Expanding with Insight

STRIVE's Investments in Data-Informed Practices to Strengthen Programs and Evidence

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Expanding a program while maintaining its quality is a challenge for many sector-focused training organizations (organizations that train people for sectors of the labor market in which there is strong local demand). STRIVE, a sector-based training organization that began as a small organization in East Harlem and is now operating nationally, is committed to expanding its programs responsibly while building its evidence base. In partnership with MDRC, STRIVE is drawing insights from its historical program data, developing tools to improve its data systems, and advancing its research and development agenda. If STRIVE meets its expansion targets, these conditions could support a rigorous evaluation.

This brief explores how STRIVE has developed tools to monitor and strengthen its programs as it expands nationally.

The STRIVE Program Model

For over 40 years, STRIVE has offered students both career and personal development services. In 2023, it launched a national expansion plan to serve 10,000 people annually by 2033, from 2,000 annually. As part of this effort, STRIVE is replicating WorkAdvance — an evidence-based sector

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training model — in New York City, Atlanta, Birmingham, New Orleans, and northern New Jersey. STRIVE has adjusted its program model to align with central features of WorkAdvance, and has partnered with MDRC to assess whether STRIVE's programs are being carried out as designed and whether STRIVE is making progress on building evidence of its program effectiveness.

This work, called STRIVE Forward, follows STRIVE's evaluation roadmap, which outlines steps to build the organization's ability to evaluate its own programs and its readiness to participate in a rigorous evaluation conducted by an outside party.[1] STRIVE Forward uses data on students in New York City who have participated in two of STRIVE's programs: **Career Path,** which includes job readiness training and occupational skills training, career coaching, job placement, and lifelong services; and **Fresh Start,** a program for people reentering the community following incarceration that incorporates holistic services to support students in their learning pathways.[2]

Lessons for Expansion

Using a common framework for assessing evaluation readiness, MDRC and STRIVE developed logic models for Career Path and Fresh Start, assessed data practices, and built data tools to support expansion and inform program improvement.[3]

Develop Logic Models to Connect Actions to Outcomes

- **Discussions about how to describe STRIVE's programs in a logic model revealed that it valued — and needed to measure — its commitment to providing comprehensive services to its communities' most vulnerable populations.**

Logic models illustrate how a program's activities ("inputs") connect to immediate changes in conditions ("outputs") and participants' outcomes. While many sector programs offer supportive services to their participants, in developing its logic model, STRIVE sought to integrate those services at each step in the logic represented, from needs assessments being a part of the application, to services being integrated with training workshops, to expected life-skills achievements among the outputs and outcomes. Fresh Start also includes reentry-focused services such as support for post-traumatic stress disorder.

Assess Data System Capabilities

- **A review of STRIVE's program data revealed some important gaps, which prompted new data-system investments that have improved STRIVE's data quality and enabled better service delivery.**

The discussions about the logic model made it clear that STRIVE needed reliable data systems to track program engagement and outputs. MDRC worked with STRIVE to connect the logic model's inputs and outputs to measures in its customer relationship management system, where data on program applications, enrollment and ongoing engagement, and milestone achievements are recorded and monitored. This initial work laid the foundation for the data analytics work that followed. The analyses stress-tested the logic models to help describe the critical pathways from inputs to outcomes and milestones of progress along the way, and explored what might facilitate or hinder student progress along those pathways.

MDRC's review of student data from 2018 to 2025 revealed that key demographic and background fields were often incomplete prior to 2021. Since then, STRIVE's data analytics team has standardized historical student data and implemented stronger data-entry procedures to ensure essential fields are completed going forward. For example, STRIVE added a "prefer not to answer" response to sensitive questions in 2024, in alignment with MDRC's recommendation, to recover missing information and improve data accuracy, and embedded data-collection redundancies for important fields in its program processes that were minimally burdensome for its staff. For example, students might be more comfortable disclosing background information to the organization after program application and enrollment, so the updated processes gave STRIVE support staff members opportunities to recapture missing information on separate program participation and case management forms. These improvements help STRIVE better understand and support its diverse student population while strengthening its ability to assess its own program performance and make progress on its evidence-building goals.

