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A New Way to Use Data

PRECISION CARE FOR BETTER OUTCOMES IN PSYCHIATRIC RESIDENTIAL TREATMENT FOR CHILDREN

Kristen E.M. Gay and Peter York

February 2018
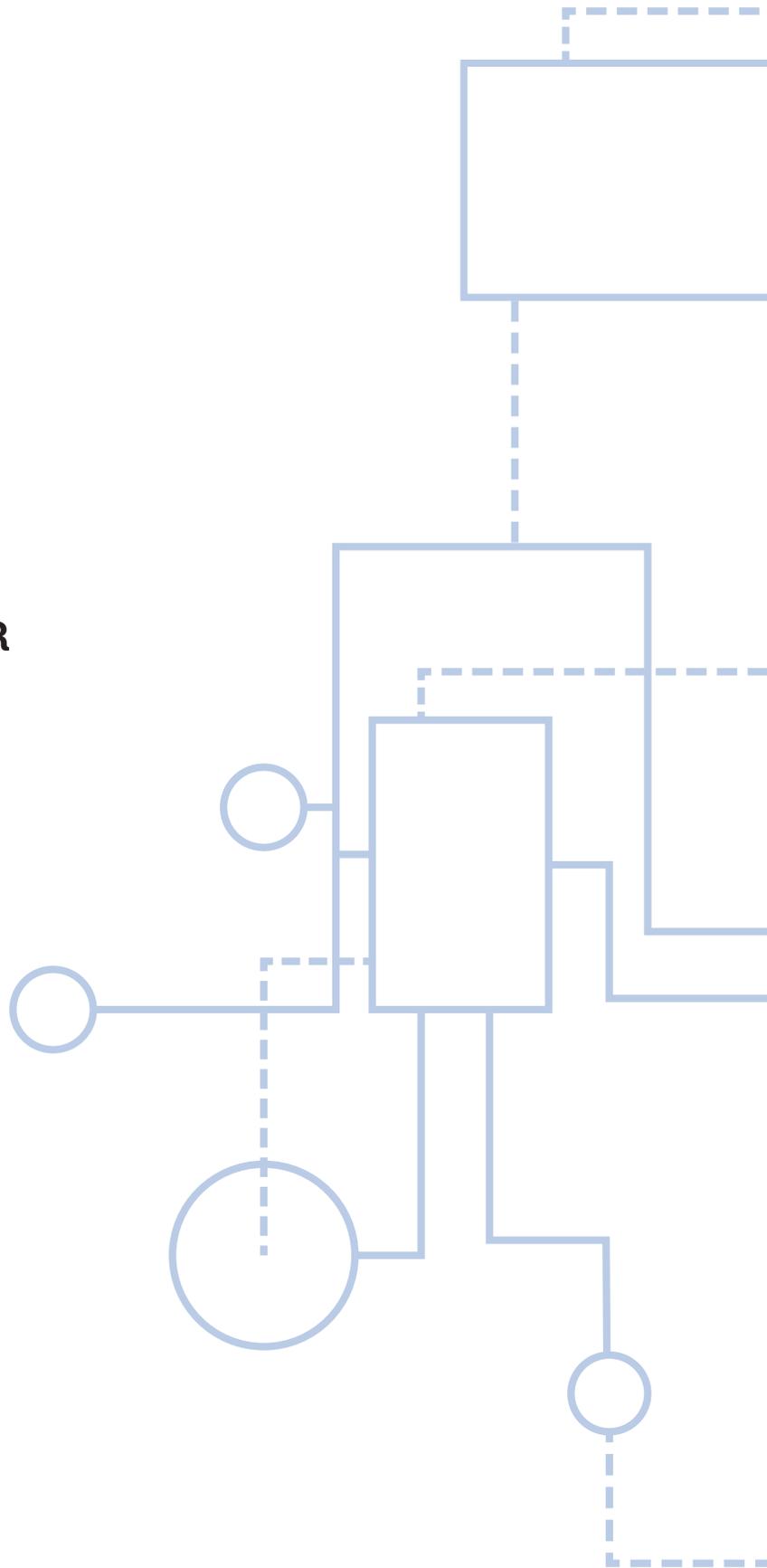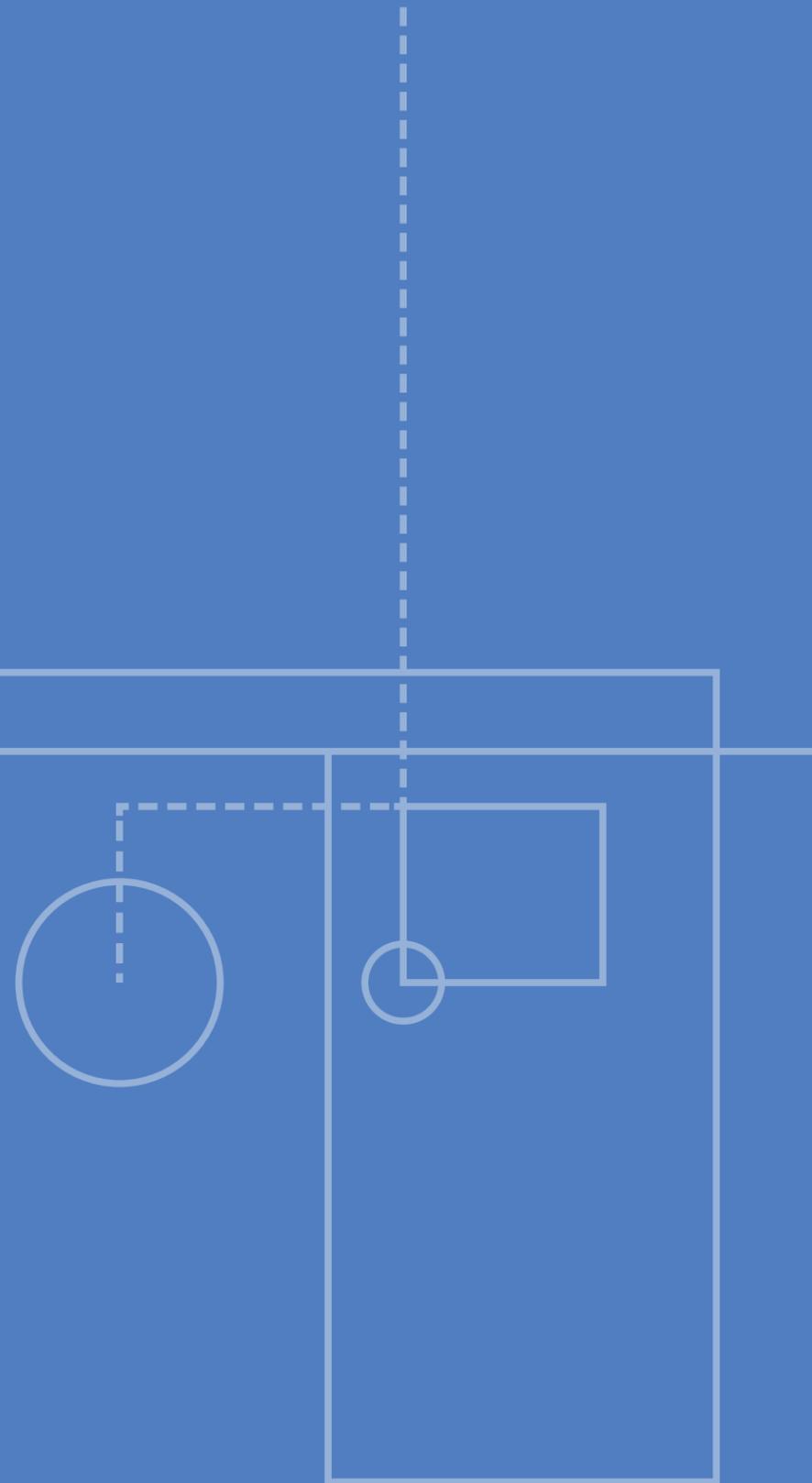
Dear Reader,

