



EVALUATION OF ELECTRONIC CASE REPORTING

The Evaluation Center | Western Michigan University
March 2026

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Terminology

The following abbreviations and acronyms are used throughout this report.

AIMS – APHL Informatics Messaging Services platform

APHL – Association of Public Health Laboratories

CDC – U.S. Centers for Disease Control and Prevention

CDPHE – Colorado Department of Public Health and Environment

CSTE – Council of State and Territorial Epidemiologists

eCR – Electronic case reporting; refers to the process and data being studied

eICR – Electronic initial case report; refers to the individual reports transmitted by the eCR system

EHR – Electronic health record; broadly refers to any electronic patient data system or record

ELR – Electronic laboratory report; refers to data automatically transmitted from a Laboratory Information Management System (LIMS) to a public health agency.

EMSA – Electronic Message Staging Area

HCO – Health care organization

“In production” – General terminology used by some PHAs to denote data that is being received and processed into a PHA’s surveillance data system

IT – Information technology

NBS – National Electronic Disease Surveillance System Base System; a CDC-developed information system for public health departments to manage reportable disease data and send notifiable disease data

PHA – Public health agency

PPV – Positive predictive value

RCKMS – Reportable Conditions Knowledge Management System

STLT – State, Tribal, local, and territorial

SQL – Structured Query Language; a standardized programming language used with relational databases

UTDHHS – Utah Department of Health and Human Services

WMU – Western Michigan University; refers to the study team based at The Evaluation Center

Acknowledgments

The authors would like to thank the following individuals for their assistance with this project, including providing information, data, guidance, and feedback, as well as analysis and reporting.

- Brandi Campbell, Belay Consulting
- Julia Aiken, Colorado Department of Public Health and Environment
- Rebecca Sandahl, Colorado Department of Public Health and Environment
- Annie Fine, Council of State and Territorial Epidemiologists
- Devra Barter, Council of State and Territorial Epidemiologists
- Gillian Haney, Council of State and Territorial Epidemiologists
- Shaily Krishan, Council of State and Territorial Epidemiologists
- Kata Chillag, Davidson College
- Rebecca Berger, Florida Department of Health
- Shelby Fawaz, Florida Department of Health
- Jacqueline Cassman, Minnesota Department of Health
- Anna Lintelmann, Minnesota Department of Health
- Siobhan O'Toole, Minnesota Department of Health
- Sripriya Rajamani, Minnesota Department of Health
- Sarah Solarz, Minnesota Department of Health
- Kristen Merrell, Montana Epidemiology and Scientific Support Bureau
- Angela Herbert, Nebraska Department of Health and Human Services
- Fnu Kanishka, Nebraska Department of Health and Human Services
- Chelsie Lee, Nebraska Department of Health and Human Services
- Vince Rea, Nebraska Department of Health and Human Services
- Amie Wu, Nebraska Department of Health and Human Services
- Laura Conn, U.S. Centers for Disease Control and Prevention
- Melinda Thomas, U.S. Centers for Disease Control and Prevention
- Teri Bills, Utah Department of Health and Human Services
- Rachelle Boulton, Utah Department of Health and Human Services
- Janelle Delgadillo, Utah Department of Health and Human Services
- Alina Paegle, Utah Department of Health and Human Services
- Eric Walls, Utah Department of Health and Human Services
- John Akwetey, Western Michigan University
- Cecelia Chapleau, Western Michigan University
- Rob Lyerla, Western Michigan University
- Valerie Marshall, Western Michigan University
- Brad Watts, Western Michigan University (study lead)
- Lori Wingate, Western Michigan University (study lead)

Executive Summary

This report presents the results from a two-phase study examining the quality of electronic case reporting (eCR) data and the utility of eCR data to state, Tribal, local, and territorial public health agencies (PHAs) in the United States. The study was conducted by a team at The Evaluation Center at Western Michigan University, in collaboration with CSTE, and with input from the U.S. Centers for Disease Control and Prevention.

A quantitative approach was employed to evaluate eCR data quality based on four key performance measures: completeness, timeliness, sensitivity, and positive predictive value (PPV). Using a three-month sample of data on a set of lab-diagnosed conditions (syphilis, gonorrhea, and hepatitis C) from two participating PHAs, eCR data were collected, assessed, and compared with electronic lab reports (ELRs) to demonstrate relative quality. The findings suggest that eCR data exhibits high overall quality that is similar to ELR data. Both eCR and ELR data exhibited high levels of completeness across the 25 examined data elements. The timeliness assessment found that at least half of all electronic initial case reports (eICRs) arrived within minutes of the corresponding ELR; however, the proportions arriving earlier or later varied across the two participating PHAs. The examination of sensitivity showed that eCR sensitivity was high and ELR sensitivity was essentially universal. Finally, PPV of eCR data varied by condition but was high overall at 74.5% across the three conditions.

A qualitative approach was used to explore the utility of eCR data to PHAs. Staff from six PHAs across the United States participated in virtual group interviews with the WMU study team. A semi-structured interview protocol was used to guide the participants through discussions of how they intake and use eICRs, how eCR data compares to data from ELRs or manual reports, how their PHA uses eCR data, the impact of eCR, and future plans for eCR data implementation and use. The transcripts from these sessions were coded by two members of the study team and analyzed to identify common themes related to the utility of eCR data. The findings from the qualitative analysis suggest that although many of the PHAs who participated were not yet fully integrating eCR data into their surveillance systems at the time the interviews were conducted in 2024, they had at least begun using eCR as a supplemental source of data for case investigations. Furthermore, the interviewees agreed that the quality of eCR data was high and provided a more complete description of an individual's disease experience than ELRs or manual reports. They noted that the richness of eCR data helped their case investigations and indicated that it had helped epidemiologists in their PHA to identify cases that may not have otherwise been caught.

Overall, this report aims to contribute to the growing body of knowledge regarding eCR data quality and utility. The findings generally indicate that eCR data is of similar or higher quality and utility than ELR data. However, readers should also consider the study's limitations, particularly the small sample size, which stems from a limited number of PHAs.

Background

What is eCR?

Electronic case reporting (eCR) is a process for the automated exchange of information from health care organizations (HCOs) to public health agencies (PHAs) as part of their public health reporting requirements. eCR is intended to be a faster, easier, and more complete way of sharing information than traditional public health reporting methods, such as manual reporting. It is part of the U.S. Centers for Disease Control and Prevention's (CDC) broader data modernization effort.¹

The eCR process involves operations across HCOs, electronic health record (EHR) IT vendors, and PHAs. When a provider at an HCO enters information on conditions, lab results, or other criteria, it is then processed through the APHL Informatics Messaging Services (AIMS) platform. If the data meet decision criteria in the Reportable Conditions Knowledge Management System (RCKMS), a report will be automatically generated and sent to the relevant PHA.² The individual messages transmitted are referred to as electronic initial case reports (eICRs) and contain a standard set of data elements established by HL7 (2025).

Currently, state, Tribal, local, and territorial (STLT) PHAs across the country are at different stages of eCR implementation. PHAs that are receiving eCR data may be at different stages of implementation, with some placing eICRs into a test environment and still relying on ELRs and manual reports to inform surveillance. Other PHAs are in production with eCR and actively bringing data from the eICRs they receive into their surveillance systems. In many cases, the level of implementation varies by condition.

Study Background

In 2023, with support from the CDC, the Council of State and Territorial Epidemiologists (CSTE) issued a request for proposals to identify an evaluation consultant to collaborate on an evaluation as part of a long-term examination of the quality and utility of eCR. Through a competitive proposal process, CSTE selected a study team based at The Evaluation Center at Western Michigan University (WMU). The stated purpose of the study was to evaluate the performance of eCR relative to existing processes for transmitting public health information, including electronic lab reports (ELRs) and traditional manual reports (i.e., reports transmitted via mail, fax, email, phone, or manual-entry web-based portals). However, manual reports were not included in the report due to a lack of availability from PHAs that participated in the study.

