, mis-Behavior, and Course performance (as described in Bruce et al., 2011; Faria et al., 2017). These indicators are desirable for their low-cost and ease of use: as they are already being tracked in schools, implementation is relatively straight-forward. Research suggests these “ABC systems” are useful (Faria et al., 2017), but we believe that these measures only touch the tip of the proverbial iceberg in their impact.

Although these systems are accurate in predicting students who are at risk—in a 2016 analysis of Ohio schools, nearly 78% accuracy was achieved in predicting high-school dropouts (Stuit et al., 2016)—they are not very robust: these systems generate many false-alarms (21% in this same system), and optimizing for a low rate of false-alarms leads to a reduction in accuracy. Much more importantly, in our estimation, these systems are slow. The indicators are typically measured only once or a few times per year by a school or school district. In fact, many existing systems of this kind are designed to make predictions in one school year based on measures obtained an entire year ago. This means that these systems often detect failures, rather than opportunities for prevention. They identify individuals, classrooms and schools in crisis, rather than identifying solvable problems.

More than just seeing problems, we must be able to see the causes of problems. Grades and
Attendance can tell us *when* but not *why* students might be having problems in school. We believe that having a deep and holistic picture of the root causes of an individual’s or a school’s problems is essential for designing effective, targeted interventions. An ABC system only provides basic support related to attendance, mis-behavior, and course performance. It is therefore unsurprising that after adopting an ABC system, schools do not tend to go beyond the standard intervention practices like discipline, parent-teacher meetings, or tutoring (Faria et al., 2017). But a deeper data-driven understanding of when and why an educational failure is ahead, whether at the level of a student, a classroom, or a school, would be a fundamental tool for educational reform.

And we already know that there are many predictors beyond the ABCs that can provide the impetus for more targeted interventions. Research suggests some of the most important factors include psychological aspects like attitudes, motivation, and learning strategies (Richardson et al., 2012); illnesses like asthma, depression, anxiety, obesity, and ADHD (Neil and Christensen, 2009; Calear and Christensen, 2010; Power et al., 2012; Bruzzese et al., 2011); deficits in social and emotional skills (Durlak et al., 2011); parental (non)involvement in school (Hill and Tyson, 2009; Jeynes, 2005); and involvement with delinquent peers (Henry and Huizinga, 2007). There are numerous interventions that have been successful in addressing these problems (e.g., Yeager and Walton, 2011; Taras and Potts-Datema, 2005). But because the current generation of early warning systems only track the ABCs of risk factors, and have no real data about any of these causal factors, they leave schools ill-equipped to provide the supports that students need *when* they need it.

Methods developed by groups like ours to support preventative medicine, provide a model for next-generation early warning systems in education. Scholars envisioning the future of healthcare describe this digitally and data-enhanced future as one that is predictive, preventative, participatory, and personalized (Hood and Galas, 2008; Swan, 2012); made possible by super low-cost always-on self-tracking devices that establish baseline measurements and subtle changes over time. And this vision is already being realized through the use of pervasive mobile devices like smartphones (Dogan et al., 2017). For example, changes in location patterns collected from a smartphone GPS sensor can predict clinical changes in mood that relate to social engagement with 80% accuracy (Grünerbl et al., 2015). Smartphones are rich with data sensors and provide the means to collect regular behavioral and self-report data (Miller, 2012), and teenagers are also among the largest demographic for smartphone ownership (eMarketer, 2016). If early warning systems were built to leverage students’ smartphones, and the new sensors we are others are developing, they would provide would provide massive gains in the accuracy, reliability, and precision of intervention.

As the HUMAN Project has begun to innovate in healthcare we have come to the firm conviction that we are uniquely suited to build out these capabilities into education. The kind of measures of social engagement, activity, mood, and motivation which we have found can be the *products* of early stage depression, in the education domain are *causes*. Many of the social, health, financial, and criminal indicators we have recently learned to measure as correlates of health are turning out to be the key causal measures that schools and educators need access to in real-time. We propose to build on that model and to extend our causal and predictive tools towards educational attainment.