We believe to truly optimize success in the delivery of mental health care and build better systems, providers need to deliver the right treatment to the right client at the right time. Traditionally, organizations collect data and report on what happened in the past. This approach, though informative does not enable providers to determine what intervention is most effective for a client in the moment, limiting impact of treatment and potentially increasing costs.

This paper presents how Silver Springs-Martin Luther School is changing their approach to data, by using machine learning to more precisely predict and prescribe the treatment that has the most likely pathway to success for each client. This innovative use of data has the potential to revolutionize the way mental health treatment is delivered by improving clinical decision-making and thereby improving providers' ability to match the right interventions with the right client. We know that getting clients the right treatment at the right time vastly improves their quality of life and this project gives us the tools to make this a reality.

The next phase of this project is to expand the work of Silver Springs-Martin Luther School to other providers and create a shared learning platform so all participating providers can learn from each other and together improve the delivery of mental health care. If we are to understand best what types of data predict future success, we need to facilitate the replication of this project so we can learn from one another.

Sincerely,

Joseph Pyle, M.A.
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Psychiatric Residential Treatment in the Continuum of Care for Children in the Philadelphia Region

Children in the Philadelphia region have access to a range of mental health services from the typical 50-minute outpatient mental health appointment to a much more intensive stay in a psychiatric hospital. One step on the continuum is psychiatric residential treatment, an intensive mental and behavioral health service for children and adolescents whose behaviors are so unsafe that they cannot live in a community setting. Often children require psychiatric residential treatment because they have done something dangerous like harming themselves or someone else. Psychiatric residential treatment often serves as the last resort when other less restrictive treatment strategies have failed.