This team worked closely with CDC and CSTE to develop evaluation questions, identify suitable indicators for assessing quality, define a data sample appropriate for measuring outcomes, and recruit

¹ For more information on eCR, see <https://www.cdc.gov/ecr/php/about/index.html>

² For more information on RCKMS, see <https://www.rckms.org/about-rckms/>

STLT PHAs to participate in the study. The result was a two-phase study relying on quantitative methods to examine data quality and qualitative methods to examine data utility.

Prior eCR Studies

As the first step of the study, the WMU team conducted a scoping review to understand the extent and nature of existing research on eCR (Marshall et al., 2023). The 14 articles originally included in the scoping review provided background on how eCR has been assessed in other contexts and informed the development of this evaluation study. Since that review was completed in 2023, eight additional articles have been published. Of the 22 identified articles about eCR published between 2018 and 2025, nine are non-empirical commentaries or descriptive accounts of the status or potential benefits of eCR (not discussed here due to limited relevance to the present study).

Thirteen empirical studies examined various aspects of eCR, including data quality, cost, implementation, and ability to detect additional disease cases. Of particular relevance to the present study's evaluation of eCR data quality, seven studies (Conn et al., 2025; Digital Bridge, 2019; Mishra et al., 2019; Mishra et al., 2023; Rajamani et al., 2022; Todd et al., 2022; Whipple et al., 2019) measured eCR data completeness, and four studies (Conn et al., 2025; Mishra et al., 2023; Rajamani et al., 2022; Whipple et al., 2019) assessed timeliness as a dimension of data quality.

Six of the seven studies that addressed completeness used some variant of the percentage of data present in a data element as a measure of the concept. Where the studies differed was in the type, selection process, and number of data elements that were analyzed. For example, Mishra et al. (2019) calculated completeness for only medications and patient contact information, while Digital Bridge (2019, p.38) assessed 24 data elements "classified as required by epidemiologists to initiate case investigation." In each instance, the study authors employed their own methodology to select a subset of eCR data elements for analysis, and none calculated the completeness of all data elements. Three studies took an alternative approach by examining the number of data elements provided by eCR as a measure of completeness (Mishra et al., 2023; Todd et al., 2022; Whipple et al., 2019).

The completeness studies generally reached similar conclusions, indicating that eCR data were highly complete across most or all of the data elements examined. One exception was found in the study by Rajamani et al. (2022), which reported moderately low completeness for the ethnicity and email contact data elements in eICRs from select HCOs; however, completeness was high for the other examined data elements. To provide a basis for understanding the relative level of completeness, most studies also calculated completeness for data elements in ELRs, which were compared with eCR data. Only Conn et al. (2025) measured completeness for manual reports and compared the results with ELR and eCR data. Their study used data from a sample of reports provided by the Florida Department of Health and found that completeness levels for two data elements, race and ethnicity, were high for eCR data and only slightly greater than a matched group of ELRs, but noticeably higher than matched manual reports.

Timeliness was examined in four studies, each of which used different measures. Three studies looked at timeliness through the lens of transmittal time. Rajamani et al. (2022) measured timeliness as the time it took for a report to transmit from an HCO to a PHA. That study found eICR transmittal was nearly instantaneous relative to manual reports or ELRs, which were mostly sent in batches on a

delayed schedule. Mishra et al. (2023) defined timeliness as the difference between the time of the patient's encounter at an HCO and the time when the PHA received the resulting report. The authors found that the duration was shorter for eICRs than ELRs. Conn et al. (2025) measured timeliness comparatively by calculating the mean and median differences in transmission timestamps between a sample of eICRs and corresponding matched ELRs, as well as between a sample of eICRs and corresponding matched manual reports. They found that nearly all eICR transmission times were earlier than the matched ELRs or manual reports—99% and 98%, respectively. The examined eICRs had mean and median transmittal times that were several hours earlier than matched ELRs. However, relative to manual reports, the difference was several days, which could impact the response speed of public health investigations.

Whipple et al. (2019) used a time study approach, conceptualizing timeliness as encompassing the processing time necessary to prepare, submit, and respond to the information in a report. The authors measured the average time it took individuals to submit a report to public health and the average time required for the PHA to investigate and close a case. Their results indicated that eCR reduced the time required for both steps of the process.

The remaining nine empirical studies on eCR published between 2018 and November 2025 included the following:

- Four studies examined trigger compliance (Digital Bridge, 2019; Dixon et al., 2019; Mishra et al., 2019; Mishra et al., 2023). They all found that eCR successfully identified and transmitted eICRs based on the reporting rules.
- Two economic evaluations focused on the cost of implementation. A study examining implementation among multiple early adopters found large variations in the estimates of eCR expenses (Digital Bridge, 2019). Another study that focused on a single university health center concluded that the savings realized from adopting eCR would cover its costs in less than five years (Hartsell et al., 2024a).
- Two studies (Creswell et al., 2025; Flattery et al., 2023) examined eCR's value in terms of identifying additional cases of occupation-related lung diseases (asbestosis, farmer's lung disease, and silicosis) not identified through other means.
- The one study that focused on the barriers and facilitators associated with eCR implementation revealed the importance of the non-technical aspects of eCR (Hartsell et al., 2024b).

Evaluation Questions

In collaboration with CSTE, the study team reviewed the literature and identified two key evaluation questions:

- (1) **What is the quality of eCR data?** The purpose of this question is to collect evidence of eCR's quality and effectiveness as a reporting system. The four dimensions of quality assessed in this study include data completeness, timeliness, sensitivity, and positive predictive value (PPV). This question was addressed through quantitative methods.
- (2) **What is eCR's utility to PHAs?** The purpose of this question is to learn how PHAs use eCR data and their perceptions of eCR's utility. This question was addressed using qualitative methods.

Part 1: What is the Quality of eCR Data?

The quality of eCR data was measured through quantitative methods focusing on four indicators: completeness, timeliness, sensitivity, and PPV. These indicators each address specific aspects of data quality and may be used to provide a relative comparison of eCR data with ELR received at a PHA. Table 1 provides definitions of how the completeness, sensitivity, timeliness, and PPV indicators were calculated.

Participating Sites

CSTE notified PHAs about the opportunity to participate in the evaluation during monthly CSTE eCR Workgroup meetings, which are attended by a variety of individuals working on eCR implementation across the U.S. Any PHA that initially expressed interest was provided with a document listing participation criteria, which included requirements such as receiving eICRs and ELRs, collecting timestamps for report receipt, the ability to provide line-level data, and ingestion and use in surveillance to calculate sensitivity and PPV measures.³ The participation criteria also originally requested that PHAs provide information from manual reports; however, the criteria was dropped when no PHAs indicated that they were able or willing to share manual report data. Ultimately, two recruited PHAs were willing and able to supply the quantitative data necessary to evaluate eCR data quality in this study: the Colorado Department of Public Health and Environment (CDPHE) and the Utah Department of Health and Human Services (UTDHHS). The data provided by each PHA varied due to differences in their level of eCR implementation. CDPHE provided data on completeness and calculated timeliness using guidelines set by the study team. UTDHHS provided data for completeness, sensitivity, calculated timeliness, and positive predictive value (PPV).

Data Collection and Analysis Procedures

The study team collaborated with CDC, CSTE, CDPHE, and UTDHHS to determine appropriate analysis measures and to select suitable samples of data elements and disease conditions for the analysis. To provide a comparative basis for assessing eCR quality, ELRs were identified as the most relevant alternative format for transmitting data on reportable conditions from healthcare providers and laboratories to PHAs, as mandated by state regulations. Manual reports from providers, which are received through mail, fax, email, phone, or entered manually into web portals, were not available from the participating sites for this analysis.

Data from a three-month sample period (May 1 to July 31, 2025) of eCR and ELR data was requested for three conditions: syphilis, gonorrhea, and hepatitis C. These conditions were selected in consultation with CSTE because they have a high report volume, require laboratory testing (making ELRs reliably available), and were seen as notable surveillance conditions by CDPHE and UTDHHS.

