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Classifying and Describing Exemplary Data Use in Temporary Assistance for Needy Families (TANF) Agencies

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ABSTRACT

State human service agencies often collect a wealth of administrative data, but the extent to which those data are accessed and leveraged for evaluation or program improvement varies greatly across time, states, and agencies. The current study is focused on data use in state agencies administering the Temporary Assistance for Needy Families (TANF) program, a federal cash assistance program for families with low incomes. Using data from a national needs assessment administered to state and territory TANF agencies ($n = 43$), we identified three categories of data use: basic (describing 22 state TANF agencies; 51%), advanced (9; 21%), and exemplary (12; 28%). We examined the relationship between data use and agency characteristics and found that a culture of communication, collaboration, and transparency around data, as well as the development of quality external partnerships, are associated with higher quality agency data use. Factors like new data systems, data access tools, or increased financial resources were not consistently associated with higher quality agency data use; in particular, new data systems were inversely correlated with data use in the years immediately after implementation.

1 | Introduction

1.1 | Value of Data Use in Human Service Agencies

Public sector human service agencies[1] administer state and federal social benefits programs intended to benefit families experiencing adversity. Both the importance of this mission and the accountability expected of any agency that manages public funds obligate these organizations to monitor their performance and improve wherever possible.

Identifying success in human services agencies—and even further, pinpointing the policies and practices that drive that success—is a tremendous challenge. It requires the analysis of data on services that were provided as well as information about the past, present, and future circumstances of participating families.

Human service agencies collect data on the services and benefits provided and the individuals who receive them and may also access data from other domains such as employment and education. Data from multiple programs can be linked to create comprehensive, cost-effective data sources to understand program participation and build evidence about what is effective to address individual and family adversity (Axelsen et al. 2007; Goerge et al. 1994; Goerge and Wiegand 2019; Heflin et al. 2022; Ribar et al. 2008). Using data to inform program improvement is an important goal for any agency or organization serving families. Multiple examples of using data to understand and improve outcomes across human service sectors can be found in the literature (e.g., Giordono et al. 2022; Leung and O'Leary 2020; Maguire-Jack et al. 2020). Two specific examples of administrative data being used to improve programs and outcomes in the TANF context include:

- Analyses of administrative TANF data linked to administrative wage data identified factors associated with positive earnings with direct implications for TANF program design and improvement (Edelhoch et al. 2020; Mitchell et al. 2018; Wu et al. 2008).
- Analyses evaluating the effects of state-level changes to the TANF program on TANF program recipients (Davis et al. 2020; Patton et al. 2015).

By leveraging the amount of data available to agencies and maximizing their analytic use, human service agencies can better understand program efficacy and design programs and policies that best support the populations they serve. As agencies share their results and replicate approaches, the evidence base for effective human services flourishes.

This article describes an analysis of data used by agencies administering the Temporary Assistance for Needy Families (TANF) program, although the key findings and conclusions are applicable to other human service agencies. Like many human services programs, TANF is intended both to remediate families' immediate needs and to set those families on a path toward long-term economic self-sufficiency and well-being. TANF is a federal cash assistance program for low-income families that was implemented in 1996 through the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA; About TANF 2019). Individuals are eligible for TANF if they have children and meet the necessary financial eligibility and work requirements. TANF is a block-grant funded program, meaning states get a sum of money from the federal government to run their TANF program, and states have significant flexibility in how they design and implement the program within those funds. As such, there is variation across states in aspects like the length of time an individual can receive TANF and the amount of monthly cash benefit an individual receives.

Prioritizing and improving data use in TANF agencies—particularly at the state and local level—is essential to promoting evidence-based policy-making and ensuring TANF is being designed and implemented to best serve families. Understanding the effectiveness of the TANF program at the state-level—both how it works and for whom—is critical, given the ability of the TANF program to serve caregivers and children with significant economic need, the variation in how the program is implemented within states and localities, and TANF's mandate to not only address short-term needs but also to foster long-term benefits. This article uses data from a national needs assessment of TANF agencies to identify agency characteristics that are most strongly associated with exemplary data use. By increasing our understanding of what aspects of agency practice and culture foster better data use, TANF agencies can identify strategies and tools for improving data use in their own agency.

1.2 | Measuring and Fostering Data Use in Human Services Agencies

While neither the importance of understanding program effectiveness nor the potential to use administrative data to analyze program implementation and access is a controversial idea, there remains a disconnect between aspiration and reality.

Program analysts, researchers, information technology professionals, and other stakeholders perceive "effective data use," and the investments and capacities necessary to foster that data use, in different ways. To date, the academic literature reports little empirical research that examines levels of data use and what fosters high-quality data use in TANF or any other human service agency. Most of what is known about these topics stems from case studies or expert interviews (Allard et al. 2018; Stevenson et al. 2002; VanLandingham and Silloway 2016). Published case studies describe the pathways to exceptional data use for one or two agencies (Hotz et al. 1997). For example, a case study of Rhode Island described the steps needed to build an integrated data system and achieve fact-based policy (Hastings 2019), and another article described the successes and challenges of building a longitudinal data system in Utah (Kugle and Smith 2006). These case studies are useful for describing one state or agency's path to building strong data use, but they are unable to compare successful agencies with agencies that have been less successful. Conceptual frameworks have been created to guide agencies toward data-driven practices and to help build analytic capacity, but these are often theoretical or focused on only one aspect of data capacity, such as data sharing across agencies and organizations (see e.g., Barton Cunningham and Kempling 2009; Fusi 2021; Krishnamurthy and Desouza 2014; Pappas et al. 2018).

