KNOWING MORE MEANS DOING BETTER:

DATA, TECHNOLOGY AND THE FUTURE OF COMMUNITY HEALTH IMPROVEMENT

WILL SNYDER and ANGIE GROVER

When the Affordable Care Act codified community health needs assessments (CHNAs), most nonprofit hospitals were working from a relatively thin deck of data cards: census, state vital statistics and a community survey, if the budget allowed. The picture of a community's health was impressionistic at best — a few broad strokes applied every three years and quickly dated.

The data landscape available to community benefit professionals today bears little resemblance to that of a decade ago. Nationally curated datasets on social determinants of health, near-real-time local information from community health workers and social service providers, geographically precise population-level indicators, and platforms purposely built to synthesize it all have transformed what is possible in the virtuous cycle of assessment to implementation to evaluation. At the same time, the arrival of artificial intelligence is reshaping both what is possible and what Catholic health ministry leaders must guard against.

HOW HEALTH DATA HAS CHANGED

The classic CHNA data stack drew heavily on sources with inherent lag. The decennial census, American Community Survey five-year estimates, county-level mortality files and state behavioral risk factor surveys are invaluable. However, they describe a community as it was, not necessarily as it is; a CHNA in 2019 might have been working from observations collected as early as 2012. For rapidly changing communities — those absorbing new immigrant populations, experiencing economic shifts, or recovering from the COVID-19 pandemic — that lag matters.

Three structural changes have begun to close that gap.

First, the proliferation of secondary data platforms has enabled the assembly of a far richer picture without replicating expensive primary research for every assessment cycle. Tools have layered economic mobility, environment and social factors onto traditional health metrics. Platforms designed specifically for community health work integrate dozens of these sources into a single, queryable environment. This allows planners to move from a broad, county-level view down to a census tract or even a block group without changing tools.

Second, the geographic granularity of available data has improved substantially. Earlier CHNAs often had to characterize entire counties or multicounty service areas as a single unit. Today's platforms can break down data by ZIP code, census tract or neighborhood — revealing pockets of need that aggregate statistics obscure. A community that appears healthy at the county level may contain a census tract where life expectancy trails the national average by a decade. Identifying and prioritizing this geography is now a tractable data problem rather than an expensive research project.

Third, community-sourced and real-time data inputs have grown. Electronic health records (EHRs), community health worker encounter data, surveillance data and social service referral systems generate ongoing information about unmet needs that supplement the periodic snapshot of a formal CHNA. Plus, the cost of running a survey or collecting qualitative data through interviews and focus groups has decreased significantly.

When these streams are connected, organizations can monitor whether implementation strategies are reaching the right populations in the right quantities — and make adjustments before the next three-year cycle requires it.

ASSESSMENT, IMPLEMENTATION AND EVALUATION

The best community health work treats the CHNA and community health improvement plan (often known as CHIP or implementation strategy) as a continuous loop, with evaluation data feeding back into both implementation plan refinement and the next assessment.

Data platforms support this loop most effectively when they are configured to do three things simultaneously: describe the community (assessment), track progress against prioritized interventions (implementation monitoring), and measure impact over time (evaluation). The distinction between these functions matters. A platform optimized purely for CHNA production — generating a rich community profile report — may offer little infrastructure to track whether a diabetes prevention program is reducing hemoglobin A1C (HbA1c) levels in the ZIP codes where it operates. Organizations should ask, when evaluating data tools, how well they support the full cycle rather than any single phase.

Implementation monitoring is arguably the most underdeveloped of the three. Many organizations can describe a community's needs in considerable detail and can report the dollars spent on community benefit programs. Fewer can confidently demonstrate that those programs are reaching the highest-need populations, at the right intensity, and producing measurable health change. This is partly a data infrastructure problem and partly an organizational capacity problem — but it is also, increasingly, a solvable one.

Evaluation frameworks that draw on the same community data used in the CHNA allow organizations to assess not just outputs (number of people served, services delivered) but outcomes (changes in health indicators, reductions in preventable emergency department visits, improvements in self-reported health status) in the geographies and populations targeted by implementation strategies. When an organization can show that its community health worker program is concentrated in census tracts with the highest rates of uncontrolled hypertension and that those tracts are showing measurable improvement, it tells a fundamentally different and more compelling community benefit story.

UNDERSTANDING AI IS INCREASINGLY NECESSARY

AI has arrived in community health data work. Understanding where it genuinely helps and where it requires disciplined caution is now a core competency for anyone responsible for a CHNA or community benefit program.

On the positive side, AI makes several previously burdensome tasks substantially more tractable. Natural language processing tools can scan thousands of pages of community input, including focus group transcripts and interview notes, and surface recurring themes far faster than human reviewers. This is particularly valuable in the community engagement phase of a CHNA, where qualitative input is often rich but underused because limited resources prevent thorough analysis.