³ See Appendix C for the original participation criteria document.

The WMU Institutional Review Board reviewed the research and data-sharing plan and formally confirmed that no additional modifications or ongoing review were necessary. Additionally, the formatting of the data was tailored to adhere to various state rules regarding privacy and data disclosure in Colorado and Utah, which were formalized in data-sharing agreements as necessary to meet the requirements of each PHA.

To calculate completeness, each PHA provided line-level data containing extracts of 25 selected data elements⁴ for all ELRs and eICRs received during the three-month sample period. UTDHHS provided data on syphilis, gonorrhea, and hepatitis C, totaling 18,940 reports, including 12,965 eICRs and 5,975 ELRs. CDPHE provided data on syphilis and gonorrhea, totaling 46,732 reports, including 28,065 eICRs and 18,667 ELRs. To adhere to their respective state regulations regarding data privacy and confidentiality, both CDPHE and UTDHHS recoded all extracted data elements with a “1” to signify that the data element contained data meeting validity criteria, a “0” to indicate invalid data, or a “999” to indicate that the data element was blank, prior to its delivery for this analysis. The validity criteria are described in Appendix D. The study team calculated completeness using the Stata statistical software package, using the recoded, individual-level data from reports during the study period.

Chi-square tests for independence were performed to test whether the completeness values in Tables 2-6 were due to statistically significant differences. For the purpose of this report, chi-square statistics with a resulting *p*-value of less than 0.05 were defined as representing a significant difference in the distribution of the completeness values being compared. Most differences in the distribution of completeness categories were statistically significant, which is also a function of the large number of reports in each analysis sample. Tables with all chi-square and the associated *p*-value results are in Appendix A.

UTDHHS and CDPHE calculated timeliness by determining the portion of eICRs arriving before the first corresponding ELR and the average time difference. Raw time-related data could not be shared with the study team since timestamps are considered personally identifiable information. Aggregate timeliness indicators were instead provided to the study team.

Sensitivity was calculated by UTDHHS using data from reports submitted by providers and labs that had already been onboarded and recognized as eCR-capable. Reports from HCOs not onboarded to eCR were excluded to avoid biasing the sensitivity calculations towards ELR. The sensitivity data included 310 confirmed or probable cases determined within the three-month period: 116 gonorrhea cases, 55 syphilis cases, and 139 hepatitis C cases.

PPV was also calculated by UTDHHS. The calculations were made based on case determinations made during the three-month study period using reports received by the PHA during the previous three months. Additionally, because UTDHHS rules mandate the generation of reports for both negative and positive STI tests, the analysis sample was limited to only reports generated from positive results. The purpose of using only reports generated from a positive lab test was to prevent the large number of negative test results from artificially decreasing the PPV for these conditions.

⁴ Common names for the requested data elements are listed in the results tables, starting with Table 2.

According to UTDHHS staff, negative test results cannot be used to determine a case as confirmed or probable; however, they serve other purposes for public health monitoring.

Table 1. eCR Evaluation Calculations

	Completeness	Sensitivity	Timeliness	PPV
Definition	The degree to which selected data elements within a set of reports are populated with valid information.	The degree to which a report identifies cases later determined through public health investigation to be confirmed or probable. Sample is limited to onboarded HCOs only and excludes nonlocal cases. ⁵	Relative speed at which data moves from a health provider's electronic health record to a public health agency for eCR compared to ELR.	Likelihood that an eICR is associated with a confirmed or probable case of a specific disease or condition.
Numerator	Number of eICR/ELRs in the sample that contain information in the data element meeting the PHA's validity criteria. ⁶	• Data point A: number of confirmed and probable cases with a corresponding eICR for a given condition • Data point B: number of confirmed and probable cases with an ELR for a given condition • Data point C: number of confirmed and probable cases with an eICR and corresponding ELR for a given condition	Number of eICRs received by the PHA before the corresponding ELR based on the timestamp corresponding with the first time of entry into the PHA's surveillance database.	Number of de-duplicated eICRs adjudicated in the timeframe of analysis by the PHA to be a confirmed or probable case. ⁹
Denominator	Number of eICR/ELRs in the sample.	Number of confirmed and probable cases for a given condition (from onboarded HCOs only).	Number of potential cases ⁷ with both an eICR and ELR.	Number of de-duplicated eICRs received for the condition during the preceding three months of analysis.

Findings

The study findings related to each quantitative indicator of data quality are presented in this section.

⁵ Onboarded HCOs are those that can transmit via eCR as recognized by UTDHHS based on their standards at the time. Non-local cases are those where the individual resides outside of the PHA's jurisdiction.

⁶ Validity criteria for the recoding of each data element are provided in Appendix C.

⁷ Potential cases are reports that have been received but not yet investigated.

Completeness

Table 2 shows the completeness by data element for eICRs and ELRs for CDPHE and UTDHHS.⁸ The completeness calculation represents the percentage of all reports received, except for the pregnancy indicator data element, which is limited to reports for females aged 12 to 50. Overall, most data elements exhibited very high levels of completeness (i.e., greater than 90%).

It should be noted that even small differences between report types were usually statistically significant⁹ due to the large sample sizes. The complete results of the significance tests are provided in Appendix A.

Table 2. eCR and ELR Completeness Comparison

Data Element	CDPHE		UTDHHS	
	eCR (n=28,065)	ELR (n=18,667)	eCR (n=12,965)	ELR (n=5,975)
Patient ethnicity	94.1%	73.2%	88.1%	99.1%
Patient race	85.4%	48.8%	84.2%	98.4%
Patient area code	97.0%	-	95.0%	96.0%
Patient phone no.	97.0%	75.0%	95.6%	96.0%
Patient street	95.2%	91.4%	91.4%	88.7%
Patient city	99.7%	96.8%	99.9%	98.1%
Patient state	99.7%	96.8%	99.9%	98.2%
Patient zip code	99.6%	96.2%	99.8%	98.1%
Facility name	99.9%	99.9%	100%	100%
Facility street	99.6%	88.6%	95.1%	97.9%
Facility city	99.9%	93.0%	100%	99.9%
Facility state	99.9%	93.0%	100%	99.9%
Facility zip code	99.9%	93.0%	100%	99.6%
Lab name	99.4%	100%	100%	100%
Reference range	-	78.0%	35.2%	69.9%
Specimen source	76.0%	24.1%	83.0%	100%
Specimen type	-	91.6%	-	-
Test name	97.6%	100%	99.9%	100%
Observation ID	100%	100%	98.9%	51.9%
Result	100%	100%	100%	100%
Test status	100%	100%	100%	100%
Admission date	97.7%	-	100%	42.2%
Discharge date	93.7%	-	61.7%	26.6%
Report Date	99.9%	100%	100%	100%
Pregnancy ind.	-	-	29.5%	-

Notes: “-” indicates the data is missing because the information was not collected or was not available for that report type. In the CDPHE data, patient area code was included in the patient phone number data element. Reference range information at CDPHE is qualitative and does not provide a numeric range. In eCR data, specimen source is coded with both source and type information, while ELR data stores specimen information into both source and type. CDPHE did not ingest admission and discharge information from ELR at the time of the study. Pregnancy status is calculated only for females aged 12-50, n=2,882.

⁸ Data elements in CDPHE and UTDHHS data were matched based on variable description.

⁹ Based on chi-square tests for independence and a standard of p<0.05.

Table 3 summarizes the completeness of data elements in CDPHE's eCR data by condition. Overall, completeness was high across all data elements and conditions. The largest difference between conditions was in the specimen source data element, which was significantly lower in reports for syphilis than for gonorrhea. According to CDPHE, the difference in specimen source completion is largely due to how the specimen for each test is collected.