Residential treatment is provided in an out of home, congregate care setting 24 hours a day, 7 days a week. The cost of providing psychiatric residential treatment services is very high and often exceeds $100,000 per year (1). Children as young as six years old are eligible for psychiatric residential treatment. Lengths of stay in a psychiatric residential treatment facility vary greatly and can range from 3-6 months to years. These economic and social realities beg the question of what type of psychiatric residential treatment is most effective in helping children reach long term success.

Currently, psychiatric residential treatment programs play an important role in our mental health continuum of care, but do psychiatric residential treatment programs improve the long-term outcomes for the children served? And how do we know?

Though psychiatric residential treatment programs have been collecting data for years, it often is historical in nature. Data sets usually include demographic information, children's mental and behavioral health histories, and behaviors that occurred while the youth were in care, such as critical incidents, physical restraints, and/or behavior rating scores. This data describes what happened in the past.

Some agencies also collect aftercare data. For example, the Silver Springs-Martin Luther School (SS/MLS) Psychiatric Residential Treatment Program conducts an aftercare study that tracks children who are discharged from the psychiatric residential treatment to a less restrictive setting (e.g., a family member, foster family, adoptive family). The child's caregiver is contacted six months, one year, two years, and three years' post-discharge to ask whether the child has been at home, in school, and out of trouble. The results are encouraging and tell us what happened to the child once s/he left residential treatment. But this use of data does not help us make decisions about what will help a particular child achieve a positive long term outcome.

The Problem

How do providers know that psychiatric residential treatment is the right treatment for *this* child?

How do providers know that *this* psychiatric residential treatment is the right treatment for *this* child at *this* time?

Furthermore, upon discharge, how do providers best know what combination of services and supports would set *this* child up for success?

In the document *Elements of Effective Practice for Children and Youth Served by Therapeutic Residential Care,* the Casey Family Programs reported psychiatric residential treatment programs need to serve "...the right youth, with the most appropriate interventions, for the shortest amount of time necessary to achieve the key therapeutic and permanency planning goals."

Currently, psychiatric residential treatment programs play an important role in our mental health continuum of care, but do psychiatric residential treatment programs improve the long-term outcomes for the children served?

If psychiatric residential treatment providers are to fulfill this expectation, the way data is used must change. Instead of looking retrospectively at data to describe the type of children who were referred to an organization last year, we want to use data to help us match children who are referred to us with the most effective services. Instead of only reporting whether a child required hospitalization post-discharge, data needs to be used to help providers proactively prescribe the best set of aftercare services to help children optimize their chances of successful outcomes.

So, how can the collective behavioral health field do this?

A Proposed Solution: Precision Care Using Administrative Data and Machine Learning Algorithms

The current practice for determining the effectiveness of interventions involves conducting experiments where members of a population of interest are randomly placed into either a treatment group or a no-treatment group. The purpose of an experiment is to determine if the program made a "significant difference" on the average outcome score for the entire population. The only true use of these studies is if the program is implemented exactly as it was implemented during the experiment, and with exactly the same type of population as that used in the study, then the average score of the whole population will be better than if there were no program at all. These results, while important for understanding if interventions will work for an overall population, are not useful guides for making treatment decisions for individual cases; if a treatment works for the average member of a population, it is both scientifically and statistically untrue that it works for every member of a population.

The tides are changing on the perceived value of "evidence-based" studies for guiding interventions. In an important article in the Stanford Social Innovation Review, *Reconsidering Evidence: What It Means and How We Use It,* Lisbeth Schorr writes about Nobel Prize winning economists, medical researchers and others who use evidence-based research, and specifically tightly controlled experiments (i.e., randomized control trials), to look for the "silver bullet" solution in a world that requires many solutions for many different contexts. She points out that, "when it comes to addressing serious problems... in health and education, the world is beginning to discover that the most effective interventions consist of far more than individual, circumscribed programs. This may help to explain why the tide seems to be shifting away from a narrow focus on experimental evidence of program impact" (2).

Lisbeth Schorr is pointing out what the medical community has already begun embracing—we need more "precision" when it comes to intervention decision-making. Since 2011 there has been a movement afoot within medicine, known as "precision medicine," which is defined in a report produced by the National Research Council, as "the tailoring of medical treatment to the individual characteristics of each patient." The report goes further, pointing out that precision medicine "does not literally mean the creation of drugs or medical devices that are unique to a patient, but rather the ability to classify individuals into subpopulations that differ in their susceptibility to a particular disease, in the biology and/or prognosis of those diseases they may develop, or in their response to a specific treatment. Preventive or therapeutic interventions can then be concentrated on those who will benefit, sparing expense and side effects for those who will not."

Precision medicine is possible due to two technological advances: 1) bigger, better data; and 2) more accurate and precise analytics, specifically machine learning. As noted in a recent publication about integrated precision medicine, the medical community is now able to harness the power of electronic health records to practice precision medicine to improve patient outcomes.