Predictive analytics offer another area of real value. Machine learning models trained in clinical and community data can identify populations at elevated risk for specific conditions — including diabetes complications, preventable hospitalizations and housing instability — before those risks become crises. For hospitals with strong EHR infrastructure and community partnerships, this kind of risk stratification can direct community health workers' time toward the people most likely to benefit from intervention.

AI also accelerates the synthesis of complex, multisource datasets. A platform using AI-assisted analysis can identify correlations across dozens of community indicators that a human analyst would struggle to detect. For example, it can flag unexpected relationships between building violations and pediatric asthma rates at a geographic level that is actionable. For organizations without dedicated epidemiologists on staff, this capability levels the playing field considerably.

AI RISKS LEADERS MUST EVALUATE

The same capabilities that make AI valuable in community health work also introduce risks that organizations grounded in Catholic social teaching should take especially seriously.

Algorithmic bias is the most documented risk.[1] AI models trained on historical health data will, without careful oversight, amplify existing disparities. A predictive model trained on claims data from a predominantly insured population may underidentify risk in uninsured communities that access care differently. This is not a theoretical concern: Researchers have documented cases where widely used clinical algorithms embedded racial bias into care recommendations, with real consequences for patients.[2]

For community benefit professionals, the practical implication is that AI-generated insights should be treated as inputs to human judgment, not substitutes for it. When a platform flags a census tract as low-priority based on aggregated indicators, that designation should prompt questions such as, "Who lives there, and are their needs captured by this data?" rather than trigger an automatic resource allocation decision.

A related risk is data quality and representativeness. AI is only as good as the data on which it is trained and applied. Communities that are least well-served by the healthcare system are often least well-represented in the data sources that AI systems draw upon. Rural populations, recent immigrants, people experiencing homelessness, and communities with low rates of formal healthcare utilization may appear healthier in data-driven analyses simply because their encounters with the health system are infrequent. AI tools that promise to identify needs must be evaluated carefully for how they handle data gaps and sparse populations.

Privacy and consent represent a third area of concern. The more granular and personalized the data underlying a community health analysis, the more important it is to be certain that individuals whose information is included have meaningfully consented to its use. Organizations should establish clear governance frameworks — specifying who owns community health data, how it is stored and protected, and what uses are authorized — before deploying AI-enabled tools that depend on sensitive information.

Finally, there is the risk of what might be called data displacement: the substitution of quantitative analysis for community voice. The richest AI-assisted CHNA is no substitute for genuine engagement with the people whose health is at stake. Communities, especially those that have historically experienced research as an extraction rather than a partnership, may be reasonably skeptical of AI-driven conclusions about their needs. Preserving robust, trust-based community engagement processes, including qualitative listening, co-design of priorities and transparent communication of how data is used, remains essential even as the analytical sophistication of CHNA tools advances.

ACTING RESPONSIBLY, ETHICALLY

For the Catholic health ministry, community benefit is an expression of the conviction that health is a fundamental human right. That conviction does not change as the tools available to act on it evolve.

What changes is the standard of stewardship. When data is limited, organizations can be excused for gaps in knowledge about community needs. When data is abundant and analytical tools are powerful, the obligation to know and to act on that knowledge equitably rises accordingly. The communities most in need of health investment are increasingly visible in the data if organizations choose to look and have the infrastructure to see.

The data revolution in community health is ultimately not a technological story. It is a story about whether institutions with the resources and the mission to improve community health are willing to use the best available tools with appropriate humility, listen carefully as they analyze, and hold themselves accountable to outcomes rather than activities. That has always been the standard. The tools to meet it have simply gotten better.

WILL SNYDER is co-founder and CEO of Metopio. **ANGIE GROVER** is co-founder and chief operating officer of Metopio. Metopio is a software and data company focused on population and place-based analytics.

NOTES

1. Laura J. Horsfall et al., "Clinical Algorithms and the Legacy of Race-Based Correction: Historical Errors, Contemporary Revisions and Equity-Oriented Methodologies for Epidemiologists," *Clinical Epidemiology* 17 (2025): https://doi.org/10.2147/CLEP.S527000.

2. Ziad Obermeyer et al., "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations," *Science* 366, no. 6464 (2019): https://doi.org/10.1126/science.aax2342; Shyam Visweswaran et al., "Online Database of Clinical Algorithms with Race and Ethnicity," *Scientific Reports* 15, no. 10913 (2025): https://doi.org/10.1038/s41598-025-94152-5.

JOURNAL OF THE CATHOLIC HEALTH ASSOCIATION OF THE UNITED STATES www.chausa.org

HEALTH PROGRESS®

Reprinted from *Health Progress*, Summer 2026, Vol. 107, No. 3