Publication

An Artificial Intelligence Driven System to Predict ASD Outcomes in ABA

Large datasets and advances in data science allow patients, providers, and payors alike to strategically think about ABA services for ASD like never before

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An AI Driven System to Predict ASD Outcomes in ABA

Large datasets and advances in data science allow patients, providers, and payors alike to strategically think about ABA services for ASD like never before. We describe how RethinkFirst has assembled a patent-pending AI driven system that leverages the largest published ASD and ABA dataset to identify novel patient profiles and predict patient progress better than previously published research. The use cases from this AI system can transform how we think about and optimize autism service delivery moving forward.

Background

Predictability is a critical concern for all stakeholders in any healthcare context. Patients and payors want to predict how long and at what cost a course of treatment will have. Providers want to predict treatment intensity and resources needed to optimize patient outcomes. And, patients, payors, and providers all benefit from the ability to forecast what a course of treatment will look like for the near term.

Precise predictions around how much Applied Behavior Analysis (ABA) therapy is needed for each unique individual with autism spectrum disorders (ASD) has historically been more of an art than a science. The ability to accurately predict ABA dosage and duration is an increasingly greater value as the need for services increases and uncertainty around cost becomes more variable. For example, the prevalence of ASD diagnoses have increased to 1 in 44 individuals (CDC, 2021), annual costs can vary between $17k-$130k (Autism Speaks, 2022; Eldevik et al., 2009), and treatment duration can range from 5-40 hours per week and for 18-months to 5-years (Larsson, 2012).

To help improve predictability with dosage recommendations, past researchers have tried to model the relationship between hours per week of ABA and goals mastered (e.g., Linstead et al., 2017a, 2017b) or changes in assessment scores (e.g., Ostrovsky, 2022). The results of these studies typically suggest that hours of ABA alone account for only a moderate portion of goals mastered using linear models (r^2 .35 to .67)[1], slight improvement when using nonlinear models (r^2 increase from .35 to .60), or no relation between hours per week and changes in assessment scores. One limitation to these studies, however, is that the sample sizes have been relatively small[2], often including hundreds of participants and with the largest including 1,468 patients (Linstead et al., 2017b).

Related to identifying and improving the predictability of a patient's treatment course, past researchers have also used statistical techniques to identify subgroups within ASD with unique patient profiles. A recent review of this work is well summarized by Parlett-Pelleriti and colleagues (2022). In short, they reviewed 36 different studies and found the median number of patient clusters was 3 with the minimum and maximum identified being 2 and 7, respectively. Necessarily, the clusters identified in these studies centered around the data the researchers used which mostly were diagnostic scores, overall and subdomain scores from assessments, and developmental profiles. As noted by others (e.g., Braverman & Gottlieb, 2014), however, many bio-socio-behavioral-economic factors can influence healthcare outcomes. Thus, it is unknown whether the number and composition of the clusters identified in previous studies would hold if a greater number of variables were added into cluster analyses. Further, as with predictive modeling above, the sample sizes in these studies were relatively small with the median size being 220 patients.

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[1] Of note: r^2 can range between 0.0 (not great) to 1.0 (perfect). In laboratory settings, r^2 > ~.85 are typically considered good. In nonlaboratory settings, such as the context of this work, r^2 > ~0.65 are typically considered good.

[2] Small here is a matter of perspective. From a research perspective these have been the largest studies to date. But, from the perspective of the heterogeneity of individuals who receive a diagnosis of ASD, it is highlight unlikely these participants are representative of the entire population for whom we would want the results to generalize.

A final limitation to the above studies is that the product was primarily a static published manuscript in an academic journal. As a result, readers who find the information useful are unable to automatically bring those models and the patient clustering information into their daily practice to inform their decisions.

The purpose of this paper is to show how RethinkFirst has created a patent-pending artificial intelligence (AI) system that creates patient profiles and predicts patient progress better than past research to-date. Specifically, the AI System uses continuously collected data from an ever-increasing number of individuals with ASD across 48+ variables spanning demographics, diagnostic and assessment information, socio-behavioral, social determinants of health (SDOH), and characteristics of ABA. The system uses unsupervised machine learning to identify patient clusters that consider a more holistic view of each individual patient. Further, those same clustering variables combined with supervised machine learning allows us to predict patient progress with greater precision than past research (r^2=.90 for linear regression; r^2>.94 using machine learning). Because the system continuously collects more data and we are learning how to better incorporate more variables, the static view presented here involving 31,294 patients spanning 615 unique ABA organizations will only improve over time. Most importantly, the results of this work are fed back into a technological platform that users can directly access to improve patient outcomes.

