As Quality Rating and Improvement Systems (QRISs) for early care and learning continue to develop and mature across states, strong data systems that can inform early learning system decisionmaking are needed. Today, most states use data systems to implement a QRIS, though these systems vary widely. More broadly, the QRIS data systems are just one piece of a bigger movement toward integrated early childhood education data systems at the state level to foster evidence-based, data-driven decisionmaking by policymakers. When used strategically, data can inform both continuous quality improvement of QRIS components and reflective decisionmaking to guide the development of models that better meet the needs of early learning providers. But data that are collected without a clear purpose in mind or a capacity to analyze them can undermine the usefulness of a data system and, ultimately, waste resources. A recent overarch- ing assessment of state-level early childhood integrated data systems noted that state agencies’ technical capacity for integrating data was
generally fine, but their ability to understand and learn from the data collected needed improvement.\(^3\)

A QRIS data system can support two kinds of goals: monitoring inputs and assessing impact. First, data systems play an important role in monitoring the fidelity with which the QRIS model is implemented. Data, such as the amount of coaching delivered, topics covered during coaching visits, QRIS staff characteristics, QRIS assessment timing, and early learning provider characteristics, enable decisionmakers to track the characteristics of providers served and the specific supports they receive.

Second, data systems can help stakeholders assess the impact of the QRIS on provider quality and, ultimately, child outcomes. Typically, QRISs collect data that let stakeholders track provider quality ratings to assess the relationship between model implementation and quality ratings. These analyses, which rely on administrative data, cannot demonstrate causal linkages between QRIS components and outcomes, but they can show whether quality improvement supports correlate as expected with quality outcomes measured in the system.

How well do QRIS staff collect and use the data? Currently, little is known about the goals that individual state or local agencies have for their QRIS data and how they actually use their data systems for monitoring or assessing impact. Potential issues range from how the front end of the data system is used for entering data (such as data element definitions, entry format, and completeness) to the extent to which the back end of the data system enables data linkage and export for monitoring and evaluation.

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This report focuses on several key challenges that the QSLA data system faces and proposes solutions to inform system leadership.

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**About This Research**

This report highlights several broad data-use lessons drawn from the RAND Corporation’s experiences as a research partner with Quality Start Los Angeles (QSLA), the QRIS in Los Angeles County. We analyzed QSLA data from 2013 through 2019 to examine trends in early learning provider QRIS tier ratings, rating component scores, Classroom Assessment Scoring System (CLASS) scores, and Environment Rating Scale (ERS) scores. We analyzed QSLA data from 2018–2020 to examine coaching and technical assistance supports. In our current partnership, we did not assess data related to child outcomes, but given QSLA goals, those outcomes are a logical next step for data system development.

We shared our findings from administrative data analyses in real time through rapid feedback memos and conversations with QSLA leaders. We aimed to address systemwide questions that QSLA staff had not yet tried to answer with administrative data. This work sheds light on the strengths and challenges of data use as the QSLA system evolves. After our data analysis, we held discussions with QSLA stakeholders about the results and the strengths, goals, and challenges in the administrative data. QSLA staff and RAND researchers then developed an inventory for administrative data improvement, which informs this report.

This report focuses on several key challenges that the QSLA data system faces and proposes solutions to inform system leadership. Even with good intent and a strong data system infrastructure, data use might not always be implemented as expected. We provide background context on the QSLA system, and share five examples of QSLA lessons learned for other QRISs or early learning systems to consider as they create or expand their own data systems. We conclude with several broader implications for QRIS data system creation and use.

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**Overview of Quality Start Los Angeles**

QSLA is a county-level QRIS that supports over 800 center-based and family child care providers serving children from birth to age five. It is one of the members of Quality Counts California (QCC), the state’s
QRIS consortia, led by the California Department of Education and First 5 California. Los Angeles County was among the earliest implementers of a QRIS in the nation, beginning in the early 2000’s with two separately operated QRISs. Through state directives and lessons learned from initial implementation of QRIS across the state, Los Angeles County created a single QRIS, and officially launched QSLA in 2016.