As scholars who partner with state human services professionals, we heard from many of their struggles to build capacity in data, research, and technology. Hiring and retention can be a significant challenge to building and sustaining analytic capacity. It can be difficult to find applicants who are qualified to do analytic work and also have interest in state government work and policy analysis (Goerge 2018). The high competition from the private sector, with attractive salary and benefit packages, makes this even more difficult (Kreuter et al. 2019).

Additionally, state TANF employees often have very full workloads and high-priority compliance tasks to complete. TANF agency staff have identified lack of staff time as the top barrier to data use (Goerge et al. 2021). As such, if data analysis is not prioritized by teams or made a dedicated part of an individual's job role, advanced data analysis is unlikely to happen due to competing demands (Dube et al. 2022; Lambert and Atkins 2015). Limited technology and data tools, and analytic skills within the agency present additional constraints (Goerge et al. 2021). And while external partnerships are one way for state agencies to augment data capacity (Gooden et al. 2014), building the analytical skills of existing, internal government employees is crucial and beneficial because internal employees already hold institutional and program knowledge that is critical for accurate and efficient data analyses.

State agencies working in silos and being protective of their data also hinders analytic capacity (Goerge 2018). It takes significant time and buy-in across all levels of the organization to break down those silos and promote data-sharing and integrated analyses (Hastings 2019). Finally, if the understanding and use of data is not prioritized by state and agency leaders, it is difficult for managers and staff to find the time and resources to produce advanced data analyses for program improvement (Derrick-Mills 2015). All of these barriers make evident the challenges TANF agencies face when working to build data capacity. Many states that have notable data capacity have been building and maintaining that capacity for decades. Strategies to build capacity exist and must be employed to build capacity more broadly.

The research described in this article includes original survey data and a document review to comprehensively measure what TANF agencies across the country are doing with their data—and correlate those efforts against agency data capacity, as reported by agencies and demonstrated in public documents. We identify the practices and capacities that are common to states with strong data use, but we also determine whether those characteristics are particular to those states or whether they are found at similar rates in states that struggle to use data effectively. We take a national perspective, including a study population of 43 states.

1.2.1 | Defining Exemplary Data Use

Because there is no existing empirical scholarship measuring the use of data in human service agencies, one initial challenge was to operationalize a measure of data use in human service agencies. What practices or results indicate that a state is using data effectively? In defining "exemplary data use," we began with the following assertions. These assertions subsequently guided the operationalization of the data use measure employed in this study.

First, data use by TANF departments should go beyond the production of data and regular reporting of statistics; analyses must go beyond descriptive to be evaluative as well. Data use should be in service of improving programs, better serving children and families, and building evidence. Exemplary data use is defined as the ability to use data and produce analytic findings that can directly inform program improvement.

Second, with an eye toward a commitment to evidence-based policymaking, exemplary data use includes generating high-quality analyses and being transparent and forthcoming with findings by sharing results publicly through internal channels or external partnerships. Analytic results for internal consumption only are not held to the high standard of public scrutiny, and they are not sufficient for the development of evidence-based policy across states and around the nation. For every TANF agency to independently discover what works for families would entail monstrous duplication of efforts. Thus, rigorous, widely disseminated analysis, which is often facilitated by external partnerships, is a requirement of exemplary data use.

2 | Methods

We used data from a national survey and a public document review to operationalize and classify data use in state TANF agencies across the nation. Characteristics of TANF agencies were then examined in relation to a data use score to identify what agency characteristics and practices are strongly associated with exemplary data use.

2.1 | Data Sources

The data for this analysis draws on two data sources, a national survey of TANF agencies conducted in 2019 and a cataloged review of publicly available TANF reports. These data were collected as part of the TANF Data Innovation (TDI) Needs Assessment. The TANF Data Innovation (TDI) project was launched by the Office of Planning, Research, and Evaluation (OPRE) and the Office of Family Assistance (OFA) in the US Department of Health and Human Services' Administration for Children and Families in late 2017. The goal was to accelerate the use of TANF administrative data for program improvement and evidence building at the federal, state, and local levels.[2] The national comprehensive needs assessment was conducted in 2019 to characterize the landscape of agencies' use of TANF data and understand agencies' aspirations and barriers to data use.

2.1.1 | Survey

The central component of the needs assessment was a national survey of TANF agencies that collected firsthand information about the agencies' capacities, capabilities, and current use of data. The online survey was distributed to the TANF administrators of the 54 states and territories that operate TANF. Survey data collection occurred between February and July of 2019.

To be comprehensive, the survey contained seven topic modules, focusing on different areas of TANF data usage: TANF Data Use and Opportunity, Data Collection and Documentation, Data Infrastructure, Data Sharing, Research and Analytic Capacity, Federal Reporting, and Payment Integrity. Each module was designed to be completed by the agency's subject matter expert on the topic and written to take no more than 15 min to complete. The modular design allowed us to target questions to the staff who were likely to be most knowledgeable in those topics and reduce the time burden imposed on any one staff member. Survey modules were assigned to TANF agency staff by the TANF administrator or their designee. Descriptions of the target staff for each module guided the survey assignments. Administrators were also provided with a copy of the questions contained in each module to inform the assignment process.