Overview of the AI System

Figure 1 shows an overview of the five steps of the AI system. First, users of a variety of RethinkFirst products enter data around ABA session characteristics, a patient's contact with ABA therapy, a patient's performance on various clinical targets, and background information about the patient. Second, the data from the individual products are extracted and loaded into relational tables in a data warehouse. Third, a series of analytic scripts referred to as the AI engine (more below) carryout the analyses required to build dose response curves leveraging the variables that comprise patient cluster profiles. Fourth, a user interested in leveraging the models for a specific use case (more below) enters information about a patient. Lastly, the desired information is presented within a product platform for user interaction and further data collection.

Figure 1.

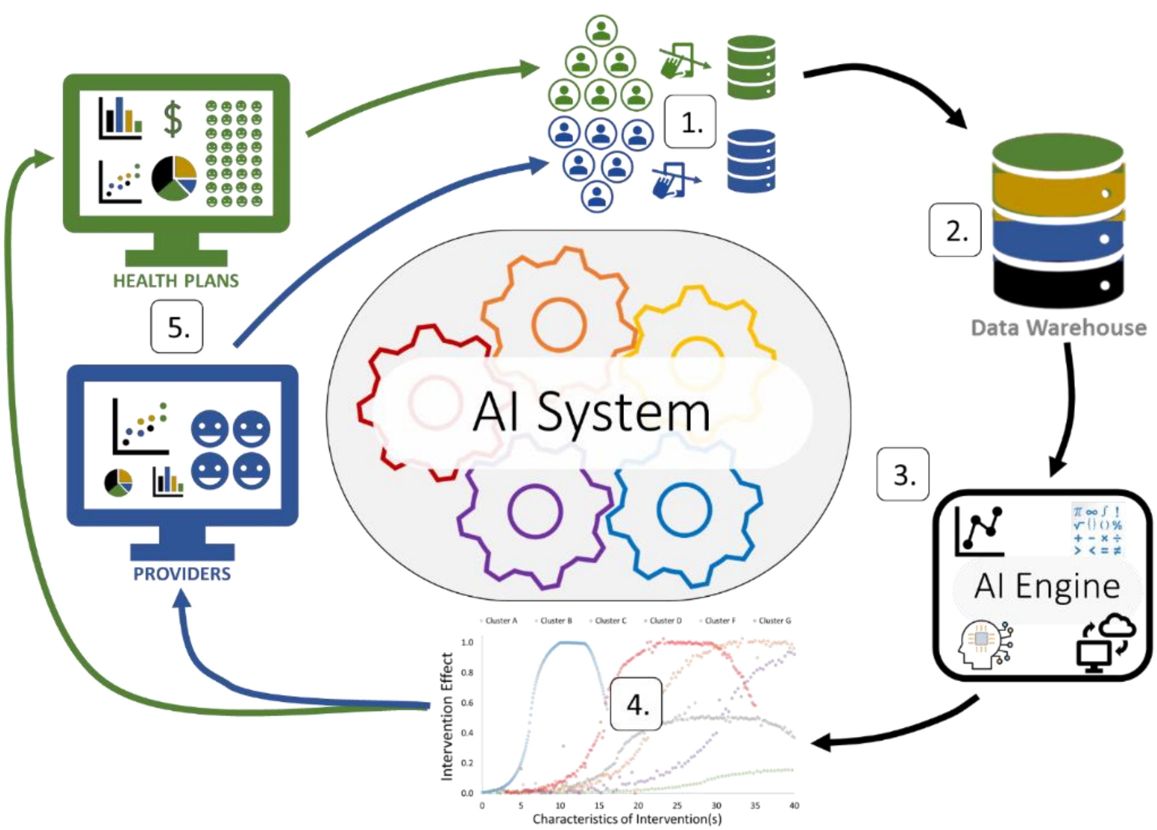
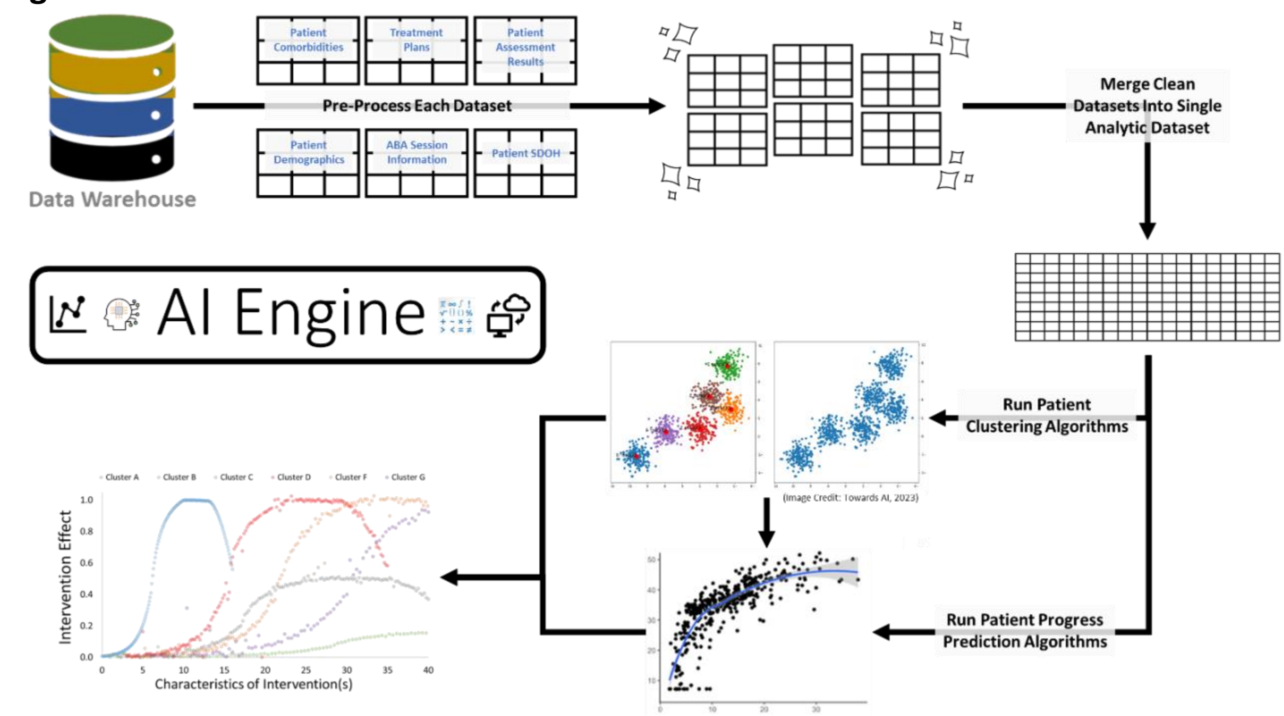