The QSLA consortium is made up of seven different partner organizations, which are involved in the planning, management, and implementation of QSLA:

- Los Angeles County Office of Education (LACOE)
- First 5 Los Angeles
- Child Care Alliance of Los Angeles (CCALA)
- Child360
- Los Angeles County, Child Care Planning Committee
- Los Angeles County, Office for the Advancement of Early Care and Education
- Partnerships in Education, Articulation, and Collaboration in Higher Education.

Given the consortium’s numerous partner organizations and collaborative governance structure, a high-quality data system is especially important to monitor activities and report to various local and state stakeholders. QSLA employs a multi-partner structure to govern and provide system components, including an early learning provider assessment that leads to a site quality rating, quality improvement supports that include technical assistance to help providers prepare for their assessment, ongoing coaching to support instructional improvements, professional development opportunities and financial incentives, and data systems.

The rating system is organized by tiers, adhering to the QCC Rating Matrix. According to this system, programs can receive a rating from Tier 1 to Tier 5, with Tier 5 representing the highest quality rating. Seven elements, each scored on a point system, determine the tier rating for centers (five elements are used to rate family child care):

1. child observation
2. developmental and health screenings
3. minimum qualifications for lead teacher/family child care home
4. effective teacher-child interactions (CLASS assessments)
5. ratios and group size (centers only)
6. program ERS
7. director qualifications (centers only).
Determining the goals of the QSLA data system can help drive refinements and additions to the system and help guide data-collection practices. A RAND survey of QSLA stakeholders in July 2019 identified the following three goals for administrative data use:

1. Determine the impact of coaching and assessment technical assistance.
2. Understand QSLA implementation and whether it is aligned with the intended model.
3. Monitor and supervise coaches and technical assistants.

Thus far, QSLA staff have primarily used data to monitor implementation, identify areas of highest need, and inform model changes. We sought to provide a more in-depth look at how these data might be used for examining changes in tier ratings and scores over time.

Focusing on implementation monitoring is appropriate for QSLA’s current stage of development—specifically, a few years into implementing a single QRIS model using a multi-partnership arrangement. At this stage, QSLA data users’ priorities should be to ensure data quality and usability for analysis and pinpointing where the data system can be strengthened, before moving on to outcome assessment. Taking these steps now will help later analysis be more accurate and beneficial to stakeholders. Future steps include moving toward analysis of program impacts.

QSLA leadership are willing to examine their current data practices, identify areas for improvement, and act on recommendations for change. At the same time, they recognize that a multi-county data system, over which they lack full control to adapt as needed, poses a challenge. Additional challenges are presented by the multiple partner organizations that might share the same goals, but currently enact different data practices.

For this report, we focus on the data associated with the QSLA components we initially studied: program coaching visits, assessment technical assistance, and tier rating assessment information entered into iPinwheel.
analyses were limited in sample size and not representative of all coaching visits. We also found that lack of consistent practices for entering methods and topics data prevented fully understanding what support the coach or TA provided. For example, coaches often recorded the coaching method as “other” in log entries. Discussing these findings with partner organizations revealed that some coaches recorded “other” as the method when they observed a classroom but delayed giving the provider feedback until a later visit (instead of selecting “observation and feedback” as the method). Other coaches would select the “observation and feedback” option even when they conducted only one of those activities. And still other coaches entered “other” when they used more than one method during a visit rather than entering all methods used. We also discovered that many coaches and providers reported using “coach modeling” during coaching visits, but they recorded using this approach in fewer than 10 percent of coaching logs. And even though coaches can add notes to describe their precise methods, those notes are in open-ended data fields that are difficult to analyze systematically.

**Lessons Learned at the Local Level**

We highlight five broad challenges that QSLA staff faced and associated lessons learned in developing data systems to monitor QSLA implementation and to examine longitudinal trends. We describe each lesson by identifying the issue, describing examples from QSLA experiences, and providing recommendations for addressing the identified challenges. We believe that these challenges are not unique to QSLA and that other QRISs and early learning system leaders can benefit from the lessons learned and recommendations we provide.