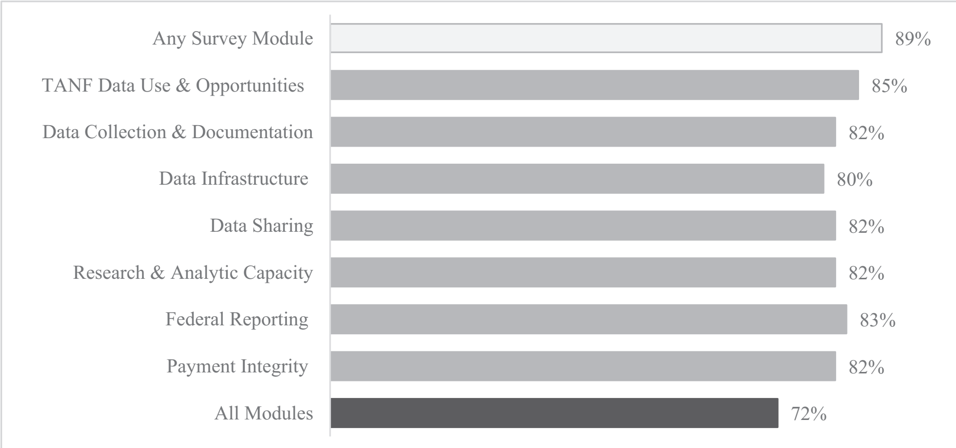

FIGURE 1 | Completion rate of needs assessment survey modules. *Note:* $n = 54$ states and territories with TANF agencies invited to participate in the needs assessment survey, of which $n = 48$ out of 54 (89%) states completed at least one survey module.

We used pilot testers with experience in TANF and human services agencies and with expertise specific to the survey topics to pilot test each survey module. We avoided using current state agency staff to avoid pilot testing with potential survey respondents.

In total, 48 out of 54 states and territories (88.9%) participated in the survey, completing at least one of the content modules (see Figure 1).[3,4] Two states declined to participate, and the remaining four states never began the survey. Participating agencies assigned staff respondents to the seven survey modules with an average of 3.7 staff (median 4) per agency and a total of 167 unique individuals completing modules.[5] Individual respondents reported their roles in the agency. The most common role was executive leadership (29%), followed by program staff (22%), reporting or data analysis (19%), and other or information technology (12%). Each respondent also indicated whether their job involved "working across multiple programs, including TANF" or "working solely or mostly on TANF." Overall, program staff tended to be most concentrated on the TANF program, while executive leadership, reporting or data analysis staff, other staff, and especially information technology staff were more likely to work across human service programs. For national findings from the survey, including how states described their barriers to and use of data in aggregate, see Goerge et al. (2021).

2.1.2 | Public Document Review

We conducted a review of public documents (such as reports and published evaluations) to complement the survey data. Data collection and coding were conducted in 2018–2019, and the gathering of public documents for review included anything published in the 5 years prior. Three staff collected documents and four staff coded documents, double-coding over 25% of documents, and a supervisor oversaw both tasks. Of the total document collection, 291 documents ultimately met coding criteria and were included in the data set.

Document collection was primarily subdivided by state or territory and search source. Sources for document collection included the websites of the state-level TANF agency or the umbrella agency containing TANF, the Department of Health and Human Services (HHS) Office of Planning, Research and Evaluation (OPRE) Self-Sufficiency Research Clearinghouse digital library, and Google Scholar. All 54 states and territories were included in the public document review, so these data are representative of all TANF state and territory agencies.

After document collection was completed, the team reviewed and coded each document. Information collected about each document included which data sources were used and how they were integrated; data collection and analysis strategies; evidence of research partnerships or collaborations that utilize state TANF data; and the level of actionable analysis available to an agency. Through the collection and coding of relevant documents into a workable data set, the public document review indexed the overall quantity and quality of *publicly available* reports and articles containing TANF data analyses for each state or territory.

2.2 | Measuring Level of Data Use

The key objective of this study was to empirically define and measure quality of data use with the data available from the needs assessment survey and public document review. These data sources give us a detailed picture of state self-reported data use as well as objective data via published examples of data use. We recognize TANF agencies have varying practices of publishing analyses on internal and external websites, and our measure of data use will favor states that have a regular practice of publishing findings. However, we posit transparency to be a key component of exemplary data use, so these indicators are useful for identifying the states with more established practices of transparency through sharing analyses and results.

As discussed above, we defined exemplary data use to include (1) the ability to use data and produce analytic findings that can inform program improvement; and (2) transparency through public dissemination of analytic findings. A state agency demonstrating data use that meets both these criteria within the constraints of state government is worth highlighting as an example for other TANF agencies.

We operationalized this definition using a 5-point scale. The scale includes three indicators from the public document review data set and two self-reported needs assessment survey items. Indicators from the public document review include:[6]

1. Any recent (5 years before data collection) publication that uses TANF administrative data in any way (1 point);
2. Any recent publication that uses TANF administrative data and includes some interpretation or analysis[7] (1 point); and
3. Any recent publication by an external partner (e.g., university, research organization, and other government entity) that uses TANF administrative data from the state[8] (1 point).