These administrative datasets are a goldmine of information about each and every patient that can be anonymized and analyzed to identify sub-populations for whom different characteristics and diagnostic criteria make them more or less likely to succeed with specific types and dosages of treatments. With these administrative datasets in hand, the medical community has begun improving precision by applying machine learning algorithms (4). Not too long ago, the Senior Vice President of SAP Analytics, Mike Flannagan, stated, "imagine if you could take results of all of the tests... and the results of the treatment that was done, and aggregate and anonymize all of that data, and apply machine learning to learn...which treatments were the most effective, not only could you reduce the amount of the [treatment] that was required for a patient, but you could also reduce the amount of patients who received an unnecessary dose—or who received a type of [treatment] that didn't work" (5). Now there are many efforts proving Flannagan right, including ones conducted by IBM, the Massachusetts Institute of Technology, Microsoft and the Knight Cancer Institute.

It is time we apply precision medicine to other fields, including psychiatric residential treatment; let's call it "precision care."

"Doctors have always recognized that every patient is unique, and doctors have always tried to tailor their treatments as best they can to individuals. You can match a blood transfusion to a blood type—that was an important discovery. What if matching a cancer cure to our genetic code was just as easy, just as standard? What if figuring out the right dose of medicine was as simple as taking our temperature?" (3)

— President Obama, January 30th, 2015

The Application of Precision Care in Psychiatric Residential Treatment: The Silver Springs-Martin Luther School Project

Silver Springs-Martin Luther School (SS/MLS) conducted a precision care project to determine if the administrative dataset for its residential treatment program held the keys to figuring out what works for each child. SS/MLS engaged Community Science, a research and evaluation firm with staff expertise and experience in leveraging administrative datasets and applying machine learning algorithms to build precision care models for government agencies and nonprofit organizations. SS/MLS's administrative dataset contained 717 cases of children who were discharged to a family setting and surveyed for three years post-discharge.

The precision care modeling process required getting the data ready and applying the scientific method in order to be certain that precise treatment solutions were true cause and effect. A top data scientist from the University of Washington, Pedro Domingos, in his book, *The Master Algorithm*, points out that machine learning algorithms can apply "the scientific method on steroids, making observations, forming hypotheses, testing hypotheses, and refining hypotheses, millions of times faster than any scientists could do" (6). Specifically, machine learning procedures were applied to the SS/MLS data and accomplished two things:

1/ Identification of all matched comparison groups (sub-groups) of children who shared similar background and diagnostic histories. For example, children who had intellectual functioning deficits were one comparison group that the machine learning algorithms identified.

2/ Determination of what worked for each sub-group/comparison group. In any treatment program, there are different intervention decisions made by various clinicians and practitioners for children who share the same contextual, diagnostic, and treatment histories. The fact that these variations occur for the same "group" of children is an opportunity to witness naturally occurring experiments. This is analogous to children coming into a program, being matched based on their diagnoses, histories and circumstances, and then being randomly assigned to different treatment methods in order to conduct an experiment to see if a particular treatment, combination of treatments, and/or specific dosages make a significant difference. Within administrative datasets, which are the treatment logs of periodic intervention decisions, these treatment differences by clinicians are "naturally occurring experiments." Through their different treatment decisions, clinicians are for all intents and purposes "randomly" assigning treatments to the same group of children. With the advent of machine learning, we can now find these treatment differences to discover what "best" works for each group of matched children.

The results of the precision care modeling process achieved the following:

1/ The identification of eight comparison sub-groups of children who were matched based on their diagnosis, medicine protocol at intake, and caregiver situation. For example, one group of children included those with the Axis 2 diagnosis of Intellectual Disability, while another group included children with no Axis 2 diagnosis but with an Axis 1 diagnosis of Conduct Disorder.