The HUMAN Project

The Human Project is a signature research initiative at New York University developed to solve our community’s toughest challenges—from preventing diabetes and asthma to improving schools, ending poverty, and beyond. Started in 2016 with a $25MM investment, we have developed a
quite of tools now deployed in a preliminary cohort which will be extended this winter to 10,000 additional New Yorker participants. These participant-partners share the tiny bits of information they create from moment to moment in their daily lives. This allows scientists discover hidden patterns and chart a course to making New York – and our greater society – a healthier, cleaner, happier place to live. As designed, the database will contain over 3000 children and will follow them for 20 years as they mature through school and secondary education. This provides an unparalleled dataset for relating a host of non-traditional measures to educational outcomes during data analysis.

Each participant in our study is equipped with a standard smartphone and a low-cost fitness tracker that provides a continuous stream of biometric and psychological data from: (1) built-in sensors (GPS, accelerometer), (2) phone usage and social activity data (e.g., Facebook/Twitter), and (3) more than one hundred surveys and games that are delivered on a regular basis to measure traits like attitudes, mental health, personality, emotion, cognition, and decision-making. In addition to smartphones, at enrollment every participant undergoes a comprehensive physiological exam, equips their home with beacons that track movement patterns and social structure within the home, and consents to the analysis of their medical, financial, criminal justice and educational records. As we continue to monitor individuals over the course of 20 years, this dataset will eventually provide the most comprehensive picture of human behavior ever created, spanning multiple stages of life.

Unlike many studies that focus on a single racial, economic or neighborhood subgroup, our data is designed to be a perfect statistical mirror of the community it examines. (New York city, the demographically richest region in the nation is our starting point with other communities scheduled for inclusion beginning in 2020.) We use a sampling strategy that ensures participants, and the conclusions we draw from them, are recruited to reflect the precise demographic structure of the population we hope to understand. We select individuals using a multi-stage area probability sampling procedure based on a method pioneered by the US Health and Nutrition Examination Study. Importantly for education, our study will include 3,000 individuals in the target age range of 12-18, as well as their parents and siblings. These features of our study design—large representative data spanning all aspects of human behavior and functioning across time—put us in a position to develop robust predictive models of illness and maladjustment that would facilitate the delivery of personalized interventions in the largest school district in the United States.

A Tale of Two Early Warning Systems

Melissa enters high school at Academy High with bright hope for the future. She performs quite well in freshman and sophomore years, and her junior year starts out much the same. But towards the end of her junior year she begins to drift. Inexplicably, she starts getting into trouble at school, and her course performance declines soon after.

Mrs. Higgins, who is Academy High’s student counselor, uses a traditional Early Warning System to help identify students that need her support and guidance. The system uses students’ Attendance, Behavior, and Course performance to make risk assessments. When Mrs. Higgins checks the system near the end of the school year, she sees that Melissa is in crisis, and being the diligent counselor that she is, Mrs. Higgins flies into action. Although Mrs. Higgins does her best to get Melissa back on track, Melissa continues to drift, and by senior year Melissa has dropped out of school.

This is the kind of story that gets told under a traditional ABC system. Rather than giving an early warning, the system identifies a student who is already in crisis. Attendance, Behavioral incidents, and Course performance are “criterion” variables—the outcomes that we are trying to predict and ultimately improve. If we measure these variables, they will be strong indicators of
their own values in the future, but they will *lag behind* the mechanisms that are causing them to change. It is only by measuring *causative mechanisms* that we can identify *when* and *how* students need support. By measuring these causal factors, next-generation early warning systems provide a means to intervene early and with precision.

In contrast to Figure 1, Figure 2 tells the story of Melissa from the perspective of a next-generation early warning system. We see here that Melissa became severely depressed (Mental Health); her depression then gave way to social isolation (Social Connectedness); in turn, she became friends with a new group of peers who were delinquent and had a negative impact on her (Positive Peers)—only then does she become delinquent herself and she disengages from school (Good Behavior, Grades). By measuring these other factors (Mental Health, Social Connectedness, and Positive Peers), we can see what happened more clearly and we can see it much sooner: the first sign of trouble was Melissa’s declining mental health. This happened *six months* before her school conduct was seriously affected. If she had been given support when she needed it, the rest could have been avoided.