Table 3. CDPHE eCR Completeness by Condition

Data Element	Gonorrhea (n=4,805)	Syphilis (n=23,260)
Patient ethnicity	92.0%	94.5%
Patient race	86.1%	85.2%
Patient area code	99.4%	96.6%
Patient phone no.	99.4%	96.6%
Patient street	99.9%	99.7%
Patient city	99.9%	99.7%
Patient state	99.9%	99.7%
Patient zip code	99.8%	99.7%
Facility name	99.9%	99.9%
Facility street	99.9%	99.9%
Facility city	99.9%	99.9%
Facility state	99.9%	99.9%
Facility zip code	99.9%	99.9%
Lab name	99.9%	99.9%
Reference range	-	-
Specimen source	99.4%	71.2%
Specimen type	-	-
Test name	98.5%	97.5%
Observation ID	100%	100%
Result	100%	100%
Test Status	100%	100%
Admission date	98.0%	97.6%
Discharge date	96.6%	93.1%
Report Date	99.9%	99.9%
Pregnancy ind.	-	-

Notes: "-" indicates the data is missing because the information was not collected or was not available for that report type. Specimen source is coded with both source and type information.

Table 4 summarizes completeness by data element for ELR in CDPHE's data. It should be noted that eCR had a greater number of data elements available than ELR; therefore, no completeness is reported for the admission date, discharge date, and report date data elements. Most completeness levels are similar across conditions, except the patient race and specimen source data elements, which were notably lower in the syphilis ELR reports.

Table 4. CDPHE ELR Completeness by Condition

Data Element	Gonorrhea (n=1,311)	Syphilis (n=17,356)
Patient ethnicity	61.8%	74.1%
Patient race	77.0%	46.3%
Patient area code	-	-
Patient phone no.	74.6%	75.1%
Patient street	94.9%	91.2%
Patient city	97.9%	96.7%
Patient state	97.9%	96.7%
Patient zip code	97.9%	96.0%
Facility name	100%	99.9%
Facility street	87.4%	88.7%
Facility city	96.4%	92.7%
Facility state	96.4%	92.7%
Facility zip code	73.5%	61.8%
Lab name	100%	100%
Reference range	72.7%	78.4%
Specimen source	60.6%	21.4%
Specimen type	95.0%	91.4%
Test name	100%	100%
Observation ID	100%	100%
Result	100%	100%
Test Status	100%	100%
Admission date	-	-
Discharge date	-	-
Report Date	100%	100%
Pregnancy ind.	-	-

Notes: "-" indicates the data is missing because the information was not collected or was not available for that report type. Patient area code is included in the patient phone number element in CDPHE data. Reference range information is qualitative in CDPHE and does not provide a numeric range. Specimen source is coded with both source and type information. CDPHE did not ingest admission and discharge information from ELR at the time of the study.

Table 5 summarizes completeness by condition for the eCR data from UTDHHS. In most cases, completeness levels were similar and high across conditions. Rates of completeness in the discharge date data element were moderate across the three conditions and likely reflect that not all patients would be expected to be discharged at the time of the report or that the report was not generated from an inpatient stay. The completeness of the pregnancy indicator data element was low for all three conditions, despite being limited to only those capable of becoming pregnant.

Table 5. UTDHHS eCR Completeness by Condition

Data Element	Gonorrhea (n=740)	Syphilis (n=6,315)	Hepatitis C (n=5,910)
Patient ethnicity	90.0%	86.4%	89.8%
Patient race	88.9%	80.0%	88.2%
Patient area code	98.9%	96.9%	93.7%
Patient phone no.	98.9%	96.9%	93.7%
Patient street	94.6%	95.8%	86.2%
Patient city	100%	99.9%	99.9%
Patient state	100%	99.9%	99.9%
Patient zip code	100%	99.7%	99.9%
Facility name	100%	100%	100%
Facility street	97.6%	94.9%	95.1%
Facility city	100%	100%	100%
Facility state	100%	100%	100%
Facility zip code	100%	100%	100%
Lab name	100%	100%	100%
Reference range	39.6%	31.2%	38.9%
Specimen source	100%	71.7%	100%
Test name	100%	99.9%	99.9%
Result	100%	100%	100%
Test Status	100%	100%	100%
Admission date	100%	100%	100%
Discharge date	66.9%	68.1%	54.3%
Report date	100%	100%	100%
Lab order ID	98.7%	99.6%	98.2%
Pregnancy ind.	12.2%	35.1%	22.8%

Notes: Pregnancy completeness based on only females age 12-50: gonorrhea n=82, syphilis n=1,646, hepatitis C n=1,154. The discharge date was calculated across all reports, as no data element was available to verify hospitalization versus non-hospitalization status.

Table 6 compares the completeness of UTDHHS ELR data by condition. In general, completeness for most data elements was high across all three conditions. Only a few ELR data elements—admission date, discharge date, and lab order ID—exhibited a level of completeness that was substantially lower.

Table 6. UTDHHS ELR Completeness by Condition

Data Element	Gonorrhea (n=206)	Syphilis (n=1,710)	Hepatitis C (n=4,059)
Patient ethnicity	100%	99.2%	99.0%
Patient race	98.5%	98.3%	98.5%
Patient area code	99.5%	98.0%	95.1%
Patient phone no.	99.5%	98.0%	95.1%
Patient street	94.2%	94.3%	86.1%
Patient city	99.5%	98.3%	98.0%
Patient state	99.5%	98.5%	98.0%
Patient zip code	99.5%	98.3%	98.0%
Facility name	100%	100%	100%
Facility street	100%	97.7%	98.0%
Facility city	100%	99.9%	99.9%
Facility state	100%	100%	99.9%
Facility zip code	100%	100%	99.4%
Lab name	100%	100%	100%
Reference range	99.5%	83.5%	62.7%
Specimen source	100%	100%	100%
Test name	100%	100%	100%
Result	100%	100%	100%
Test Status	100%	100%	100%
Admission date	47.1%	42.1%	42.0%
Discharge date	24.8%	34.1%	23.6%
Report date	100%	100%	100%
Lab order ID	62.6%	62.9%	46.7%
Pregnancy ind.	-	-	-
Test name (Full)	100%	100%	100%

Notes: “-” indicates that the data element was not collected in ELR.

Timeliness

In this study, the timeliness of eCR was measured by determining the percentage of eICRs received by the PHA with a timestamp prior to the first corresponding ELR received for all potential cases (i.e., reports that were not yet classified as probable, confirmed, or suspect cases) where both an eICR and ELR were received. When multiple eICRs or ELRs for the same encounter were received, the earliest instance of each was used in the calculation.

The analysis of timeliness revealed that at CDPHE, the eICR arrived before the first corresponding ELR 11.8% of the time (out of 1,792 potential cases). Conversely, at UTDHHS, out of 1,537 potential cases transmitted by both ELRs and eICRs, 74.8% of the time, the eICR arrived before the first corresponding ELR.

To better understand the scale of the typical difference between arrival times of data transmitted via the eCR and ELR processes, the distribution of timeliness was examined by calculating the difference in minutes between each eICR's arrival time minus the corresponding ELR's arrival time. Table 7 displays the full distribution of arrival times reported in the CDPHE and UTDHHS timeliness data. The min (minimum) value represents the eICR that arrived the earliest relative to its corresponding ELR. Conversely, the max (maximum) value represents the eICR that arrived latest relative to its corresponding ELR.

Table 7. Distribution of eICR Timestamps Minus ELR Timestamps in Minutes

Jurisdiction	Min	1 st Quartile	Median	3 rd Quartile	Max
CDPHE	-128,237.9	0.9	5.5	169.5	126,604.4
UTDHHS	-92,672.0	-16.2	-5.0	0.0	107,223.1

Sensitivity

Sensitivity is defined as the number of cases classified as confirmed or probable with a corresponding eICR or ELR divided by the total number of cases classified as confirmed or probable. The sample of reports used to calculate sensitivity was limited to only those cases originating from HCOs that had been onboarded and certified by UTDHHS as eCR-capable by the beginning of the sample period (May 1, 2025). As shown in Table 8, ELR sensitivity was nearly universal (i.e., close to or equal to 100 percent), and eCR sensitivity was very high.