Figure 2 shows an overview of the AI engine portion of the AI system. The AI Engine is comprised of five distinct steps (Figure 2). These are: (a) pre-process the data stored in the relational tables in the data warehouse, (b) integrate the data into a single, analytic data frame, (c) conduct unsupervised machine learning relative to patient clustering; (d) conduct a suite of statistical and supervised machine learning analyses relative predicting patient outcomes using the (currently) 48 variables; and I deploy two top-performing models as API endpoints—one each for patient clustering and predicting outcomes. Below we review the results of steps (c) and (d).

Figure 2.



Unsupervised Machine Learning for Patient Clusters

Table 1 shows the patient cluster metrics when using several unsupervised machine learning clustering algorithms. Different clustering algorithms make distinct assumptions about how patients might group together and how differences among patients in the same clusters are best compared to differences with patients from other clusters. Thus, depending on the metric and algorithm used, the optimal number of clusters ranged between 8 to 56. Figure 3 below shows what the patient clusters look like in a three-dimensional space. Each color represents a unique cluster and each data point is a single patient.

The primary point made here is not about the specific number of clusters, *per se*. Rather, the primary point is that combining a more holistic set of variables with a substantially larger sample size allows this AI system to identify patient profiles beyond what has been captured in past research.

Table 1.

Clustering Algorithm	Silhouette	Calinski-Harabasz	Optimal Clusters
k-Means	0.25	8,169.60	30
Agglomerative Hierarchical	0.47	13,718.52	8
HDBSCAN	0.37	2,377.78	56
BIRCH	0.39	6,086.66	18

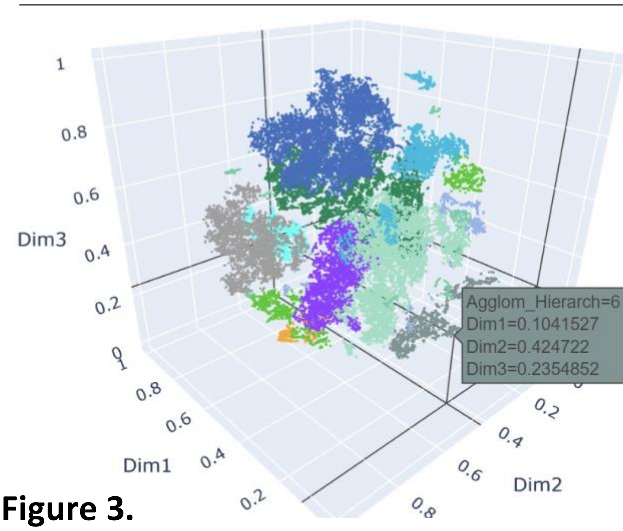
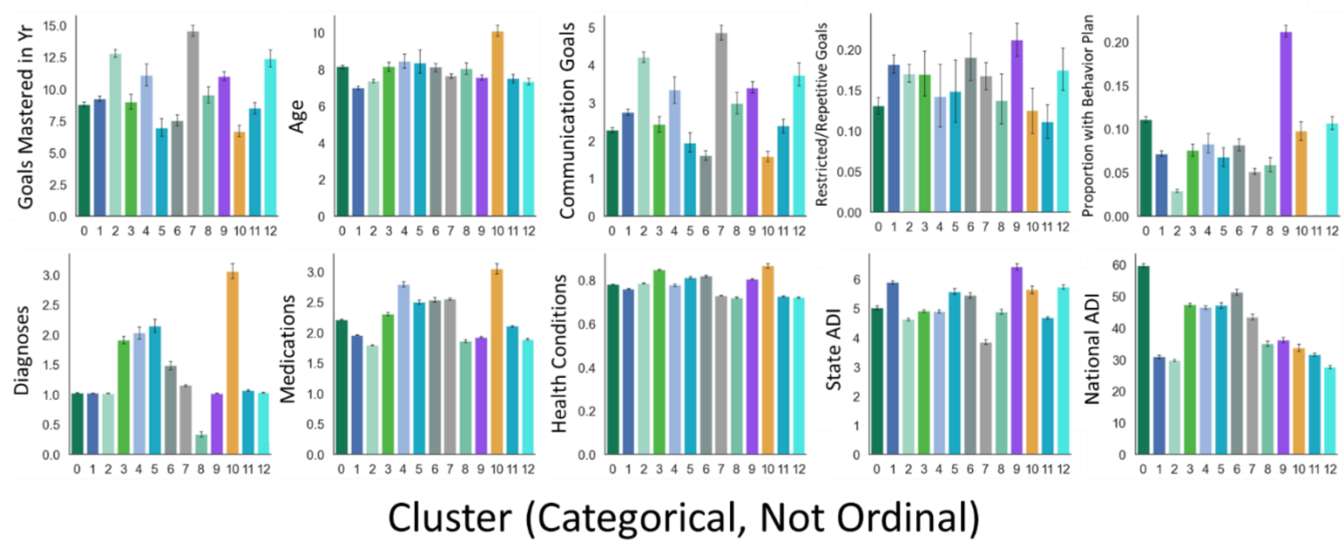


Figure 3.

To highlight the benefits of including a more holistic view of patient profiles, Figure 4 shows how patients assigned to one of 13 different clusters differ along 10 of the 48 variables included for this article. Of note, the top five variables are variables with a known relation to patient progress resulting from ABA in past research. The bottom five variables are variables known to influence healthcare outcomes more generally[3], but have not been used to predict patient outcomes following ABA.

Figure 4.



Supervised Machine Learning to Predict Patient Outcomes

Table 2.