2/ The identification of specific treatment features that significantly affected whether a child was hospitalized post discharge. For example, for many groups, specific dosages of behavioral modification made the greatest difference, while for other groups there was a specific length of stay that made the greatest difference. It is important to note that precision care modeling does not only find the "best" treatment approach. In fact, the modeling process identifies a variety of treatment options and combinations of services that can affect different levels of positive change. Of course one approach might be "best," but there are many case-specific reasons that what is best simply is not possible. For example, a particular medicine might cause an allergic reaction or undesirable side effect. What precision modeling does is find all possible treatments and services that can move the outcome needle at different levels, thereby empowering clinicians to flexibly make decisions on a case-by-case basis.
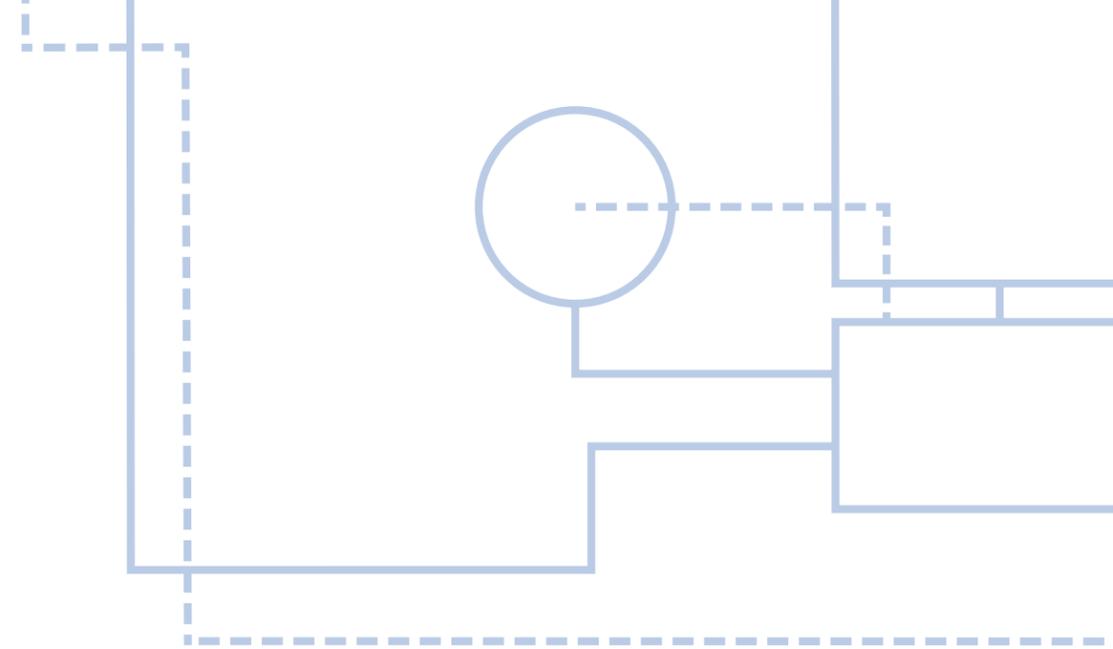
3/ A more precise evaluation of the success of SS/MLS. As just described, the machine learning process is finding all of the interventions that best work for each group of children. These results, while providing more precise and accurate care and treatment recommendations for each child, also provide more accurate and precise evaluation findings for all children being served. The precision care modeling process produces cause-and-effect evaluation results for each child. Specifically, the machine learning algorithm evaluates and produces one of the following four results for each child: 1) got what s/he needed, but didn't succeed; 2) got what s/he needed and as a result achieved the outcome; 3) didn't get what they needed, and didn't succeed as a result; and 4) didn't get what was needed, but somehow succeeded anyway. Any residential treatment facility can count all of the children who received what they needed and succeeded as a true, attributable success. Likewise, a provider should count those who didn't get what they needed and didn't succeed as an attributable missed opportunity to achieve success. The other two types of children—those who didn't get what they needed but succeeded anyway, and those who got what they needed but didn't succeed, are worthy of further research and investigation. And, the great thing about machine learning algorithms are that these specific cases can be identified and studied to assess, hypothesize and/or draw conclusions about what happened, why, and how.
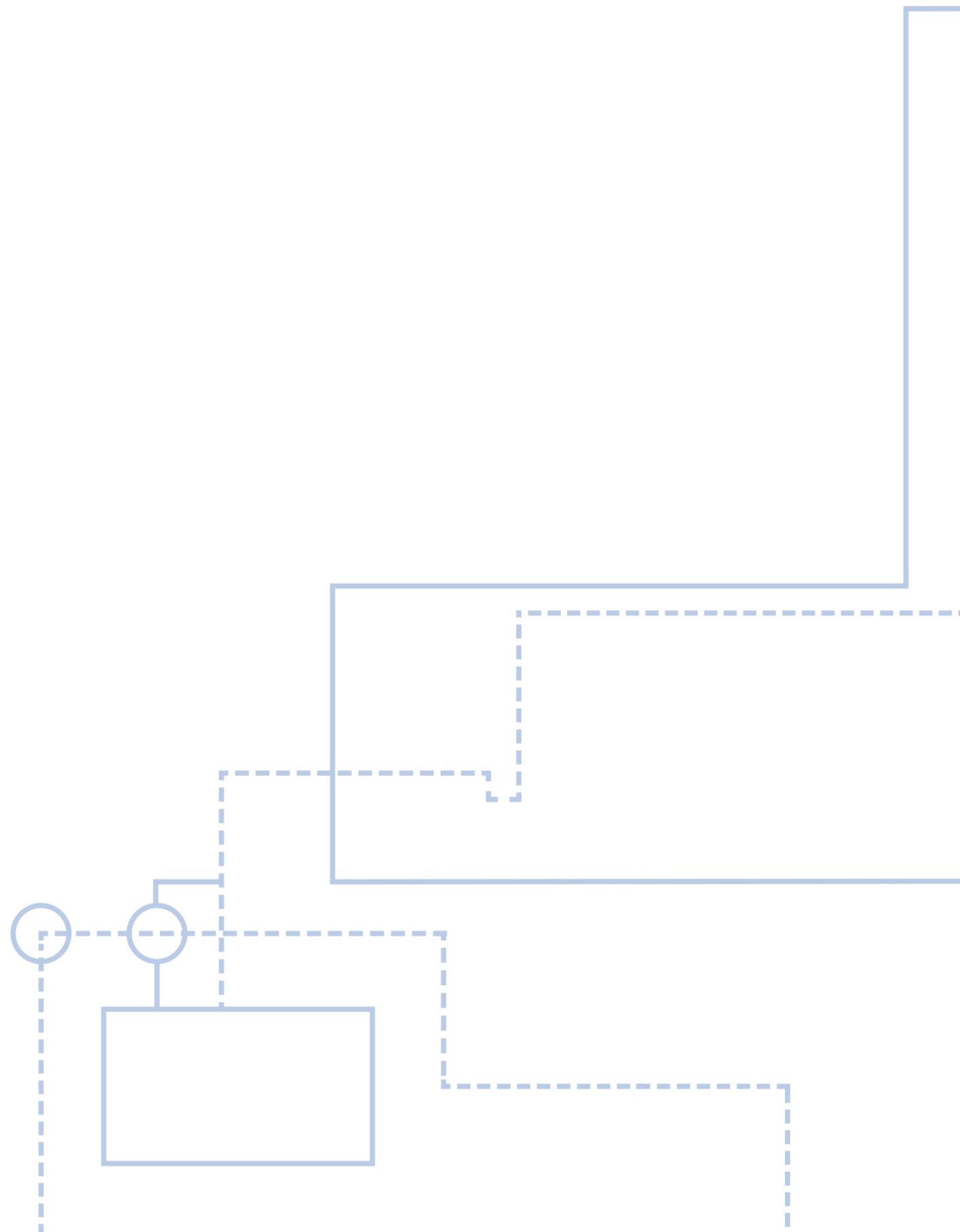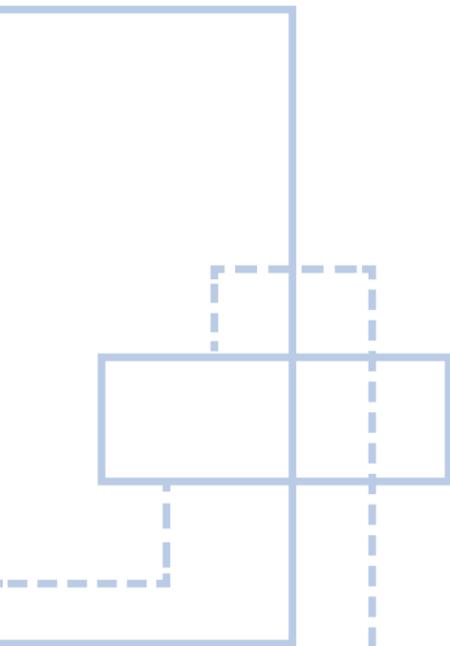
Next Steps in Precision Care for Psychiatric Residential Treatment of Children