The two indicators derived from the survey data include:

1. The TANF director rated the agency as moderately or very effective in at least six of the nine following data activities: federal reporting, other regular reports, program integrity, performance management, quality improvement, data visualization, record linkage/data integration, program evaluation, and predictive analytics[9] (1 point); and
2. An employee in a research role within the agency who responded to the needs assessment survey reports that the agency completed an evaluation in the last 5 years (1 point).

We weighted each of the five components equally in the score, with 1 point where the indicator is present and 0 where it is absent. We chose to dichotomize each indicator and give each element equal weight in the final score because each element of the data use measure represents an important and distinct aspect of data use. The resulting score ranges from 0 to 5 points, with a higher score indicating stronger data use.

We examined the initial distribution of state scores to investigate the value of grouping the 5-point scale into fewer groups to create more distinct and meaningful categories of data use. Through this process, we identified three categories of data use: basic, advanced, and exemplary data users. Basic data users have score values of 0 to 2, demonstrating limited evidence of exemplary data use. These data users are labeled "basic" because the needs assessment found that most of them perform basic reporting functions. Advanced data users have score values of 3, demonstrating some evidence of exemplary data use. Finally, exemplary data users have score values of 4 or 5, demonstrating strong evidence of exemplary data use. Fifty-one percent of responding states were classified as basic data users, 21% of states as advanced data users, and 28% of states as exemplary data users under this methodology.

States were excluded from analysis if they were missing data on any of the five indicators used to construct the data use score. In a few cases, a state's score could be inferred. For example, if a state had a score of 4 but was missing information on one component, they were included in the analyses as an exemplary data user because either 0 points or 1 point on the missing item would yield a score equivalent to exemplary data use. This resulted in a final sample of 43 states for this analysis. There was no easily apparent response bias. (e.g., the excluded states did not share a political inclination and were not geographically clustered). These 43 states are therefore a reasonable representation of the United States and allow for generalizability to state TANF agencies across the nation.

2.3 | Analytic Methods

There are two analytic steps in this study: (1) measure validation and (2) descriptive comparisons of agency characteristics by level of data use.

2.3.1 | Measure Validation

Our scale of data use was created from practical and conceptual knowledge of what constitutes exemplary data use in a state agency and was developed using measures accessible from the needs assessment survey and public document review. Because this is the first empirical scale of its kind, we used multiple strategies to validate the measure and understand its strengths and limitations.

First, we compared the results of our scale against other measures in the needs assessment survey to identify how well the construct aligns with other measures expected to be heavily correlated with exceptional data use (concurrent validity). These included staff perception of data use, frequency of leadership requesting special data analysis, and frequency of reporting aggregated data. Staff perception of data use is measured with a sliding scale response from 1 to 10 to the question "How well does your agency use data?" This question was asked at the beginning of every module of the needs assessment, so every state could have a maximum of seven different responses to this question. Consequently, we considered the minimum response to this question in each state and averaged those minimum responses within each data use level. For the other two validation items, respondents indicated the frequency of aggregated reports on a scale of yearly, quarterly, monthly, and weekly. They indicated the frequency of special data analysis requests on a scale of less than once a year to more than once a month.

Second, we solicited feedback on the data use measure and independent opinions on the data use capacity of specific states from subject matter experts (SME). SMEs included scholars and policy experts from various research institutes, universities, and government agencies who had direct experience working with state TANF agencies and familiarity with agencies' analytic capacity. They participated in 30-min calls with the research team to learn about the definition and operationalization of data use as defined in this analysis. With this definition in mind, SMEs rated the states they know well as basic, advanced, or exemplary data users. Their independent ranking was compared to how states were classified by the measure used in this analysis (predictive validity). We spoke to 12 SMEs and received at least one independent evaluation of all 54 state and territory agencies, with the most-rated state receiving 10 ratings. For states that received multiple ratings from SMEs, the ratings were averaged to identify one level of data use for that state. The difference between the SMEs' and states' ratings per the data use measure was then compared.

2.3.2 | Descriptive Comparisons of Agency Characteristics

Next, we used agency characteristics as identified in the needs assessment survey to investigate which traits are highly correlated with exemplary data use. This analysis is descriptive in nature and involves comparing means and proportions across levels of data use in the agency characteristics of interest. Agency characteristics were chosen in the areas of practices, people, and infrastructure.

2.3.2.1 | Practices. Practices are assessed with items pertaining to communication and collaboration, access to integrated data, and external partnerships. Agencies indicated their frequency of communication with other entities in the state (5-point scale from none at all to a great deal) and the frequency of communication with frontline staff (3-point scale from never or rarely to frequently). Agencies also indicate the frequency with which administrators use integrated data analysis (4-point scale from weekly to yearly), the total number of integrated data sources, and the automation of data integration. Additionally, agencies described external partnerships by indicating the existence of a recent or current data-sharing agreement with an external partner,[10] their frequency of communication with external partners (5-point scale from none at all to a great deal), their comfort in sharing data, and the quality of external partnerships (3-point scale from low to high usefulness). Finally, agencies indicated the availability of financial resources for analytics on a scale of 1–10; this characteristic was used as a proxy for leadership support.

2.3.2.2 | People. Characteristics of staff are measured through staff expertise in data manipulation and program evaluation. Agencies indicated the highest level of knowledge among analytic staff in each of these topics. Response options included extremely knowledgeable, moderately knowledgeable, slightly knowledgeable, and not knowledgeable at all. If agencies do not do this type of analytic work in-house, they could indicate "not applicable." Agencies also indicated if they had at least one staff member proficient in a variety of statistical tools, including but not limited to, R, SAS, SPSS, Stata, and Excel. An indicator was created to identify states that indicate at least one staff member proficient in any statistical tool, and at least one staff member proficient in any statistical tool other than Excel.