Table 8. UTDHHS Sensitivity

Condition	eCR	ELR
Gonorrhea (n=116)	95.7%	99.1%
Syphilis (n=55)	92.7%	100%
Hepatitis C (n=139)	81.3%	99.3%
Total (n=310)	88.7%	99.4%

'n' is equal to the number of confirmed/probable cases originating from onboarded HCOs.

One reason the sensitivity indicator for ELR was nearly universal (i.e., at or near 100%) is that positive lab results are considered necessary for making a case determination. In other words, for an encounter to be classified as confirmed or probable, it should have an associated ELR. As a result, the sensitivity of eCR data will not exceed that of ELR data.

Positive Predictive Value

PPV represents the percentage of deduplicated eICRs (i.e., when multiple eICRs are transmitted for the same encounter, they are counted as one) that were ultimately classified as confirmed or probable cases through epidemiologic investigation. For this study, the timeframe was limited to determinations made during the three-month study period. High PPV measures are generally considered desirable since they indicate the extent to which eICRs successfully alert PHAs to confirmed or probable cases. However, as discussed in the limitations section, there are exceptions where a high PPV may not be desirable.

Table 9 summarizes the PPV values for the three conditions. Since UTDHHS receives all positive and negative test reports for STIs the PPV calculation removed negative tests transmitted, since negative reports are not expected to result in confirmed or probable case determinations. The calculation also removed duplicates by counting multiple eICRs as a single report. Additionally, any reports determined to involve individuals who are not residents of the PHA's jurisdiction were also excluded from the data.

Overall, PPV was high, indicating that the majority of eICRs received by UTDHHS for the three conditions ended up being associated with confirmed or probable cases following epidemiological investigation. The PPV was highest for gonorrhea reports and lowest for syphilis. This might be a reflection of either broad reportability rules authored by UTDHHS in RCKMS to ensure no potential missed cases (not evaluated in this study) or because gonorrhea requires only a positive lab test to meet a probable/confirmed case definition, unlike syphilis and hepatitis C, which require additional clinical information for case determination.

Table 9. PPV

Condition	PPV
Gonorrhea (n=126)	98.4%
Syphilis (n=426)	63.4%
Hepatitis C (n=973)	76.3%
<i>Total, all conditions (n=1,525)</i>	<i>74.5%</i>

'n' represents the confirmed/probable cases in the sample, excluding those involving non-residents of the PHA's jurisdiction.

Part 1 Summary

The results of the quantitative portion of this study provide evidence that eCR data consistently have high quality, similar to ELR data. Among the data elements examined in the study, more had higher completion rates in the eCR data than in the ELR. However, completeness levels were very high in most data elements, ranging from 90% to 100%. Only a few specific exceptions were below 90%,

which may reflect unique attributes of how the data are collected or opportunities to improve data entry or validity.

For timeliness, the analysis found substantial variance between the two jurisdictions regarding whether eICRs or ELRs arrived earlier. The reason for the difference in arrival times is unclear and may include differences in processes across jurisdictions or among the HCOs. The range of arrival time differences was large, with the most extreme cases representing weeks between the arrival time of the first eICR and the corresponding ELR. However, at least half of all paired eICRs and ELRs in the sample (i.e., those in the second and third quartiles) exhibited arrival times that differed by only a few minutes, which is too small a difference to affect their use in clinical investigations. It should also be noted that both the eCR and ELR processes are automated and likely offer transmission rates superior to those of manual reporting processes; however, manual report data were not available to test this assumption.

Sensitivity, which was only measurable with UTDHHS data, was high—greater than 80% across conditions—for eCR data and nearly universal (i.e., 100%) for ELR data. This was largely a function of UTDHHS policy that treats ELRs as primary for STI cases. However, most confirmed or probable cases of each condition included information reported from both eICRs and ELRs.

Finally, the PPV of eICRs in the UTDHHS data was generally high at 74.5% across the three examined conditions. This finding indicates that most eICRs received are indicative of true cases of the given condition. However, PPV varied across the three examined conditions, suggesting noteworthy differences that may be related to how conditions are defined or detected. Additionally, since PPV data were provided only by UTDHHS, it is unknown whether this pattern persists in other PHAs.

Limitations of the Quantitative Study

When considering the results of the quantitative portion of the study, the following limitations, which impact the interpretation and generalizability of the findings, should be considered.

- **The PHAs in the study are not a representative sample, which limits the generalizability of the findings.** UTDHHS was identified as being further along in its implementation of eCR than the typical PHA at the time the study was conducted. Both UTDHHS and CDPHE serve populations different from those in other parts of the U.S.
- **The study does not include manual reporting.** The PHAs that participated in the study were unable to provide data from manual reports for comparison with eCR. We were unable to investigate whether eCR offers significant improvements in data quality and utility compared with manual reporting. However, other studies have found larger differences in completeness and timeliness between eCR data and manual reporting than between eCR and ELR data (Conn et al., 2025).
- **The study only looks at three conditions.** They may not reflect how data is entered for other conditions. Additionally, all three conditions entail laboratory testing and may not reflect conditions not involving a lab test.

- **The sensitivity of ELR data is elevated by the selected conditions.** An ELR is required (with rare exceptions) to make a case determination for all three conditions included in this study. As a result, ELR data sensitivity will always be extremely high.
- **High PPV values may not be universally desirable for all disease conditions or situations.** This study found that eCR data has generally high levels of PPV, with noteworthy variance across the three conditions included in the study. However, there are many valid reasons why PHAs might accept lower PPV levels for a condition. For example, a broader threshold for triggering a report may be set to broaden the number of reports generated and ensure that no cases are missed (Chubak, Pocobelli, & Weiss, 2012). Therefore, there is no clear ideal PPV level against which to compare the PPV results in this report.

PART 2: What is eCR's Utility to PHAs?

The utility of eCR data was investigated by interviewing eCR-involved personnel from six PHAs. The interviews focus on the informant's perceptions of the utility of eCR data, its quality, and the current and expected impact of eCR at their PHAs. A copy of the interview protocol used during these interviews is in Appendix B.

Participating Sites

CSTE notified PHA representatives of the opportunity to participate in the qualitative portion of the eCR evaluation. In all, PHAs representing six states were recruited to participate in group interviews: Colorado, Florida, Minnesota, Montana, Nebraska, and Utah. Each PHA was asked to invite personnel from their agency who could share their experiences and perspectives on eCR utility.

Methods

Participants

Participating PHAs were asked to select one to five individuals who work with the eCR process or use eCR data to serve as key informants for group interviews. Table 10 summarizes the job titles of individuals who participated in the interviews and gives examples of responsibilities (across jobs from multiple PHAs) with respect to eCR.

Table 10. Job Titles and Example Responsibilities of Interview Participants

Job Title / Role	Example responsibilities related to eCR
eCR Coordinator	• Onboard health care organizations (HCOs) • Validate and improve eCR feeds (collaborate with HCOs and IT) • Support operability (collaborate with Association of Public Health Laboratories Informatics Messaged Services [AIMS]) • Evaluate eCR data quality • Train epidemiologists
Senior Business Analyst	• Analyze eCR data to make evidence-based improvements to eCR.
Informaticist / Analyst	• Import eCR data into surveillance system • Evaluate eCR data quality
Epidemiologist	• Integrate eCR data into surveillance system • Monitor and evaluate data quality • Serve as liaison to state and local epidemiologists • Author conditions in RCKMS
Team Lead, Electronic Data Exchange	• Develop strategy for electronic data exchange • Oversee eCR and ELR • Evaluate eCR
Team Lead, Electronic and Disease Reporting	• Oversee eCR and ELR • Oversee integrated surveillance system • Oversee syndromic surveillance • Train epidemiologists
Data Modernization Lead	• Manage infectious disease surveillance system
Data Modernization Business Lead	• Recruit and onboard HCOs
eCR Project Manager	• Support eCR implementation

Interviews

The group interviews with PHA informants followed a semi-structured interview protocol that was developed with input from stakeholders, including representatives from CSTE and CDC. The main interview questions are listed below, organized by the overarching topics. Follow-up questions were asked as needed, based on responses.