Use Data to Learn

- **Analyzing program data can help staff members understand how participants are progressing through programs and set benchmarks for the future. Through initial analyses, STRIVE learned that its students, whose background profiles show substantial structural barriers to economic mobility, reach milestones and find employment at rates comparable to those of students at well-known sector training providers.**

Most STRIVE students are male and Black or Hispanic/Latinx, many have children or other dependents, and few have higher education degrees or jobs when they enter Career Path or Fresh Start.[4] Experiences with homelessness or houselessness and the criminal justice system are common. STRIVE enrolls individuals with multiple, interrelated barriers to employment without screening out those who may need or benefit from intensive support and case management, and offers alumni lifetime access to its services.

STRIVE's definition of program success includes both training completion and job placement within 90 days of graduation. A funnel analysis — an analysis of the decreasing number of people who reach each successive stage in a process — examined the critical milestones that emerged during the logic model exercises.[5] Funnel analysis can provide a clear picture of how participants either progress through a program or drop off before reaching important milestones, from enrollment to job placement. It showed that STRIVE students complete the program and obtain jobs at rates comparable to those of students at peer workforce programs with strong evidence bases, and that outcomes among STRIVE students are similar regardless of gender, age, education level, and housing stability.[6]

Use Data to Create New Analytics Tools

- **MDRC and STRIVE codeveloped and tested two tools: a predictive analytics tool set to support student success, and an employer-partner-quality dashboard to strengthen the training-to-job pipeline.**

The predictive analytics tool approaches student success through a focus on building individuals' skills, to allow STRIVE to identify struggling students in a timely fashion and help them gain the skills needed for the workplace. The employer-partner-quality dashboard takes a systems approach to student success, to help STRIVE facilitate labor market conditions that are favorable for its program graduates. These tools can be used with any program-data-tracking system. MDRC trained STRIVE staff members to use and manage the tools independently.

Using data on STRIVE's Career Path program in New York, MDRC developed code to integrate predictive models into STRIVE's data-monitoring practices. The resulting tools predict a student's likelihood of achieving program success using only application data, aligning with STRIVE's goal to identify support needs early.[7]

Testing showed that the models did not meaningfully distinguish between students who would be placed in a job and those who would not, suggesting STRIVE may already be effectively targeting support and reducing disparities among students that would otherwise exist.[8] While the models were not strongly predictive for the sample of students enrolled in 2021 through 2024, the tool set could yield more predictive results as STRIVE expands to serve more students going forward, both in New York and in other regions with fewer public resources.

MDRC and STRIVE also developed a tool to assess employer partnerships, which are critical to program success.[9] The Employer Quality Index they developed together used both student-reported and externally verified job placement data to measure partnership quality in two dimensions: reliability (a "satisfied customer" view where employers continue to hire STRIVE graduates because they are appropriately skilled and reliable employees) and quality ("high-road" job characteristics where employers provide livable wages, benefits, and job stability).

MDRC built a dashboard using "traffic lighting" — a data visualization approach that uses color to reflect performance — to represent partnership quality and the strength of each attribute for an employer.[10] That dashboard provides real-time insights into which employers are providing good opportunities for STRIVE students.

MDRC has trained STRIVE to use both tools going forward, and they can also be used by other workforce providers. The first tool helps to identify which students might need more support before it is too late. The other tool focuses providers on employer relationships, which can be very helpful as they work with employers to develop potential placements for students.

Conclusion: Next Steps in STRIVE's Evaluation Journey

- **Analyses of STRIVE's program data indicate high implementation fidelity and equitable outcomes across a range of student characteristics, positioning it well for future evaluation.**

With success rates comparable to peer sector training providers and improved data systems, STRIVE is well positioned for building stronger evidence. STRIVE now has the tools to monitor and strengthen its programs as it grows nationally. STRIVE's experience illustrates how strengthening data systems and tools can support both program delivery and evaluation readiness.

Notes and References

1. MDRC, "STRIVE Evaluation Roadmap," (website: https://static1.squarespace.com/static/591ca244f7e0abb34cbf3b1e/t/6272b95e9fa48c35820465de/1651685727082/STRIVE+evaluation+roadmap+to+STRIVE+%281%29+%281%29.pdf).