Algorithm	r^2	MAE
Linear Regression	0.90	1.30
k-Nearest Neighbors	0.91	1.27
Support Vector Regressor	0.99	1.06
Random Forest	0.99	1.04
AdaBoost	0.88	1.32

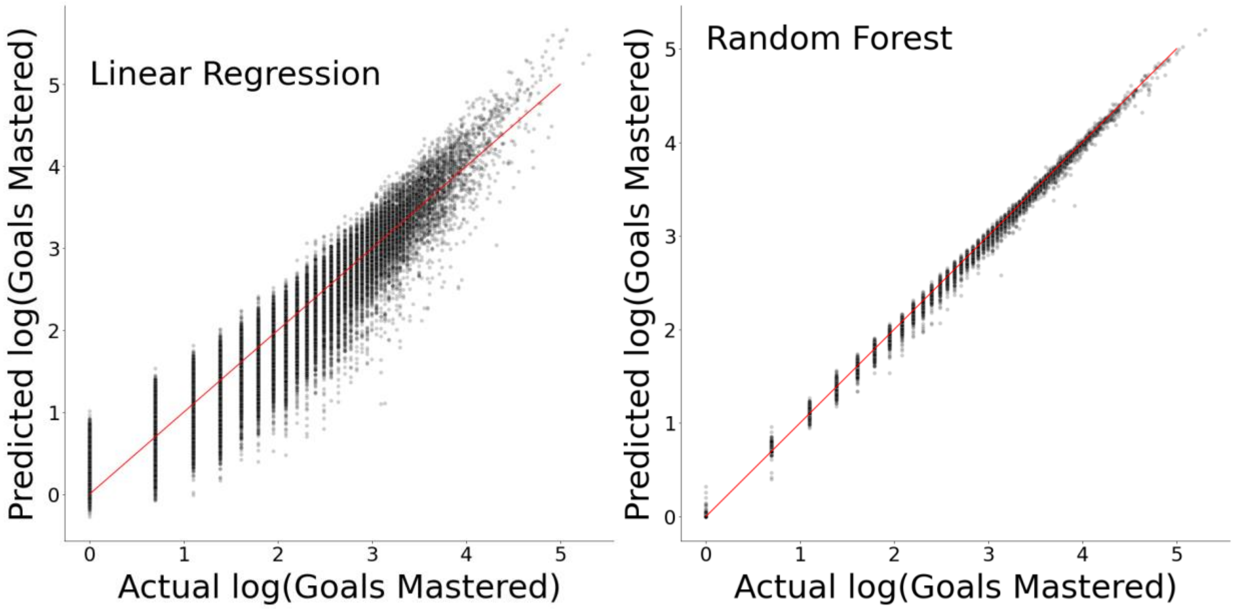
There is a tradeoff in science between preference for models that are simpler vs. those that are more precise. As such, we fit a series of models ranging from simple (linear regression—as done in past research predicting goals mastered) to complex (machine learning) to identify what approach is likely to provide the best tradeoff. Table 2 shows the results of these comparisons. Of note, the model built using linear regression accounted for 23% more of the variance in goals mastered than past research using this approach (r^2=.90 vs. .67 in Linstead et al., 2017b). This further speaks to the importance of including a larger sample size and including a more holistic set of variables to capture patient characteristics beyond diagnoses, assessment scores, and developmental profiles. Further, the results from using machine learning indicate that more complex models that account for nonlinear patterns in the data provide more precise predictions with the gains being nontrivial (i.e., within 1.12 goals mastered per year per patient, on average). When predictions were made within clusters, r^2 ranged between .95-.99 (~.20-.24 points higher than past research) and MAE ranged between 1.12-1.45. Of note, the r^2 values obtained here are ~.20-.24 higher than the cluster specific r^2 values observed by past researchers which ranged from .64 to .75 (Stevens et al., 2019).

To get a better sense of how well these models are performing, Figure 5 shows the relationship between the predicted number of goals mastered (*y*-axis) compared to the actual numbers of goals mastered (*x*-axis) for approximately 6,200 patients who were held out as a validation data set. The left panel shows the results using linear regression and the right panel shows the results using the model built from a random forest algorithm. The

[3] ADI stands for Area Deprivation Index and is a high-level proxy for the influence of neighborhood disadvantage on healthcare outcomes and healthcare disparities (e.g., Hu et al., 2018; Kind et al., 2014; Lantos et al., 2018; Link & Phelan, 1995; Ludwig et al., 2011).

axes are logged for easier visualization of the distribution of predicted and actual scores. The red line would be where data would land if the model was perfect.

Figure 5.