2.3.2.3 | Infrastructure. Agencies' data infrastructure is measured through the age of the primary data system, staff access to data (e.g., ability to extract data from the data system), data documentation, and data quality processes. States were asked how long their agency had been using their current primary data system, with response options of less than 5, 5–10, 10–20, and 20+ years. Agencies also indicated if non-IT staff were able to access data directly through a variety of methods. For data documentation, states reported the level of documentation for field definitions and code values (3-point scale from not consistently documented to well-documented). Data quality is captured through states reporting the presence of the following data quality practices: manual or automatic data audits, data validation against other systems, and training staff on data entry.

3 | Results

3.1 | Scale Validation

We validated the data use score groups with items from the needs assessment that we hypothesized to be strongly correlated with exemplary data use. First, as seen in Table 1, we validated the score against individuals' perceptions of how well their agency uses data. As expected, states that are considered exemplary data users were more highly rated for data use by their staff. Exemplary data users had an average minimum rating of 5.6 compared to 4.4 in advanced data users and 4.5 in basic data users. This large increase in staff perception of data use for states receiving a rating of exemplary data users suggests the data use score is accurately measuring the construct of strong data use. In addition, we compared the data use score levels to questions about how agency leadership uses the data. Leadership in states demonstrating advanced and exemplary data use was more likely than leadership in states described as basic data users to use reported aggregated data on a weekly and monthly basis. Similarly, leadership in exemplary data use states requested special data analyses at the greatest frequency, followed by advanced and then basic data users. These comparisons again suggest that the data use score is accurately grouping states by their level of data use.

Next, we validated the measure of data use by having the 12 SMEs independently rate states as basic, advanced, or exemplary based on their professional experience and knowledge of state TANF agencies. Results showed that for 22 of the 43 states, there was no difference in the average SME rating and the state's data use score. For sixteen states, there was a difference of one rating level between the SME's score and the state's score on the data use measure. And for five states, the difference between the SME score and the data use score was two levels—the largest gap possible. This suggests that overall, the measure of data use created for this analysis is largely consistent with the experience of SMEs who have knowledge of state TANF departments. There is not total agreement, reflecting potential variability across multiple factors including SME perspective and the time period during which the SMEs worked closely with state agencies. It also suggests there are some ways our measure of data use differs from the knowledge of the field. Future research in this area should attempt to build upon and further validate this measure to ensure it best reflects the data capacity of TANF state agencies. However, for a first attempt at creating an empirical measure of data use, this measure demonstrates good consistency and external validity with SME knowledge.

3.2 | Agency Characteristics and Data Use

3.2.1 | Practices

Results show that states scoring higher on data use are more likely to report communication between analysts and frontline

TABLE 1 | Comparison of agency characteristics (as reported in the needs assessment survey) by data use score.

	Basic ($n = 22$)	Advanced ($n = 9$)	Exemplary ($n = 12$)
Measure validation			
How well agency uses data (minimum score)	4.5	4.4	5.6
Frequency of reporting aggregate data			
Weekly	10%	22%	25%
Monthly	75%	78%	58%
Quarterly	10%	0%	8%
Yearly	5%	0%	8%
Frequency of requesting special analyses			
Monthly or more than once a month	37%	11%	42%
Quarterly or more than once a quarter	32%	78%	50%
Yearly or more than once a year	21%	11%	8%
Less than once a year	11%	0%	0%
Practices			
Frequency of communication between data users and frontline staff			
Sometimes	55%	50%	58%
Frequently	5%	13%	17%
Frequency of communication with other entities in the state			
A moderate amount	20%	67%	8%
A lot/a great deal	35%	33%	92%
Integrates more than five data sources with TANF data	48%	100%	83%
Uses automated data integration	76%	89%	82%
Frequency with which administrators use integrated data analyses			
Less than once a year	10%	0%	8%
Yearly	5%	11%	8%
Quarterly	15%	0%	17%
Monthly	65%	67%	50%
Weekly	5%	22%	17%
Average comfort in sharing data (10-point scale)	5.0	4.6	6.5
Shared data externally in the past 5 years	57%	44%	67%
Data sharing agreement with partner currently exists	23%	56%	58%
Frequency of communication with external partners			
A moderate amount	25%	44%	33%
A lot/a great deal	10%	11%	33%
Quality of external partnerships			
No research conducted	35%	0%	17%
Low usefulness	30%	33%	25%
Moderate usefulness	20%	22%	8%
High usefulness	15%	44%	50%
Availability of financial resources for analytics (10-point scale)			
Data system resources (average score)	4.7	3.1	5.3
Ad hoc analysis resources (average score)	5.0	3.4	5.9

(Continues)

TABLE 1 | (Continued)

	Basic ($n = 22$)	Advanced ($n = 9$)	Exemplary ($n = 12$)
People			
At least one staff member who is moderately or extremely knowledgeable in data activities			
Data manipulation	72%	78%	83%
Program evaluation	68%	38%	83%
At least one staff member who is proficient in tools or programming language			
Any language or tool	80%	78%	92%
Any language or tool other than Excel	65%	78%	75%
Infrastructure			
Data system age			
Less than 5 years	33%	11%	18%
5–10 years	19%	33%	0%
10–20 years	19%	11%	27%
20+ years	29%	44%	55%
State has a method of querying data by non-IT personnel	57%	89%	64%
Well-documented field definitions	53%	25%	42%
Well-documented code values	57%	25%	42%
Data quality practices			
Manual or automatic data audit	91%	67%	67%
Validate against other systems	52%	56%	67%
Train staff on data entry	71%	44%	83%