Many psychiatric residential treatment providers have expanded their capacity to collect data but lack the tools to truly understand or predict what treatment options will work best for each child. Precision medicine is showing us a way forward, and precision care modeling which is already applied in fields like child welfare and juvenile justice can now be applied to psychiatric residential treatment.

Better integration of information both within and between psychiatric residential treatment providers will lead to a wealth of data that can improve the application of precision modeling. If we are to move to precision care modeling for psychiatric residential treatment, providers should independently and collectively do the following:

1/ Apply precision care modeling to their own administrative data. If more providers conducted similar projects, we could begin to see which types of data, metrics and algorithms best predict future success. Providers could learn from each other so we can better understand more about the specifics of what works best and for whom. This would set the stage to integrate precision models across providers to improve clinical decision making.

2/ Design treatment methods, trainings and tools that are precisely tuned to specific types of cases. Once precision care models provide insights about what interventions are most effective with specific sub-populations of children, we can design precision care applications, training materials, tools, and formal processes that all clinicians can use and share to consistently improve the odds of achieving success.

3/ Developing a field-level precision care learning community. Once providers are independently ready, the field as a whole can begin aligning their data systems, metrics and algorithms in order to create a shared learning platform that will allow for the rapid research, development, evaluation, sharing and scaling of treatments that work.

Precision care, like precision medicine, is a data-driven approach to addressing the problems that all clinicians have lived with since the dawn of research: just because something works for a group, doesn't mean it works for every individual.