Consider the stories depicted in Figure 3. We see in 3.1 a student whose problems begin with a lack of social support from friends and family (Social Connectedness); this causes him to develop social phobia (Mental Health) and withdraw even further, which ultimately leads to absences and poor performance (Attendance, Grades). In 3.2 we see a student whose problems begin with delinquent peers (Positive Peers); the influence of these peers cause her to develop conduct disorder (Mental Health) and eventually she displays behavioral problems in school (Good Behavior). Finally, 3.3 tells the story of a student whose problems begin with physical illness (Physical Health); chronic pain and sleep loss cause them to experience declining Mental Health and miss some classes, which later manifests in poor course performance (Grades).

Importantly, each of these stories represents a different *first cause*. Melissa’s problems began with mental illness, while the other students’ problems began with social isolation, peer group delinquency, and physical health. Although Melissa could have benefited from psychotherapy; the other students would have benefited from different kinds of interventions. Students are dif-
Figure 2: Melissa’s Story as seen by a Next-Generation Early Warning System: Melissa becomes depressed (Mental Health), then alienated from her friends (Social Connectedness); she gets involved with a new friend group who has a negative influence on her (Positive Peers)—only then does she become delinquent and disengaged from school (Good Behavior, Grades).

Different, a fact hard to leverage effectively with traditional Early Warning Systems. And they require different kinds of help. Imagine if we decided to only track Mental Health: Melissa’s underlying issue would have been diagnosed early and accurately, but we would be slow to react for the other students and we would likely adopt the wrong kinds of interventions.

**Next-Gen Indicators**

For the purposes of our initial deployment we have proposed to focus on social connectedness, positive peers, mental health, and physical health as four categories of early warning indicators in this white paper because existing research suggests they are especially promising. There are many other indicators that could be used. Indeed, our data will allow us to identify and develop new indicators. That is also a key element of our program, and one that fundamentally relies on our database approach. Recall that the HUAMAN Project database has literally hundreds of indicator variables from which we can build Next-Gen indicators. Here we focus on building what we believe to be the most promising four initial indicators.

**Social Connectedness**

In a school context, social connectedness refers to having close affective relationships with people at one’s school (Catalano et al., 2004). Broadly speaking, students develop healthy social connections that serve them in school when they are given opportunities to socialize and when they capitalize on those opportunities; and when they have the social and emotional skills necessary to form healthy social bonds. The first part of this puzzle—opportunities—is largely under the control of caregivers, teachers, and school administrators, who structure the social environment in school (or at home) and create opportunities for social interaction. For example, Catalano et al. (2004) identifies teaching and parenting practices that can serve this goal, while McNeely et al. (2002) identifies features of a school, like its disciplinary policies, extracurricular activities, and
Figure 3: Three additional ABC/Next-Gen stories.
class sizes. The second part of this puzzle—social and emotional skills—belong to the individual, though they develop through social interaction with peers, teachers, and caregivers.

Social and emotional deficits are increasingly being recognized as contributors to school failure (Durlak et al., 2011; Parker et al., 2004; Humphrey et al., 2007; Cherniss et al., 2006; Petrides et al., 2004; McNeely et al., 2002). Individuals have different capacities to perceive, evaluate, and understand the emotions of other people (i.e., “emotional intelligence”), and in their relationship formation and maintenance skills. Individuals with stronger social and emotional skills are better able to manage stress, form and maintain relationships with peers, and adapt to new situations. In the classroom, those who are socially adept are more academically successful and engage in less deviant behavior (Petrides et al., 2004). Extreme social deficits may be associated with autism spectrum disorders (Bellini et al., 2007), or social anxiety disorder (Kashdan and Herbert, 2001), and social and emotional skills training programs been found to improve outcomes for students with these disorders (Fisher et al., 2004; Bellini et al., 2007), as well as for students in general (Durlak et al., 2011).

Our technique is to aggregate all of the social connectedness variables we measure in the HUMAN Project database and to ask which variables predict positive and negative outcomes in our students. Formally, what we would do was to run a LASSO regression on our complete set of measured variables to identify those variables that predict traditional outcome measures. The LASSO procedure not only reveals which social measures are important (and handles high dimensional data reduction efficiently) but also tells us how to optimally weight these measures to predict outcomes (both good and bad). Combining LASSO and our database derives from scratch the efficient social connectedness metric that can predict school outcomes most accurately. Having derived this Early Warning Marker from our database we are now in a position to deploy it as a
tool for real-world use. And better yet, as we deploy it in new communities the data we gather allows us to continuously LASSO-refine our social connectedness predictor in each community. In a sense, the HUMAN Project Database lets us “pull ourselves up by our bootstraps” to get started, but our predictors are never limited by this starting point, they are improved daily as we deploy them in new environments using the same techniques that got us started.