Note: The sample size reported for each level of data use represents the distribution of all states in the data use score ($n = 43$). The number of states represented in a given agency characteristic can vary by 1 or 2 due to item nonresponse. All agency characteristics are derived from self-reported information from agency staff members as part of the needs assessment survey.

staff. As seen in Table 1, 75% of exemplary data users report communicating sometimes or frequently with frontline staff, compared to 63% of advanced data users, and 60% of basic data users.

Exemplary data users are also talking to other state entities (e.g., other state agencies or departments) more often. Table 1 shows that all exemplary states report communicating with other entities in the state a moderate amount or greater, with half of exemplary data users reporting a great deal of communication with other entities in the state. Conversely, 45% of basic data users only communicate with other entities in the state a little or not at all.

Access to integrated data further speaks to collaboration between state agencies. All (100%) advanced data users and 83% of exemplary data users have access to more than five integrated data sources. This is notably higher than the 48% of basic data users who report access to more than five integrated data sources. Advanced and exemplary data users are also more likely to have automated data integration processes in place. Interestingly, all agencies report similar rates of administrators using integrated data analyses quarterly or more (~85%), but advanced and exemplary data users reported higher rates of weekly use of integrated analyses.

Higher data use scores in states also correlate with high-quality external partnerships. Exemplary data users are more likely to share data and engage in external partnerships. Table 1 shows that exemplary data users are more comfortable sharing data, on average, are more likely to have shared data externally in the past 5 years, and are more likely to have a current data sharing agreement in place with external partners. Additionally, exemplary data users report greater communication and satisfaction with their external partnerships. Almost 70% of exemplary data users with external partners communicate with those partners about data a moderate amount or greater. This is compared to only 55% of advanced data users and 35% of basic data users who have external partners. States' satisfaction with external partnerships was measured through their rating of the usefulness of partnerships. Table 1 shows that a much larger proportion of exemplary and advanced data users report external partnerships that are highly useful.

Finally, we examined how leadership support—as measured through the availability of financial resources for data activities—is associated with quality of data use. Exemplary data users reported the highest average availability of financial resources for data systems and ad-hoc analyses. Interestingly, basic data users reported greater availability of financial resources than advanced data users.

3.2.1.1 | People. Staff capabilities for data manipulation and program evaluation are high both in agencies that scored as exemplary and those that scored as basic data users. Table 1 shows that while exemplary data users have the highest rate of staff who are moderately or extremely knowledgeable in data manipulation, basic and advanced data users show fairly similar rates of staff with knowledge in data manipulation (72% and 79%). For program evaluation, agencies scored as exemplary data users still have the highest rate of moderately or extremely knowledgeable staff, but basic data users have a notably higher rate of staff knowledgeable in program evaluation than advanced data users (68% compared to 36%). Regarding the use of analytic tools, agencies rated as exemplary and advanced data users reported higher rates of staff with proficiency in any statistical language or tool other than Excel.

3.2.1.2 | Infrastructure. Finally, we examined the relationship between data infrastructure and agency data use. Interestingly, the age of the data system has an almost positive relationship with the data use score. As Table 1 shows, the largest proportion of exemplary data users have primary data systems that are 20 years or older (55%), compared to 29% of basic data users and 44% of advanced data users. Conversely, basic data users were more likely to have a primary data system that is less than 5 years old. There is also no clear pattern between strong data use and having greater access to data across staff roles. As Table 1 shows, advanced data users report the highest rate of non-IT personnel having the ability to query data (89%), as compared to 64% of exemplary data users and 57% of basic data users.

Finally, there is no clear pattern between strong data use and better data documentation or data quality practices. Overall, the rate of good documentation is low, and basic data users report the highest rate of well-documented code values and field definitions (see Table 1). Regarding data quality practices, the rate of implementing data quality practices varies across data use score groups, and not always in the expected direction (see Table 1). Notably, basic data users have a very high rate of manual or automatic data auditing compared to advanced and exemplary data users.

4 | Discussion

This analysis is the first of its kind to empirically define data use in state TANF agencies and identify characteristics of exemplary data use, as reported by a nationally representative sample of state TANF agencies. This analysis does not attempt to establish causality, but it suggests new ways of thinking about what it means to use data well and how to foster data use by looking at practices across a wide range of agencies rather than focusing on case studies of high performers.

The empirical measure of state data use identified almost one-third of state agencies as exemplary data users, compared to about 20% as advanced and 50% as basic. This suggests that our approach did distinguish a group of higher-performing state agencies, and these agencies can serve as helpful models for other agencies trying to grow their data capacity in the ways measured here (e.g., communication and data-sharing). The current threshold defined as exemplary in this study demonstrates significant analytic capacity, but it is a relatively achievable threshold; over time, as states ideally continue to develop more analytic capacity, the definition of exemplary may need to change. Additionally, while this measure has not been externally validated psychometrically, it did demonstrate adequate reliability and tended to perform as expected in relation to other survey items assessing a state's use of data. Finally, in the subject matter expert validation exercise, the SMEs' ratings and states' score on the data use measure were identical just over 50% of the time; and ratings only differed by one data use level 37% of the time. This provides evidence that this first attempt at empirically defining data use has clearly distinguished different types of data use and is accurately classifying states along the data use spectrum.