Until now, experiments provided rigorous, unbiased conclusions about what worked for populations as a whole, which proved better than the unscientific and biased decision making of human beings. These research studies led to standards of care that improved outcomes for groups of people.

Now, due to rapid advances in data science, machine learning, algorithms, and artificial intelligence, the application of the scientific method is taking the next evolutionary leap with precision modeling. The Silver Springs-Martin Luther School project is an envelope-pushing proof case. By encouraging other providers to build precision care models, we can improve clinical decision making and join a field together to form a shared learning community where everyone gets to investigate, discover and learn about what works best and for whom.
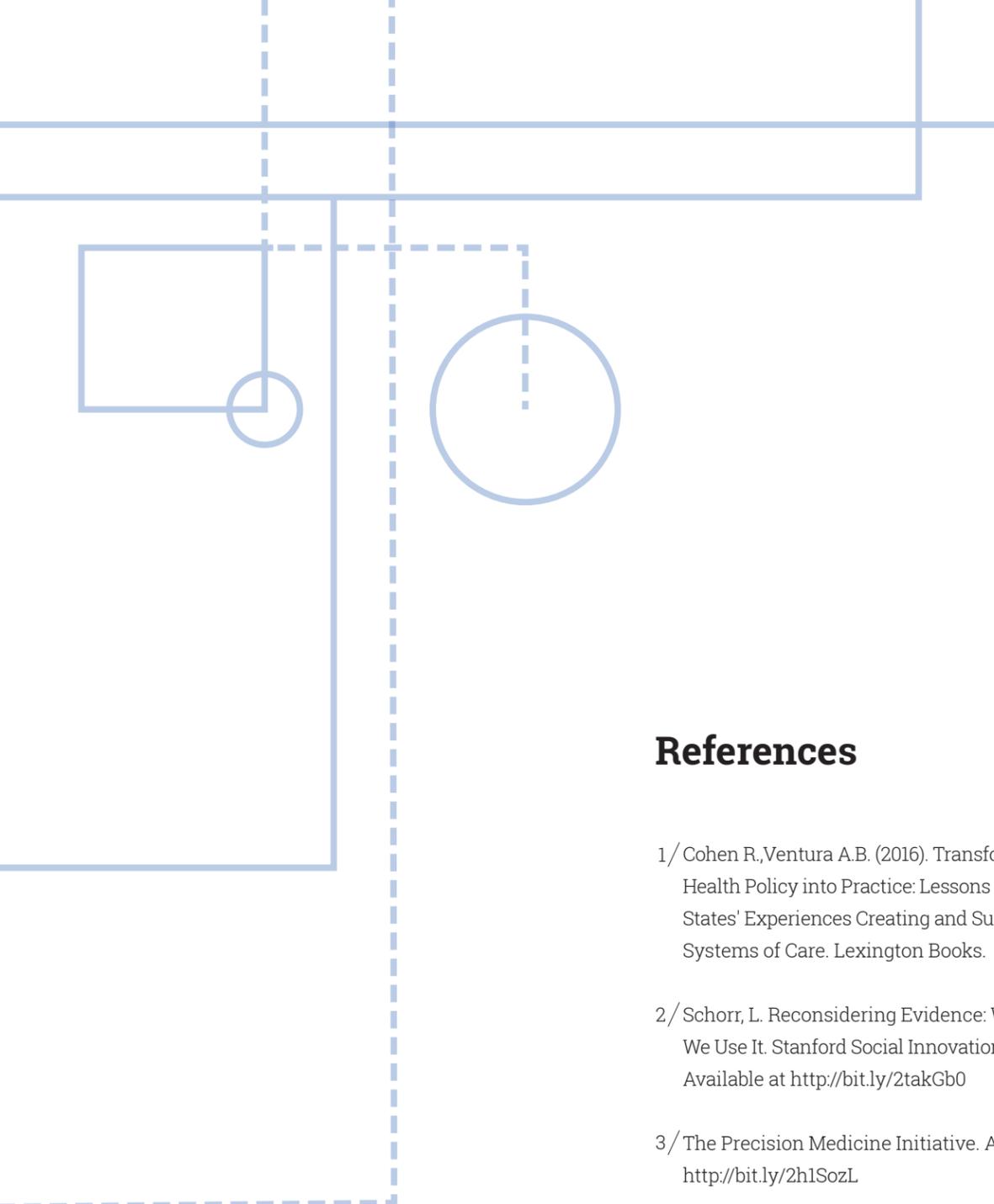
References

1 / Cohen R.,Ventura A.B. (2016). Transforming Children's Mental Health Policy into Practice: Lessons from Virginia and Other States' Experiences Creating and Sustaining Comprehensive Systems of Care. Lexington Books.