Table 11. Main Interview Questions

Main Topics	Interview Questions (not including responsive follow-up questions)
Status of eCR implementation	• What happens to eCR data after it's received by your agency?
PHA's use of eCR data	• How are eCR data used by your agency?
PHA personnel perceptions of eCR data quality	• Compared to manual reports and ELR, how are eCR data different?
eCR impacts	• How has your work changed because of eCR? (Prompt for specific examples) • What has been the most significant impact of eCR in your PHA so far?
Future of eCR	• What are your agency's next steps for eCR? • What are your long-term goals for eCR? • In the future, what do you expect to be the benefits or opportunities with eCR in your PHA? • What challenges or limitations do you anticipate?

Interviews were conducted In November and December 2024 in a single session for each PHA by WMU's team of investigators, which included a primary interviewer, note-taker, and timekeeper. Permission to record was established at the beginning of each interview, and all interviews were recorded and transcribed for analysis.

A single WMU researcher reviewed each of the interview videos concurrently with the respective transcript and made corrections as needed to ensure accuracy of the transcripts.

Data Analyses Procedures

After transcripts were cleaned, data were analyzed using widely accepted qualitative analysis practices (Miles & Huberman, 1994). Initial codes were developed by one WMU investigator based on the evaluation's focus areas and the evaluation team's prior experience with eCR. Then two investigators independently coded the transcripts using both established and emergent codes, resulting in a shared codebook. One investigator used the coded transcripts to identify key themes related to each of the main topics being investigated.

Findings

The major findings from the interviews are organized below around the main topics, including (1) status of the PHAs' eCR implementation; (2) the PHA's use of eCR data, including barriers and facilitators for use; (3) perceptions of eCR data quality; (4) eCR impacts; and (5) the future of eCR at the PHAs.

Status of eCR Implementation

Key informants were asked to describe eCR implementation at their PHAs. Table 14 summarizes the status of eCR implementation for each of the participating PHAs at the time of the interview

(November and December 2024).¹⁰ Since the question was asked in an open-ended way, the type of information shared varied across interviews.

Table 12. Summary of Implementation Status at Each PHA

PHA	Status of Implementation
Colorado	• Authored 78 conditions in RCKMS • Some HCO's onboarded and sending eCR • Receiving eICR via Rhapsody; transitioning to Electronic Message Staging Area (EMSA) • Storing eICRs in structured query language (SQL) server and test environment in EMSA • eICRs are not yet processed into surveillance system • Not in production with any conditions • eCR data accessible to epidemiologists in a parsed SQL server
Florida	• Authored 111 conditions in RCKMS • Some HCO's onboarded and sending eCR • Storing eICRs in SQL database • Processing data from eICRs (not all data elements) into Florida's Medical Electronic Reporting and Investigation Network (MERLIN) surveillance system + uploading eICR HTML files • In production with 59 conditions • eICR data accessible to epidemiologists
Minnesota	• Some HCO's onboarded and sending eICRs • Receiving eICR via Rhapsody • Processing eICRs/data from eICRs into Minnesota Electronic Disease Surveillance System • In production with 72 conditions • eICR data accessible to epidemiologists in surveillance system
Montana	• Authored some conditions in RCKMS • Processing eICRs via Rhapsody into test environment of National Electronic Disease Surveillance System Base System (NBS) • Epidemiologists can access eICR data in test environment (but generally does not happen)
Nebraska	• Authored some conditions in RCKMS • Some HCO's onboarded and sending eCR • Receiving eICR into Rhapsody • Processing eICRs/data from eICRs into surveillance system • In production with COVID only • eICR data accessible to epidemiologists in surveillance system
Utah	• Authored about 170 conditions in RCKMS • Most HCO's onboarded and sending eCR • Receiving eICRs for all authored reportable conditions to EMSA • EMSA processes eICRs/data from eICRs into EpiTrax surveillance system • In production with many conditions, but have not officially turned off manual reporting for any HCOs • eICR data accessible to epidemiologists in EpiTrax

¹⁰ PHAs are likely to have more advanced statuses at the time of this report writing than described in late 2024.

While describing the status of eCR implementation at their PHAs, key informants also described various factors that have facilitated implementation, including both IT and non-IT activities. Given the highly technological nature of eCR, it's not surprising that many of these actions are IT-focused. Examples include developing custom IT processes and software, obtaining external IT support, and developing solutions for data storage and management.

On the non-technical side, informants expressed appreciation for the extent of national-level collaboration, standardization, and communication that has characterized eCR's rollout. Regarding the mutual support among PHAs, one person explained,

I've been really warmed by these national calls with other states as we're all trying to figure this out together. And just the spirit of "there's no dumb question," ... I can ask other states for help and advice and everyone has felt very warm in their responses and advice giving.

Within their own PHAs, informants commented on the importance of engaging epidemiologists in decision-making about eCR implementation in their states. "We rarely make decisions in a vacuum about how to push the data in or what the data should look like," explained one person. They continued,

And we really heavily rely on [asking] "what is the action that will be taken based off of our data?" And that informs how we manage the data. So we do try to involve the epidemiologists in everything that we do, simply because as the end users, they're the ones who make the decisions about the data.

PHAs' Use of eCR Data

Utility of eCR data to PHAs was the major focus on the qualitative portion of this eCR evaluation. When asked how their agencies used eCR data, informants from some PHAs first clarified what roles have access to eCR data and in what form.

Key informants from five of the six PHAs indicated that they used eCR data for surveillance and case investigation, public health decision making, and research. The other PHA was early in adoption and implementation of eCR such that eCR data were not yet in use. Each of these topics is described in more detail in the following sections.

Variable access to eCR data. Some PHAs make entire eICRs available to their end users, while others process only select data elements into their surveillance systems. In PHAs that process data from eICRs into their surveillance system, the entire eICR may or may not be available to the epidemiologists as an attachment.

PHAs may limit access to eICRs because of privacy concerns. One person explained, "Because eICRs can contain so much data, and a lot of that is really sensitive, we do have really strict security levels assigned to them. They're the strictest, aside from being like a super user. But you really need to be a specialized epi to be able to view the HTML attachment."

A person from a different PHA noted that eCR data for certain conditions or programs at the agency are made available to epidemiologists through a dashboard or other file that is manually updated. One

person from a PHA where eCR data isn't fully integrated in a surveillance system explained that a substantial amount manual work is required to make the data accessible and usable to those who need it:

We have two programs that have dashboards set up, but then a few other select programs and conditions I pull just onto a spreadsheet and kind of tag them in it as new cases come about. So I pull [eCR data] every two weeks or whatever cadence we kind of agree on... It really depends on condition and who the subject matter experts are, but not one consistent workflow right now. As we're meeting with SMEs to update these conditions, then we just kind of ask what's best for you? A few also do have access to our database so they can pull data themselves, but that's pretty rare. So it's either the dashboard or Google spreadsheets at this point.

So it's either the dashboard or Google spreadsheets at this point.

In PHAs where only select data are made available to epidemiologists, decisions about which data to make available were determined based on several factors, including the quality of the data, data privacy concerns, and perceived utility to the investigation.

Use of eCR data for case investigation and case determination. When asked how they use eCR data, informants mostly discussed using it in case investigations and determining when to further investigate or follow up on cases. The examples shared by PHA informants illustrate that having access to eCR data enhances surveillance and case investigations because it includes data not otherwise readily accessible. A specific example is that eCR data includes hospitalization status, which is critical for influenza investigations. More generally, informants described their use of eCR data as “supplemental” to what they receive in ELRs. For example, if information is missing from an important ELR data element, such as race or ethnicity, they can often find it in an eCR.