Our comparison of agency characteristics and level of data use highlights the key areas where states could consider investments to improve their data use. Notably, results showed an inverse relationship between the newness of a data system and strong data use. More specifically, exemplary states were least likely to have experienced a recent data system upgrade. This suggests that investing in new data technology alone is unlikely to reap large rewards in advancing data use, especially if best practices around communication and collaboration are not implemented. The adoption of new technologies, especially those requiring significant staff time to implement, can result in operational disruptions. This can be especially true in early stages of the implementation of new technologies, which may contribute to the observed relationship (Shah 2013). To better understand the relationship between new technologies and data use, more detailed data on staff time use would be needed. We speculate, based on prior experiences with new system development in states, that significant staff effort goes into the implementation of a new system. As a result, attention to analytics, collaborations around data, and other aspects of effective data use, especially nonroutine applications, may be reduced while a new system is implemented.

Importantly, communication and collaboration around data, across departments, staff, and partners, are strengths of states demonstrating exemplary data use. This suggests that practices promoting greater communication and agency culture that values collaboration are important to facilitating effective data use. This is consistent with theories of best practices and strategies to promote data use that have been identified in the other discussions of public sector data use (Brownson et al. 2018; Lane 2018). States hoping to improve and sustain their data capacity could focus on increasing communication with other entities in the state, including frontline staff, and with external partners.

States demonstrating exemplary data use were more likely to access diverse sets of integrated data and use integrated data analyses. This suggests that transparency and collaboration across state agencies and data sources through sharing and integrating data are useful for promoting strong data use. Promoting collaboration across staff levels, teams, and agencies may increase an agency's analytic capacity.

Successful external partnerships with frequent communication between the state and the partner are also strongly associated with exemplary data use. We define a successful external partnership as one that leads to finished, published analyses; a publication with an external partner is a part of our data use score. Findings from the survey data offer insight into the types of external partners that are more likely to be successful. States with current data-sharing agreements in place with external partners and a highly communicative and satisfactory relationship with partners are more likely to leverage that partnership effectively. External partnerships are often important for programs and government agencies because they augment their analytic capacity and make advanced data analytics and publication more achievable (Yoon et al. 2018). These findings highlight that beyond just the presence of an external partnership, it is important to have a strong line of communication with partners and to ensure the partnership is mutually beneficial and satisfactory (Fallon et al. 2017). States currently engaging with external partners or considering working with external partners should consider implementing practices to ensure a working relationship that is useful to the state and the partner and has clearly defined communication expectations.

A barrier to successful external partnerships may be procurement regulations that are often burdensome and provide a disincentive to securing the most qualified external partner. Open competitions or sole-source contracts stretch the capacity of state agencies.

Leadership support—as measured by the availability of financial resources for data analytics—clearly distinguished the exemplary data users but not the advanced and basic data users. This suggests that support from leadership and financial resources is important, but not sufficient, for promoting strong data use. Because of different styles of management, analytics may be less important to a leader, resulting in smaller allocation of resources to this activity. A better understanding of how data is used and when by leadership would help specify the mechanism behind the impact of financial resources on data use.

Interestingly, a clear pattern did not emerge between staff capabilities and the level of data use. Basic and exemplary data users reported similar rates of staff expertise in data manipulation and program evaluation. Staff proficiency in statistical tools did not clearly distinguish levels of data use either. These findings suggest that while staff capabilities may affect the quality of data use, they are not sufficient on their own to support exemplary data use in TANF agencies. This is consistent with other studies showing that merely having expert staff is not always enough for building data capacity if those staff exist in silos or if there is not a broader culture of valuing data (Krishnamurthy and Desouza 2014; Lambert and Atkins 2015). Level of data use may be more related to staff time availability and support than capabilities.

The inverse relationship between age of data system and data use, in conjunction with the lack of a clear relationship between data documentation, financial resources, and data use, suggests that data infrastructure is less crucial to effective data use than the promotion of a data culture that values collaboration across teams, agencies, and partnerships. This is consistent with other research that has shown investing in technology and data infrastructure will not pay off if an established data culture is not present (Lambert and Atkins 2015).

4.1 | Limitations and Next Steps

There are limitations to this study regarding measurement and methods that warrant discussion.

First, there are likely agency characteristics that are associated with exemplary data use that were not well captured in the needs assessment. For example, the questions assessing staff skill and expertise are fairly general, leaving some ambiguity as to what staff skills actually look like in agencies. Additionally, survey data were self-reported by agency staff members who were subject matter experts for each topic, and some questions were necessarily subjective (such as the agencies' effectiveness in different data use areas). The extent to which staff responses reflect the perspective of their colleagues and agency is not observed.

Second, while this paper discusses the value and need for the greater use of administrative data to understand program participation and inform program improvement, it is critical that human service agencies use data and the associated technological tools ethically and responsibly. This will ensure that strong data use acts as a facilitator of greater inclusion and promoter of equity, rather than as a contributor of oppression and injustice in our social service systems (Eubanks 2018). Future research should examine patterns of data use to identify how data use, as defined here, relates to measures of inequality. While digging deeply into fair and equitable data practices is outside of the scope of this study, it is imperative that human service agencies use thoughtful data and technology practices to ensure accountability, equity, and transparency.