2 / Schorr, L. Reconsidering Evidence: What It Means and How We Use It. Stanford Social Innovation Journal. January 2016. Available at http://bit.ly/2takGb0

3 / The Precision Medicine Initiative. Available at http://bit.ly/2h1SozL

4 / Sitapati A., Kim H., Berkovich B., Marmor R., Singh S., El-Kareh R., Clay B., Ohno-Machado L. Integrated precision medicine: the role of electronic health records in delivering personalized treatment. Available at http://bit.ly/2n4TYRe

5 / Klobucher, D. How To Improve Precision Medicine with Machine Learning. Forbes Magazine, August 2017. Available at http://bit.ly/2CkFDoq

6 / Domingos, P. (2015). The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World. Basic Books.
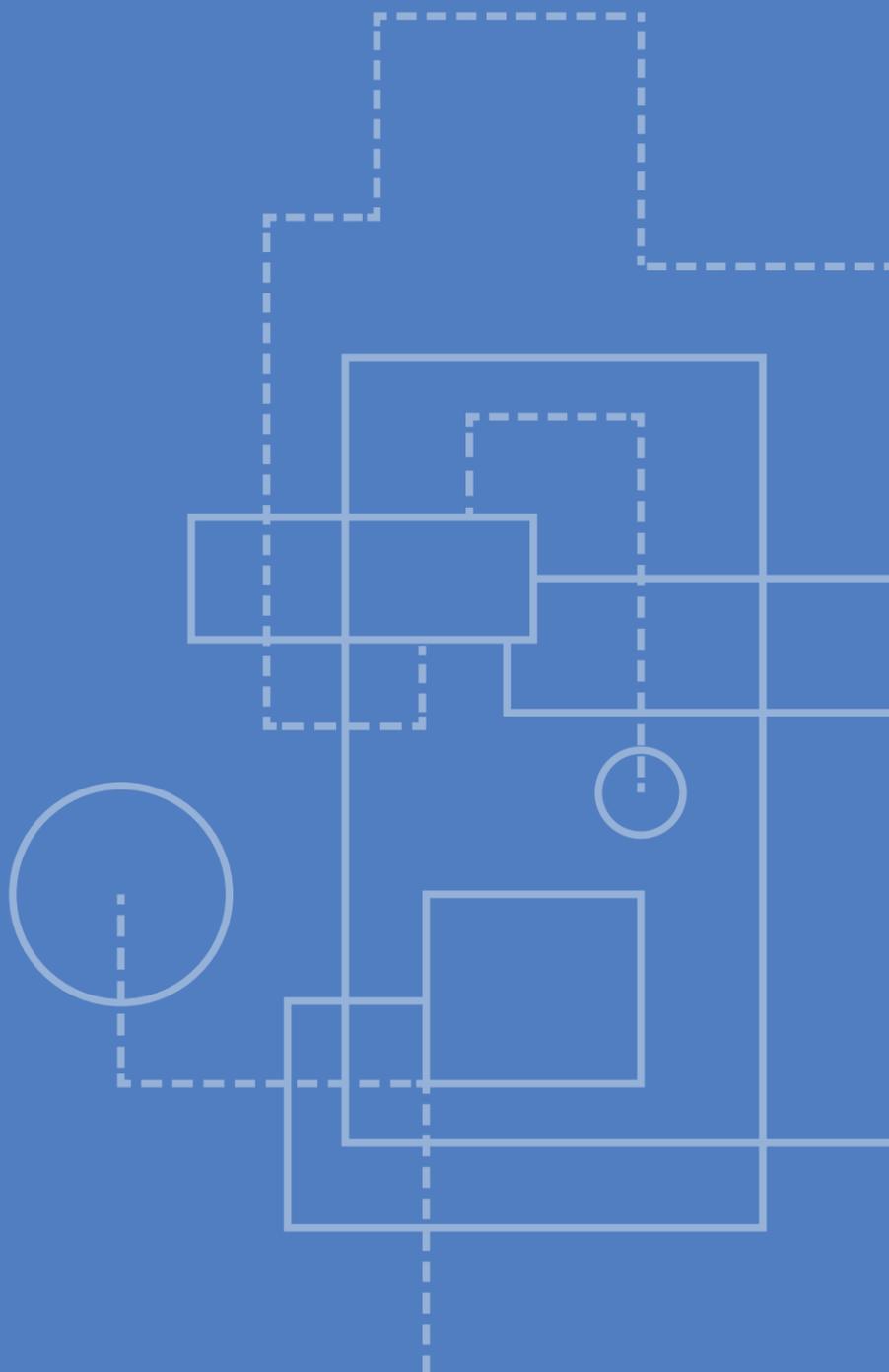
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The Scattergood Foundation believes major disruption is needed
to build a stronger, more effective, compassionate, and inclusive
health care system—one that improves well-being and quality
of life as much as it treats illness and disease. At the Foundation,
we THINK, DO, and SUPPORT in order to establish a new paradigm
for behavioral health which values the unique spark and basic
dignity in every human.

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