Positive Peers

Beyond social connectedness, it is essential that students are connected to positive social groups that allow them to develop a prosocial orientation and healthy attitudes towards school and risky behaviors. Adolescents who have more delinquent friends are more likely to engage in delinquent behavior themselves (Haynie, 2002)—leading to a greater likelihood of dropout (Battin-Pearson et al., 2000). This peer network effect is usually explained by social learning theory (Pratt et al., 2010) to reflect social processes of imitation and reinforcement learning. That is to say, in any peer network there are costs and benefits to engaging in certain kinds of behavior, and individuals learn delinquent behavioral patterns when these behaviors are rewarded or punished by others within their peer network. Students who become high-status members of delinquent peer groups, like gangs, appear to be especially prone to educational failure (Staff and Kreager, 2008). Other kinds of delinquency can lead to school problems, such as being arrested and having a court appearance (Sweeten, 2006).

One of the key concepts in social learning theory is differential association, which refers to the proportion of one’s friends that engages in delinquent behavior: The more delinquent friends someone has, the more likely they are to become delinquent. This is easy to operationalize and lends itself well to the analysis of social networks, though it is one of many features used in social network analysis (Haynie, 2001; Papachristos, 2006). We propose a second aggregation of positive peer metrics using LASSO as described above to develop a second marker.

Mental Health

Mental illness is a major contributor to problems in school. Among adolescents, the lifetime prevalence of mental disorders with severe impairment is 22% [Merikangas et al. (2010); with many more suffering from mild impairments]. Most common are mood disorders (11%; e.g., major depressive disorder), behavior disorders (10%; e.g., ADHD or conduct disorder), and anxiety disorders (8%; e.g., generalized anxiety disorder). Mood disorders tend to first appear at age 13, and behavior disorders like ADHD tend to appear at age 11, making adolescence a critical period to detect the onset of mental illness.

Anxiety, depression, and ADHD have all been linked to problems in school (Fröjd et al., 2008; Mazzone et al., 2007; Loe and Feldman, 2007), and school-based interventions have also been found to be quite effective in mitigating symptoms (Neil and Christensen, 2009; Calear and Christensen, 2010; Power et al., 2012). For example, depression is linked to difficulty in social relationships and concentration (Fröjd et al., 2008), and cognitive behavioral therapy typically leads to significant reductions in depression symptoms (Neil and Christensen, 2009). Because these mental illnesses occur gradually over time, displaying numerous early warning signs along the way, it is entirely possible to detect them at early stages through continuous monitoring (Burleigh et al., 2017).

We have already developed a detailed set of markers for this Early Warning Indicator. We propose to use a suite of standard mental health tools that we have already developed and to aggregate them using standards developed by the National Institute for mental Heath. In a way
this is a ready made toolkit that does not require the HUMAN Project database for implementation - allowing us to get started immediately with this predictor in the field. Still, we do propose using the HUMAN Project data to refine how we relate mental health to educational outcomes - something that has not been tried in a serious way before.

**Physical Health**

Like mental illness, physical illness can be an impediment to school performance. An estimated 31% of adolescents suffer from a chronic health condition (Newacheck and Taylor, 1992; Garber et al., 1990), and in 39% of these cases, the condition causes moderate or severe impairment. Two common categories of illness are those relating to respiratory health, like asthma which have a prevalence of about 10%; and those relating to gastrointestinal health, various conditions that cause children to experience recurrant abdominal pain, which have a prevalence of 10 to 15% (Garber et al., 1990). Asthma accounts for more school absences than any other chronic illness (Moone et al., 2006) and has been shown to negatively affect school performance (Krenitsky-Korn, 2011). Moreover, research into un-diagnosed asthma suggests that many children are suffering the negative consequences of asthma unknowingly (Yeatts et al., 2003). Recurrant abdominal pain is associated with more school absences and lower school performance (Youssef et al., 2006; Logan et al., 2008; Saps et al., 2009), and it also places children at a greater risk of mental illness (Hyams et al., 1996).