For some conditions, PHA personnel use eCR data to determine cases of diseases that are not reportable through laboratory notification or that otherwise have complicated case definitions, such as cytomegalovirus (CMV) infection and CMV disease, which have different criteria. They explained that epidemiologists look for clinical information such as hearing loss, small for gestational age, microcephaly, and other factors that impact case determination. Because some of that information is included in eCR data, it makes the case determination process more efficient, reducing the amount of manual follow-up required with providers or patients.

Use of eCR data to inform outreach to health care providers. Informants from one PHA described using eCR data in conjunction with disease prevalence predictions to identify public health screening practices and the need for targeted training to improve health care practice. One person explained,

We were able to automatically receive that data so the medical epidemiologists were able to extrapolate how many cases of CMV we expect to see. That team also looked at testing differences for the onboarded facilities with eCR and noticed some patterns that some facilities were doing this testing quite regularly, and other facilities didn't seem to be doing it that often. So that sort of opens the door for education and outreach and training.

Use of eCR data for research. Informants from two PHAs reported that their agencies used eCR data in research studies. In one case, eCR data were used in a research paper their state

epidemiologist wrote about long COVID. In another, they used eCR data to fill in missing addresses for more than 1,000 patients in a study using colonoscopy and hysterectomy data.

Limitations to eCR data use. Informants from all PHAs explained that the format or availability of data in electronic health records (EHRs) limits access to and use of eCR data. They identified two key challenges related to variations in (1) how providers enter data and (2) EHR differences by vendor.

Provider variations. Some data are recorded in the EHR or input by providers in ways that make them challenging to extract from eICRs and process into a surveillance system. This is especially true for data elements that are entered as free text in the EHR. One person summed up the problem by stating, “I think we’re still at that stage of [figuring out how to] make what we’re given usable because so much of it is the legacy way that healthcare providers are used to entering data. It really makes it difficult to use.” Their detailed example illustrates the challenge:

Pregnancy is one really good example of this It took six months to figure out how to extract the data because it is reported so differently between all the different clinics and all of the different healthcare providers within those clinics. You know, you’ll have Dr. A who puts it in here and Dr. B puts it in here and Dr. C does a free text and a note.

EHR vendor variations. The usability of eCR data is sometimes limited by variations and inconsistencies across EHR vendors in terms of record structure, reporting capability, and frequency of reporting. Informants from several PHAs highlighted this challenge. Commenting on the structural differences across EHRs from different vendors, one person explained,

I don’t know if one is easier or better. We built our system based on [Vendor A], and so that’s what we have expected. And so now we’re having to take data that other vendors are sending us and then kind of like fitted into our existing structure.

Regarding reporting capability, one person noted there is a gap between capabilities that EHR vendors can demonstrate for Promoting Interoperability certification requirements versus what they can actually deliver in practice. They explained, “A big problem that we’ve noticed is the difference between real-world capability and what the EMR-EHR vendors claim they can do.”

Volume. Speaking on the topic of variability across EHR vendors, one person described one of their EHR vendors as “trigger happy.” This vendor sends more updates than others and often the end user can’t tell what is new. “They may spend forever just figuring out the minor change because our system doesn’t identify what was added.” The issue of multiple eICRs being sent for the same encounter is one type of volume challenge. Another is the amount of information within a given eICR. The size of eICR files and volume of data contained within them were also described by key informants from three of the PHAs as a potential barrier to data use.

End user characteristics. PHA informants also noted that factors unrelated to the technical aspects of the system—such as users’ understanding and trust—can influence the extent to which eCR data are used, such as understanding and trust.

Informants from two PHAs explained that epidemiologists’ use of eCR data may be limited when they do not know the source of the data they are accessing within their surveillance systems or if they lack

confidence in the data due unfamiliarity. “We just have a lot of users ... who are apprehensive with change,” explained one person.

Another person noted that some staff in their agency are “maybe a little bit wary of data that comes from eCR because they’re not sure if it can be trusted, the way that ELR data can be trusted or manual investigation data can be trusted.” Another factor is the time and effort it takes to transition to using a new system or source of information.

Engaging epidemiologists may enhance their use of eCR data. Informants from one PHA emphasized the importance of educating epidemiologists about eCR and learning about their information needs. They noted that one of their “really big strengths is getting buy-in early on,” and described the process as follows:

Once we go through our process, we give them an intro slideshow, we author the condition with them, we start pulling data, they eventually are buying it. We’ve had a few teams who, you know, it takes a few times...and then we pull the first round of data and they’re like, okay, like we’re getting it now. So I feel like once they are presented with easy access data via spreadsheet, via dashboard, there is interest and there’s excitement.

They further explained that they follow up to make sure they are “authoring conditions in the way that SMEs want. And also checking in to make sure that they’re getting the data they’re expecting to get.”

PHA Informants’ Perceptions of eCR Data Quality

PHA informants were asked how they thought eCR data compared with ELR or manual report data in terms of quality. They were prompted to comment on completeness and timeliness. The responses were nuanced, highlighting factors that can affect consistency and completeness. They also remarked on the richness of eCR data and how in some situations, they receive it much faster than ELRs.

eCR data quality varies with EHR vendor and facility. As noted in the previous section, variability of data due to differences across EHRs and how providers use EHRs can limit the utility of eCR data. Informants’ comments about the quality of eCR data also revealed issues tied to EHR vendors, healthcare organizations (HCOs), and providers. As one person noted, “You have good eCRs, you have bad eCRs. Some [vendor] facilities are giving us occupational history information, alcohol consumption information, smoking status, which is amazing.” The same informant highlighted data quality issues with specific HCOs:

[Many critical access hospitals] are dinky little places, so they have to rely on somebody to come in and basically give them a solution. But looking at the data quality, [we see] that this facility never, ever has ethnicity information. For a lot of their facilities, it is literally zero percent. And a lot of issues with patient address as well, I think that is somewhere around 90 percent, which is a lot better than zero percent but patient address is something we want to be like 99 percent. That is our desired completeness.

Inconsistency in the way providers report data also leads to quality issues in terms of completeness. One person noted a lot of gaps in the social history data. They specifically mentioned tribe, occupation, and pregnancy as having low completion rates, based on their experience.

For some conditions, eCR data format can be incompatible with limitations of the HCO's EHR.

We do see some issues getting consistent data elements in, like planned treatment is an example. And that's case by case...In chlamydia and gonorrhea where we really care about that follow-up prescribed medication information. And when we brought that issue back to our HCO partners, we heard it's just not a possible thing to add into the existing eCR infrastructure and to wait for the next version update.

eCR data are richer. Informants' remarks about eCR data quality indicate that they consider eCR data to be more complete and detailed than either ELR or manual report data.

Informants from three of the PHAs highlighted eCR's superiority when it comes to race and ethnicity information, specifically. One person remarked that they "definitely notice more completeness with race and ethnicity compared to ELRs received... Obviously, the eICRs contain a lot more information than lab reports or manual case notifications." Similarly, another person explained, "If I'm comparing it with manual reporting data or ELR data, it's definitely better, because it has a lot more demographic information that we as epidemiologists usually look for."

Key informants from all PHAs stated that eICRs contain data elements that are not otherwise available, providing a more complete picture of a person's disease experience. Informants from one PHA identified several specific examples, including treatment and pregnancy (for STI); vaccination history, disease severity, and hospitalization (for influenza); hospital admission and discharge (for respiratory diseases); occupation, travel history, and death indicators (for various conditions). One person remarked, "In theory, if someone's hospitalized, you could follow them throughout that disease experience." The belief that eCR data provide a much more complete view of a case was echoed by informants from other PHAs.