**LESSON 1**

**Establish Common Data Definitions and Entry Protocols for All Staff Who Enter Data**

The quality of data entered into any data system is a key factor in how useful the data are for analysis and informing implementation and model improvement. Consistent, accurate data entry facilitates answering important questions, such as whether the QRIS model is being implemented as intended, and provides a better view of the relationship between implementation fidelity and provider quality outcomes. In the first few years of the QSLA partnership, challenges arose related to the consistency with which coaches and technical assistants (TAs) defined data elements and the completeness of data entry across all staff. Discussions with partner-organization staff revealed that although data quality checks were a part of their regular monitoring, variable definitions and entry protocols sometimes differed across organizations. These differences affected systemwide data analysis, limiting staff’s ability to use existing data to fully address several intended research questions.

**Examples**

Following each provider contact, the coach or TA logs visit details such as duration, topics covered, coaching methods employed (e.g., observation and feedback, modeling, and resource sharing), and mode of contact (in person, by phone, or via email). During data analysis of an 8-month data collection period, we found substantial missing data for these elements. For example, 10–20 percent of coaching log entries were missing the topics covered or the method used by the coach during the contact. The proportions of missing data differed by partner organization, suggesting organizational differences in data-entry expectations or monitoring. The inconsistent and high rates of missing data mean that some of our analyses were limited in sample size and not representative of all coaching visits.

We also found that lack of consistent practices for enter ing methods and topics data prevented fully understanding what support the coach or TA provided. For example, coaches often recorded the coaching method as “other” in log entries. Discussing these findings with partner organizations revealed that some coaches recorded “other” as the method when they observed a classroom but delayed giving the provider feedback until a later visit (instead of selecting “observation and feedback” as the method). Other coaches would select the “observation and feedback” option even when they conducted only one of those activities. And still other coaches entered “other” when they used more than one method during a visit rather than entering all methods used.

We also discovered that many coaches and providers reported using “coach modeling” during coaching visits, but they recorded using this approach in fewer than 10 percent of coaching logs. And even though coaches can add notes to describe their precise methods, those notes are in open-ended data fields that are difficult to analyze systematically.

**Recommendations**

To improve data quality, QRIS partners should jointly develop a written guide outlining common data definitions and data entry expectations, including best practices to minimize missing data. Frontline staff should receive common training on these guides and periodic retraining as data systems are modified. Supervisors should conduct regular data quality checks and discuss any deviations with staff within and across partner organizations, as needed. QSLA leaders view data quality as a critical first step to monitoring and evaluating their model. These recommendations are currently being considered and implemented within QSLA, using feedback provided following our initial analysis of their data.
**LESSON 2**

**Make Data Usable for Ongoing Monitoring and Evaluation**

Data collection should adhere to a clear plan for how the data will be used for implementation monitoring or impact evaluation. Data in a format that simplifies analysis will increase the opportunities to evaluate known program goals as well as those that arise in the future. When data are not easy to manipulate or export for staff or evaluator use, analyses are less likely to happen in a timely manner.

**Examples**

Some of the data are entered in iPinwheel in formats that hinder their analysis. For example, data that are entered in open-ended comment fields, instead of close-ended formats such as yes/no or multiple-choice options, require substantial time and knowledge to synthesize. This oversight might result from a lack of clear strategy at the outset of the QRIS database design for monitoring and evaluation activities. As another example, each coach or TA visit log entry is supposed to include the IDs for site staff participating in the visit, such as teachers, assistant teachers, or directors. However, the staff titles associated with the staff IDs are not stored together. So, for analysis, the data output structure requires matching staff IDs to staff titles, using data stored in two separate locations. This task requires time and in-depth knowledge of the data files’ structure. If understanding how coaching and technical assistance are delivered to different staff levels is a key question, this data-linking process could be simplified by including site staff role variables in each log file. Similarly, canceled or rescheduled visits are logged in the same way that completed visits are, necessitating manual recoding to omit them from visit analyses. A simple variable could be created to indicate visit cancellation or rescheduling.