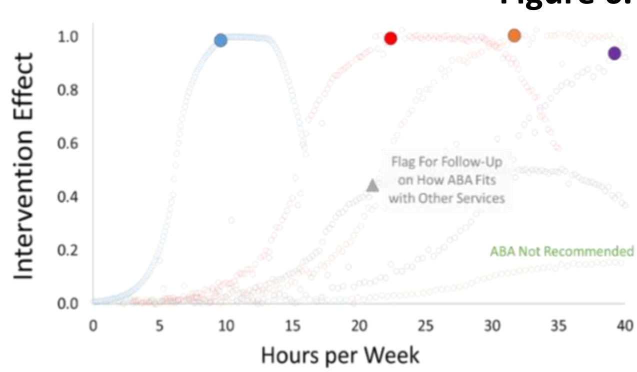


Example Use Cases

To summarize the results thus far, the patent-pending AI system and underlying AI engine is capable of identifying a greater number of patient cluster profiles within the ASD population and predicting the number of goals a patient will master with a high degree of precision. The current performance of the AI Engine is due to two characteristics of the AI system. First, the ability to leverage the largest published dataset surrounding ABA for individuals with ASD. Second, including a holistic set of patient characteristics spanning demographics, diagnostic and assessment information, clinical presentation, ABA-related characteristics, and SDOH.

But it's one thing to build these models and another thing entirely to use these models toward a practical aim. Below we describe three use cases for which the results of this model are put back into a technology platform for user access. These include: (1) recommending ABA dosage; (2) providing provider feedback around observed versus expected patient outcomes; and (3) understanding how outcomes vary along SDOH.

Figure 6.



Recommending Hours of ABA. A straightforward application of the finalized model is to have the model recommend the optimal hours per week relative to goals mastered via dose-response curves. Figure 6 shows hypothetical data wherein patient characteristics can be passed to the predictive model along with a range of hours of ABA the patient might contact. Such dose-response curves are commonly used to identify optimal therapeutic effect of an intervention in behavioral pharmacology (e.g., Dews, 1955) and have been used previously for analyses specific to ABA (e.g., Ostrovsky et al., 2022; Stevens et al., 2019). For each patient, there is likely to be a point wherein little-to-no further progress would be predicted if more hours of ABA were contacted (the large filled-in circles in Figure 6). This point of little-to-no further return could then be the recommended hours per week of ABA.

Observed vs. Expected Patient Outcomes. Another straightforward application of the finalized model would be to retroactively compare a patient's actual progress to expected progress. Specifically, a patient's unique characteristics could be passed to the model along with the hours of ABA they contacted. The model would return the number of goals expected to be mastered based on other patients who present with similar characteristics and received similar amounts of ABA. By comparing the observed patient progress to the expected patient progress, the provider or their supervisor can get feedback on how well they are providing services with current clients. In turn, payors and providers' supervisors can follow-up with specific patients and the supervising certified behavior analysts to identify why they are achieving less than expected outcomes. And, for patients for whom the provider is observing greater than expected outcomes, providers can follow-up to identify if there are related variables they can use with other patients to improve outcomes.

Associated Social Determinants of Health. Many aspects of our social environment have been repeatedly shown to play a role in patient outcomes and are referred to as social determinants of health (e.g., Braverman & Gottlieb). Because several of these variables are included in the model, the user could use these data to help identify and potentially mitigate the effects of these variables on patient outcomes. For example, similar to the previous use case, a provider could systematically identify how well each patient in their organization or on their caseload is performing relative to expected outcomes. The provider could then determine whether differences between observed and expected outcomes were associated with unique variables known to be a SDOH (e.g., race, neighborhood walkability, income, education). By identifying specific SDOH that impact the patients on their caseload or in their organization, providers would better know how to identify resources for those clients that might mitigate this effect and improve their overall outcomes.

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About Us

Since the founding of RehinkFirst in 2008, we have had the incredible opportunity to grow and learn alongside the education, employer, and service provider communities as we find new ways to support families living with autism and developmental disability. Along the way, we have built a deep reservoir of knowledge, industry-leading technology, and the largest published set of autism services data.

With RethinkFutures, we put these tools, and our clinical and technical expertise, in service of payors. We answer previously unanswered questions – including how best to match ABA service recommendations to the individual characteristics of a member – and we deliver the solutions necessary for payers to optimize care at the individual level and across their ASD provider networks. All of our solutions are built with payor considerations in mind, from easy visualization of authorization requests through customizable caregiver support programs and streamlined provider communications.

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