We envision a next-generation early warning system that detects early signs of physical illnesses by monitoring biomarkers like weight, physical activity, and condition-specific symptomatology; as well as environmental factors like air quality that place individuals at greater risk of developing illness, and records of hospital and doctor visits where formal diagnoses are made. For example, brief screeners have been developed to identify undiagnosed asthma (Yeatts et al., 2003), and smartphone sensors like GPS can be used to monitor physical activity. Monitoring for signs of physical illnesses will empower parents, teachers, and school counselors to intervene and provide effective resources to students, like asthma or gastrointestinal self-management programs (Guevara et al., 2003).

As with mental health, we can get started on this right away and then can use the HUMAN Project database to refine our toolkit and better relate it to school outcomes.

**Other Measures**

Of course there is no reason to limit ourselves to these four domains. With the HUMAN Project database in hand we can explore any domain of interest. We can test new predictors, develop new metrics and examine essentially any variable. With the HUMAN Project database and our working tools we are really only limited by our imaginations and the imaginations of those who join in our search for new educational tools.

**Our Vision**

We envision a future in which low-cost, next-generation Early Warning Systems provide parents, teachers, schools and districts with the tools to spot trends before they become problems. Tools which allow educators to see the causes of problems before they become insuperable barriers to successful education.

Imagine a school which is being encroached upon by a regional gang that is beginning to recruit in other nearby schools. In a traditional school, the principal discovers she has a problem as
children begin underperforming, as attendance drops, and gang colors become prevalent. She outlaws clothing in gang colors in the hope of slowing recruiting and reducing within-school violence. Guidance councilors begin talking with students trying to convince them to withdraw from the gang, risking retribution from gang members. In a school using our Early Warning System that would be quite different. Teachers and administrators would see Positive Peer indicators beginning to shift as the gang began interacting with just a few students and long before even those first students joined the gang. Educators would know exactly who was at risk before they joined a gang. Social Connectedness measures would reveal who was most at risk. Physical health measures would show who was already captured by violence. School districts would see the whole picture, in real time, long before violence, absenteeism and gang colors had brought the school system to its knees.

Our vision is to bring that kind of clarity to the impacts of pollution on health and asthma, to the impact of shifting economic challenges on social connectedness, to the impact of seasonal factors on depression and mental health, just to name a few. And of course critical to our vision is that the data which drives this system is obtained effortlessly and at a low cost using pervasive mobile devices, like smartphones, with apps that collect data without direct interaction from students. A much abbreviated list of the kinds of data we gather is presented in Figure 5. Using this data, the system would monitor the indicators discussed previously—in addition to others not discussed presently—and detect students when they are at-risk. In order to perform these risk assessments, the system would also be fitted with robust predictive algorithms previously validated on a large, representative sample of participants, and proven to be accurate at a level that is deemed actionable—especially with regards to false positives. This is where The HUMAN Project comes in.

Figure 5: Abbreviated list of data points for Next Gen monitoring tools.
The HUMAN Project’s Role

By the end of 2018, The HUMAN Project will already have the largest (0.5Pb) real-time dataset about individuals in high school in the world. In 10 years the New York Database alone will be 10Pb. We will have hundreds of biological, psychological, sociological, and environmental measures from 3,000 students in the NYC high school system, in addition to their siblings and parents. These measures will allow us to operationalize the four indicators described previously, as well as many others that might be useful in identifying risks or hidden potentials. Our dataset will not only be large, but it will also be unique in that it is representative sample of the population from which it derives. This will allow us to not only develop a deep understanding of the achievements and failures of students, but to conclusions that generalize to other populations—other school systems in the United States. Once we have this data, we will develop robust predictive models using advanced methods like logistic regression, principal components analysis, structural equation modeling, and support vector machines. Using these data to pull ourselves up by our bootstraps we propose to launch the initial Early Warning Systems in several urban school districts, and then to use the launched warning systems as data sources to refine and improve our tools.

By mid to late 2019 we will be in a position to deliver the foundational components that are required in a Next Generation Early Warning System: We will know exactly how to build the Monitoring tools and how to obtain the assent and compliance of participants who are to be monitored. We will have the Algorithms built, tested, and proven to be effective in predicting school outcomes. We would then aspire to work with parents, teachers, and schools to use the Warning systems that use these algorithms to generate actionable insights—linking these systems to existing services, and in some cases developing new services for undermet needs. Figure 6 presents a prospective timeline for this proposal.

Figure 6: A prospective timeline for Next Gen System development.
References