Our analysis represents a first attempt at operationalizing these concepts in data, representing one definition of exemplary data use; there are other possible ways to define the concept. While we were able to clearly distinguish some of the characteristics of the top performers, our measure had more difficulty clearly differentiating the basic and advanced levels. Our survey asked about current and recent data use. Ideally, we would measure data use over time to understand how data use changes and is impacted by investments such as the TANF Data Innovation project. A longitudinal survey, rather than a point-in-time survey that relies on recall, would better identify how agencies' data use builds or declines over time. With the current data, we are not able to speak to how characteristics may build on each other, with some providing the foundation for exemplary data use and others becoming critical only once that foundation is established. Further research into how state agencies use data should push beyond the associations identified here and toward an empirically derived road map for agencies seeking to better use data. This could involve refined measures of data use, capacity, and infrastructure; longitudinal data collection to observe trends over time; or extensions to other programs (e.g., SNAP and child care) where data use needs and capacities are likely similar.

5 | Conclusions

The results of this study highlight the importance of creating a culture of communication and collaboration in TANF agencies, developing quality external partnerships, and augmenting staff skill and capacity with an organizational structure that values and supports data analytics and transparency. Focusing on these organizational practices appears to be the most promising path to improving a state's data use.

Based on these findings, we suggest examples of strategies and practices that could be implemented to foster data use. While these recommendations are grounded in our research on TANF agencies, we believe these strategies likely apply to other human service agencies beyond TANF.

1. Encourage communication and collaboration at all phases of data use and analyses (e.g., question development, research design, and interpretation) and across different types of staff. Create opportunities for this communication, such as regular integrated meetings, shared reports, or department-wide data literacy initiatives.
2. Cultivate useful partnerships with other state agencies and external partners to complement internal agency capacity and ensure expectations around communication are clear.
3. Carefully consider the necessary capabilities when recruiting and hiring new analytic staff and leadership. Communication skills should be considered in addition to analytic skills for analytic staff; leadership hires should prioritize fostering a culture of transparency and collaboration around data.
4. Prioritize transparency and dissemination to reinforce quality, augment impact, and promote accountability.

These strategies need to be tailored to the specific needs and situations of each TANF or other human service agency, and they likely do not capture the full picture of what a given state needs. For example, some recommendations may not be feasible or need to be adjusted given the current political climate or budget constraints in an agency.

Importantly, this study highlights that certain practices are strongly associated with exemplary data use: communication and collaboration. States that actively communicate about data and analyses within and across agencies and with external partners produce more analytic work. This is consistent with what other data professionals are saying improves data use (Waller and Waller 2020). Better communication and collaboration practices can be fostered at the individual, team, and agency level, and they do not require expensive capital investments or staff training. This is an area where state agencies can pilot accessible and attainable strategies to increase the use of data and dissemination of analyses, hopefully leading to more evidence-based policymaking and program improvement for children and families.

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Ethics Statement

The MDRC Institutional Review Board (IRB #0003522) approved this study, which included the Needs Assessment Survey and research activities.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors have nothing to report.

Endnotes

[1] Data used in this study were collected from state TANF agencies, but the findings are applicable across the public sector, especially in state and local human service agencies.

[2] For more details about the TDI project, see https://www.mdrc.org/project/tanf-data-innovation#overview.

[3] We use the term "states" throughout the rest of this article to refer to both the states and the territories overseeing federally funded TANF programs as included in our study population. Due to the small number of territories, we do not distinguish respondents and nonrespondents by state and territory in efforts to avoid identifying information. Although some tribes also manage TANF programs, tribal TANF programs were not included in the study.

[4] The number of states included in this analysis is smaller ($n = 43$). Some states and all territories were excluded due to item nonresponse (see Section 2.2).

[5] In most cases, only one set of responses to each module was received from each state. In a few instances, multiple individuals from the same state completed the same module. These responses were reviewed and consolidated on a question-by-question basis (e.g., for "select all that apply" questions, any responses selected by either respondent were used for the state). Our analytic data set included only one response per state on each question.

[6] Dichotomous indicators are used rather than a cumulative count of publications in each of these categories because we acknowledge the significant barriers that exist to publishing analytic findings as a human service agency. Consequently, given our definition of exemplary data use, the ability to publish even one set of analytic or descriptive findings is indicative of strong data use.

[7] This type of publication included some form of analysis that answered a research, policy, or programmatic question, therefore moving beyond just descriptive reporting of caseload statistics. This indicator is different than the prior because it distinguishes states that publish analytic research by giving them an additional point; states only publishing caseload counts, for example, would only receive a point for indicator number (1).

[8]States receive a point for demonstrating a successful external partnership because the ability to contract and share data with an external partner, and to collaborate with them through the analysis and publication periods, demonstrates successful and strong data use through their ability to make their data usable and willingness to be transparent with the research of an external party.

[9]We first examined the distribution of this scale measuring effectiveness in data activities to identify a meaningful cut-point for the dichotomous indicator. It was important to create an indicator in which a value of 1 distinguishes the top performers in data activity effectiveness; and the current definition accomplished this distinction.

[10]This survey item was only asking about data sharing agreements in which the agency was sharing agency data with external partners.

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