We also found several challenges related to analyzing tier rating element data. For example, the reasons a site achieved a given tier rating element score were embedded in open-ended comment fields, even though the rating matrix criteria included the reasons most-commonly used (such as the site not using a particular child assessment tool annually). Thus, using these data required time-consuming manual analysis and recoding of the qualitative comment fields, which would be onerous to perform regularly. So, although the coaches have access to this information to guide their coaching plans, it is not readily usable for systemwide assessment. Similarly, the data on which sites’ quality assessments are based are stored in at least three different locations, and cannot be connected without linking multiple files and conducting additional quality checks. As longitudinal site assessments continue, this issue will become more acute.

**Recommendations**

To enhance the usability of a data system to answer systemwide questions, QRIS administrators should minimize the amount of data entered in comment fields and create close-ended data fields with drop-down menus. Systems should be designed so that data files are linkable and data can be exported for analysis without complex manipulations. For example, for QSLA, creating a new “assessment ID” variable that identifies a given assessment and thus links all assessment and score data affiliated with that assessment period would simplify analyses. With QRIS staff turnover, efforts to streamline the data system output will reduce the learning curve for new staff to productively use data for analysis and reduce the potential loss of institutional knowledge.
LESSON 3
Ensure Data Systems Can Adapt to Partnership or QRIS Model Changes

Data systems need to be flexible to accommodate a variety of changes. Most QRIS models evolve and change as new providers are added, new funds become available for service expansion, or program evaluation leads to improvements in the design. However, decisionmakers are often interested in comparing implementation measures or program outcomes over time, which can present a challenge if different time periods had different data entry requirements.

Examples
Through analysis of longitudinal tier rating and assessment data, we uncovered several issues that limit the ability of QSLA staff or researchers to answer important questions about program quality. Key issues for QSLA have been its 2016 adoption of a new partnership model and its desire to incorporate prior QRIS data from 2012 onward from two different models and organizations. However, some of the earliest tier-rating data had not been entered in iPinwheel when the new system was implemented. Although some data could be obtained from the organization that housed them prior to 2016, these data were not available for all sites. Likewise, we discovered that the database only included the current funding source for a provider and not prior funding sources if they had changed. QSLA staff would thus have difficulty in differentiating program experiences by historical funding source.

Another limit on longitudinal QSLA analysis is that tier-rating element scoring and data-entry methods have changed slightly over time. Changes in coaching and technical assistance models can present similar challenges for data entry. As QRISs evolve, changes are expected and even desired, so long as they are data driven. Such changes are occurring within QSLA as system leaders reflect on the lessons learned from the first systemwide look at using administrative data to answer research questions. Unfortunately, because of changes over time in the QSLA structure and missing historical data, QSLA leaders have a limited ability to easily address longitudinal questions, such as changes in assessment scores and tier ratings within and across sites.

Recommendations
When setting up data collection systems, QRIS administrators should consider which data elements might vary with time (for example, the coaches or TAs interacting with providers, provider funding sources, and tier-rating element scores) and how model or system changes within and across program years might affect data interpretation. Systems should be designed to capture the multiple iterations of such time-varying variables to track the historical data. Likewise, it is vital to identify research priorities and consider decisionmakers’ needs and how they might change so that the system is strategically designed to provide that information. To the extent possible, QRIS administrators should consider ways to keep the data systems agile to allow for inevitable changes, including switches to new data systems and the migration between them to preserve data across years. Establishing clear procedures for tracking variables over time allows a QRIS to examine the effects of specific model changes on implementation and outcomes and might also avert the loss of historical data with each model change.
When Multiple Administrative Data Sources Are Necessary, Ensure That Sources Can Be Easily Linked

QRIS administrators might find that some data are not suitable to include in the central QRIS data system or that their collection is not feasible because of constraints in modifying the primary database structure. Alternatively, QRIS staff might decide that certain data would be useful as part of the overall data system, but those data have been housed elsewhere and are not entered into the central database. The existence of multiple data sources—from multiple partners and changes over time—can make ongoing evaluation more time-intensive and, in some cases, depending on data quality across the sources and linking variables, questions might not be answerable. Creating processes to link distinct data sources from different organizations enhances the potential for enhanced data use.