2. STRIVE's services include mental health services, motivational interviewing (a method for changing behavior by helping clients identify and change behaviors that make it harder for them to achieve their personal goals), occupational skills training, and placement in transitional jobs (temporary, subsidized jobs that aim to teach participants basic work skills or help them get a foot in the door with an employer). For people involved in the justice system, STRIVE incorporates moral reconation therapy, a group-based cognitive behavioral treatment that helps patients develop decision-making skills by learning and applying higher levels of moral reasoning. See Gregory L. Little and Kenneth D. Robinson, "Moral Reconation Therapy: A Systematic Step-by-Step Treatment System for Treatment Resistant Clients," *Psychological Reports* 62, 1 (1988): 135–151, https://doi.org/10.2466/pr0.1988.62.1.135.

3. Diana Epstein and Jacob Alex Klerman, "When Is a Program Ready for Rigorous Impact Evaluation? The Role of a Falsifiable Logic Model," *Evaluation Review* 36, 2 (2013): 375–401.

4. The U.S. Office of Management and Budget defines "Hispanic/Latino" as any person of "Cuban, Mexican, Puerto Rican, South or Central American, or other Spanish culture or origin." See U.S. Census Bureau, "Why We Ask Questions About… Hispanic or Latino Origin" (website: https://www.census.gov/acs/www/about/why-we-ask-each-question/ethnicity/, n.d., accessed on January 6, 2026). In recent years, some research publications and other sources have started using "Latinx" as a gender-neutral reference to this population. See Andrew H. Nichols, *A Look at Latino Student Success: Identifying Top-and Bottom-Performing Institutions* (The Education Trust, 2017).

5. For an example of a funnel analysis, see Frieda Molina and Donna Wharton-Fields, "Filling All the Seats in the Room: Using Data to Analyze Enrollment Drop-Off," *InPractice* (website: https://www.mdrc.org/work/publications/filling-all-seats-room, 2019).

6. Evidence from peer workforce programs includes: Mark Elliott and Anne Roder, *Escalating Gains: Project QUEST's Sectoral Strategy Pays Off* (Economic Mobility Corporation, 2017, https://economicmobilitycorp.org/wp-content/uploads/2018/01/Escalating-Gains_WEB.pdf); Richard Hendra, David H. Greenberg, Gayle Hamilton, Ari Oppenheim, Alexandra Pennington, Kelsey Schaberg, and Betsy L. Tessler, *Encouraging Evidence on a Sector-Focused Advancement Strategy: Two-Year Impacts from the WorkAdvance Demonstration* (MDRC, 2016, https://www.mdrc.org/sites/default/files/2016_Workadvance_Final_Web.pdf); Randall Juras and Larry Buron, *Summary and Insights from the Ten PACE and HPOG 1.0 Job Training Evaluations: Three-Year Cross-Site Report*, OPRE Report 2021-155 (Office of Planning, Research, and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services, 2021, https://acf.gov/sites/default/files/documents/opre/cross-site-_3-year_report_august2021_508_qc.pdf).

7. The predictive analytics tool allows users to run very simple or very complex machine learning models, depending on what is most useful for their specific situations. For small programs or resource-constrained providers, using simple predictive models may be sufficient to appropriately identify students who need more support. Running complex machine learning models can be resource-intensive and may add only marginal value to predictive accuracy, while results may be difficult to interpret. See Camille Preel-Dumas, Richard Hendra, and Dakota Denison, *Keep It Simple: Picking the Right Data Science Method to Improve Workforce Training Programs*, OPRE Report 2023-058 (Office of Planning, Research, and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services, 2023).

8. Other reasons for poor predictive model performance could include the exclusion of postenrollment indicators that may influence job placement (for example, program engagement, skill gains, or job search behaviors); the importance of unobservable characteristics that are not apparent until later in the program (for example, motivation, personal networks, or soft skills); small sample sizes, since much of STRIVE's pre-2021 data could not be used due to missing data elements; or external factors such as local labor demand or macroeconomic shifts, which can outweigh individual-level predictors in determining job placement.
9. Lawrence F. Katz, Jonathan Roth, Richard Hendra, and Kelsey Schaberg, "Why Do Sectoral Employment Programs Work? Lessons from WorkAdvance," NBER Working Paper 28248 (National Bureau of Economic Research, 2020), https://doi.org/10.3386/w28248.
10. See Developer Docs, "Traffic Lighting" (website: https://docs.visier.com/developer/Analytics/explore/visual%20actions/traffic%20lighting/traffic%20lighting.htm, n.d., accessed on January 6, 2026)

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