Examples

QSLA has a culture of ongoing data collection and use to inform their decisionmaking. But we identified some practices that impede optimal data access. Several QSLA data sources that are housed separately within respective partner organizations, but not in iPinwheel, could contribute to systemwide evaluation. For example, iPinwheel does not have fields to specifically identify which sites are new to QSLA in the current fiscal year or to identify sites’ assessment technical assistance cohort (that is, the sites receiving TA support at a specific time period). Staff and evaluators need these variables to assess potential differences in timing or levels of support received. iPinwheel also does not include the incidence of a site’s requests for a tier-rating clarification or a site’s request for a technical review to challenge their rating. Some partner organizations maintain these data, but linking the information to iPinwheel exports on request would require manual effort and create additional staff burden.

Some data efforts are duplicated across iPinwheel and other data sources. This is because QSLA partners sometimes find iPinwheel ineffective for storing or reviewing data for their day-to-day implementation monitoring needs (such as generating quick reports for specific aspects of coaching support). As a result, staff create their own spreadsheets using their own data manipulations, even though the data are already in iPinwheel. Moreover, when QSLA staff enter provider-level contact information into iPinwheel, this information might not be kept up to date, thus contradicting the contact information maintained by the partner organizations themselves. Therefore, systemwide questions or evaluation activities that require contact information, such as identifying the current teachers at a site or email addresses for survey mailing, cannot rely on iPinwheel.

Recommendations

Where possible, QRIS database designers should attempt to minimize the burden of duplicated data sources or the creation of additional administrative data systems within the QRIS that need to be linked. Interviewing users about the reasons they create workarounds will help pinpoint the problems. If multiple data sources are necessary, the next step is to establish good data-linking practices, such as a common set of identifiers that all data sources must maintain to enable easy merging of datasets. Within QSLA, adding fields to iPinwheel for data elements that are part of ongoing evaluation, such as technical assistance cohort and tier-rating technical review status, would minimize reliance on different administrative sources and support data quality across partners. Creating automatic linkages to existing workforce registry data would also reduce QRIS data burden and duplication and would ensure the accessibility of useful data for QRIS evaluation.
LESSON 5

Ensure Data Systems Can Connect Quality Improvement Supports to Outcomes

Ultimately, QRIS leaders want to know whether their quality improvement models are improving provider quality. To enable this analysis, data systems must be able to link model components—such as coaching or technical assistance—to such outcomes as tier ratings or classroom assessment scores. This linkage requires advance preparation to identify the key goals for data use and research questions of interest and ensure that the data system is built to address them. As we discussed earlier, early learning program quality questions are not answerable if the appropriate data are not collected intentionally and in an ongoing manner.

Examples

One of QSLA leadership’s goals for data use is to determine the impact of coaching on program quality. However, this question cannot be answered directly with the administrative data available. For example, QSLA stakeholders would like to know which coaching supports relate to CLASS score improvements, particularly improved teacher-child interactions. Addressing this question requires data on specific coaching session foci, methods, time spent, and CLASS scores. Current data fields do not fully capture the content of coaching sessions and the identified needs of each classroom. Only a portion of QSLA classrooms have an external CLASS observation each year that can be used to guide classroom quality improvement plans. Furthermore, administrative data cannot easily capture all the nuanced and qualitative characteristics needed to relate QSLA strategies to outcomes of interest. However, QSLA partners can identify the hypothesized mechanisms that lead to change (e.g., an in-depth focus on a specific CLASS topic or the strength of the coach-provider relationship) and work toward ensuring the data system records more of those mechanisms.

QSLA stakeholders also would like to understand how coaching is delivered to different staff members (e.g., lead teachers versus assistant teachers) and potential effects on quality improvements. Earlier, we discussed some challenges related to tracking staff who receive support, which hampers the ability to address this question. Similar constraints apply to tracking how coaching is specifically tailored to classroom needs, as we noted previously, for understanding the full content of visits and the targeted needs of different classroom staff. Nevertheless, the QSLA data system does capture the quality improvement plan goals and action steps for each classroom and whether those action steps were completed. Thus, QSLA stakeholders need to consider which aspects of the quality improvement plan data might be useful to analyze to produce actionable results at the system level. The QSLA database should capture those elements. For instance, do certain action steps related to improving teacher-child interactions tend to move the needle on average CLASS scores?

Recommendations

QRIS administrators should design data systems to address key goals and answer the questions of greatest interest. But those questions might also be the most complicated to answer and require additional data entry and analysis. In some cases, an administrative data system for implementation monitoring might not be sufficient to answer impact questions. QRIS leaders should seek to understand and support the staff effort needed to maintain good data and the ability to analyze the data collected on an ongoing basis. Having a clear sense of the key questions to explore with administrative data will help to design the system appropriately for the intended use and minimize unnecessary effort. For example, to understand the effectiveness of coaching efforts, QRISs might need to consider adding data fields that can capture a more detailed set of quality improvement goals and action steps for each classroom. They should also consider conducting regular external observations in all classrooms to guide quality-improvement planning and assess changes in classroom quality.
Implications and Future Directions

As QRIS stakeholders continue to implement data systems, the QSLA experience using its data system for implementation monitoring offers several implications for other QRIS leaders to consider. These include the need to

- **Plan ahead:** QRIS leadership and partners should think ahead to how they want to use and report the data—both for implementation monitoring for continuous quality improvement and for long-term impact analysis. High-quality data are beneficial and worth the investment only if they are strategically used.

- **Reach agreement on—and periodically revisit—goals for data use:** Stakeholders should find agreement on the policy and practice questions that the QRIS data should consistently be able to answer. Questions must be prioritized because database creation and maintenance and staff time to collect, maintain, and monitor data entry quality are costly. Also, QRIS administrators should revisit the goals periodically to modify a goal or implementation strategy using the data already collected via the QRIS.

- **Continue data quality monitoring:** Continue periodic review of data entry quality to ensure accuracy and consistency. Reinforce good data-entry practices among users to minimize missing data to improve the usefulness of the QRIS for continuous quality improvement and eventual impact evaluations.

- **Centralize key data elements in one system or provide data linkages:** Although housing all data in one system can provide efficiencies in data analysis and staff training, it might not always be feasible. If multiple data sources are necessary, maintain identifiers in each dataset that make it possible to link data across databases. This will allow users to make more use of the data.

- **Provide adequate staff time:** QRIS budgets should account for the time needed for initial and ongoing training for staff on data entry quality and provide adequate time in their staffing models for both data entry and supervisor monitoring. Staff who do not have adequate training and time for data entry are not likely to produce high-quality data.

- **Maintain historical data:** Make sure that data elements are captured consistently over time, as this will facilitate longitudinal analysis.
Notes

1 According to the BUILD Initiative’s Quality Compendium website, which provides details on QRIS components, 43 of 44 QRISs report using a data system. BUILD Initiative, “Quality Compendium,” webpage, undated. As of May 15, 2020: http://www.qualitycompendium.org


3 Sirinides and Coffey, 2018.


About This Report

Quality Start Los Angeles (QSLA) is a county-level quality rating and improvement system that supports center-based and family child care providers serving children from birth to age five. The RAND Corporation conducted a developmental evaluation focused on three QSLA components: program coaching, assessment technical assistance, and quality tier rating perceptions. Through the course of this work, researchers identified strengths and challenges with the QSLA data system that are the focus of this report.

The study was undertaken by RAND Education and Labor, a division of the RAND Corporation that conducts research on early childhood through postsecondary education programs, workforce development, and programs and policies affecting workers, entrepreneurship, and financial literacy and decision-making. This study was commissioned by First 5 Los Angeles.

More information about RAND can be found at www.rand.org. Questions about this report should be directed to cannon@rand.org, and questions about RAND Education and Labor should be directed to educationandlabor@rand.org.

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