One person also noted that eCR may enhance completeness for sensitive data elements. They explained,

We've been studying the way that people are willing to talk about their vaccination status, their race and ethnicity, their refugee status. And a lot of the times, people are not willing to talk to the government about those types of things, but they are willing to talk to their doctors about it or their doctors have historical information about those types of things. So I think that's another opportunity that eCR offers is data quality in general, but also specifically around things that are difficult for health departments to collect.

eCR can be more timely than ELR. Informants from some PHAs stated that there are conditions for which eCR reporting is more timely than ELR. Informants from one PHA offered two specific examples. For tuberculosis, they sometimes receive eICRs up to two days before they receive an ELR. In case of birth defects, they receive flat files instead of ELRs, which arrive monthly or even annually. Compared to that method, they receive eCR data much more quickly. Speaking more generally, another person said, "There have been a handful of scenarios where the eCR has come in before the ELR and have notified our SMEs first...It can be the faster approach of getting some true cases."

Concerns about eCR data quality. In some cases, the quality of the data relates to limitations of the technological infrastructure such as variations in EHRs' use of value sets. While informants noted that

race and ethnicity data tend to be more complete with eCR, one person raised a concern. They explained,

Data elements like race and ethnicity can be limited by the code set that's allowed to be reported. So we have issues where the answer to the race question is "declined to answer," but it can only really be reported as "other."

Informants from two PHAs referred to ELR as "the gold standard," implying that eCR hasn't quite reached that level of quality. One person remarked that the epidemiologists in their PHAs "definitely feel that ELR is a more reliable source than eCR." By way of explanation, they mentioned that providers may enter erroneous information.

eCR Impacts

When asked how eCR has affected their PHA, the informants' responses were mixed. On the positive side, some said it has led to increased case reporting and enhanced their case investigations. Impact on staffing and workload was a common theme, but opinions diverged in terms of the ways in which eCR is affecting workload and staffing. Some informants couldn't comment on impacts, either because they started worked at a PHA after the introduction of eCR or because the rollout has been slow so they haven't noticed any effects yet.

Increased case reporting. Informants shared examples of receiving more reports of cases because of eCR and identifying cases that would have gone undetected. One person explained that because of information coming through eCR, they have been "able to catch a few instances" of clinics or facilities not sending ELRs." In one PHA's jurisdiction, a small hospital wasn't reporting at all until they adopted eCR. Regarding influenza hospitalizations, one person observed, "there are cases that simply would not be detected if it were not for eCR." Another said, "We've also had quite a few wins, particularly with [Tuberculosis] in finding new cases that had not been reported previously."

Enhanced case investigation. Informants gave various examples of how eCR improves their case investigations. One PHA found "significant reduction in case investigation time with the advent of eCR as well as improved completeness of our case management reports."

Related to the richness of data available through eCR compared with ELR, case investigators have more information to start with. One person explained what this is like for an epidemiologist:

Going through that eCR, they're like, "oh, this patient doesn't have a lab test, but they have a particular medication or a travel history that might indicate this person being a potential case." And they can start case investigation at that point. They don't have to wait for any other document to flow in. I think that's where they might see a difference in the regular workflow of how they were doing things before. But I don't see it changing that much to be honest. It's more going to be like they're catching those cases early and they're not just not dependent on one particular document which used to be ELR or manual reporting.

Impact on PHA staffing. One PHA's informants discussed an increase in staffing needs as a result of eCR implementation. They said due to demands related to data modernization, increased reporting, and internal data validation, they have hired 3.5 FTE staff "who are solely dedicated to eCR." In contrast, someone from a different PHA described a decrease in staffing needs as a result of eCR

adoption. They said because of eCR, they were able to “really reduce staff and FTE spent on case intake for COVID-19.”

Others offered more nuanced views of eCR's impact on staffing at their agencies. Rather than an overall increase or decrease in staffing, some noted a reduction in manual workload burden. Automation of case investigation frees up human resources that can be re-allocated to other tasks that may be more productive, efficient, or meaningful. One person offered the following explanation:

We're adding work to the electronic data exchange team. But we cut a lot of the work out of the epidemiology team. A lot of the grunt work. So that they can perform the work that they actually need to be doing – the evaluations, the surveillance, the case investigation. Then the analysis and the decision-making. That's the stuff that they're really good for. Calling a doctor to get the patient's whatever – pregnancy status – is a waste of their time. And so we may be adding work to my team, but we are decreasing the work of the epidemiologists.”

Future of eCR

Informants were asked about the future of eCR at their PHA. Given the nature of the question, their responses were to some extent speculative, but they offer insights into how they expect eCR to evolve and affect the work of public health. Their comments about the future of eCR revealed generally optimistic expectations for eCR to have multiple positive impacts, such as the following:

- reduce the burden on HCOS
- improve PHAs' working relationship with HCOs
- fill in data gaps
- increase efficiency
- increasingly identify cases that might otherwise go undetected, especially for chronic and acute conditions that don't rely on ELRs
- inform public health decisions for chronic disease and non-infectious conditions
- track hospitalization
- enhance the work of disease programs beyond the main surveillance system
- inform research on topics such as immunization coverage, health care access, and antibiotic resistance.

While optimistic about the eCR's potential to enhance the efficiency and effectiveness of public health reporting and response, informants also expressed concerns about sustainability of resources needed to support eCR. Specifically, because federal funding for work necessary to implement eCR was largely supported by COVID-19 relief dollars and therefore not permanent, some informants said that they didn't think they could count on long-term funding for eCR. One person explained, “When grants start to fade or funding starts to fade, we are very concerned about the amount of work that's required from eCR and managing that with potentially limited staff.” Another asked, “How do we, after investing so much time and effort and money, how do we still find those funds to keep the program moving forward when we don't have this really unusual pot of money to lean on?”

PHA informants were asked to describe their next steps with eCR. Reflecting the range of their implementation levels, their responses varied widely. Examples include:

- migrating to cloud storage
- rolling out eCR into production

- authoring all reportable conditions
- making eICRs human-readable and providing only the most recent eICRs to epidemiologists
- working on eCR data privacy policy and related communications
- evaluations or workgroups to examine various aspects of eCR data quality and utility

Part 2 Summary

The purpose of the qualitative portion of this study was to learn about eCR's utility to PHAs in various stages of eCR implementation.

PHAs' use of eCR data: PHA informants described using eCR data for case investigation and case determination. Since eCR data hasn't been fully integrated into most PHAs' surveillance systems, eCR data are often treated as supplemental, rather than a primary source of information. In at least one location, eCR data revealed a previously unknown issue with an HCO's testing protocols.

Use of eCR varies with how end users' can access the data (e.g., whether integrated into their surveillance system or as full eICRs, special files, or on-demand or through special requests). Informants also noted that inconsistencies in how providers enter data and how electronic health records are structured can limit the usability of eCR data. The volume of eCR data is also sometimes a barrier to its access and use.

Informants also noted that end users who are less familiar with eCR are less likely to use it in their work. Similarly, informants noted that as end users gain more exposure to eCR, they tend to develop a stronger understanding of it, use it more often, and see greater potential in it. They noted that engaging end users in decision making about eCR and educating them about it may facilitate use of eCR data.

PHA personnel perceptions of eCR data quality: Informants explained that eCR data quality varies across EHR vendors and reporting facilities. Overall, they agreed that eCR data are richer than what is available from ELRs. They noted that eCR data provides a more complete view of a person's disease experience, which increases the efficiency of case investigations. Informants provided examples of situations when eCR data arrives much earlier than other types of data, such as with tuberculosis and birth defects.

eCR impacts: Informants gave some examples of how eCR has helped them identify cases they wouldn't have identified otherwise. An especially notable example was a facility that was not reporting at all before eCR. They also discussed how it has enhanced case investigations, largely because of the richness of the information.

Impact on staffing was a common theme, although the perceptions of the impact varied. Some said eCR required more staff, some said less, while others saw tradeoffs in the type of staffing needed, such as between technical and clinical roles. Informants generally agreed that eCR should allow epidemiologists to use their time and skills more efficiently, although for some this is an expectation for the future.

Future of eCR at the PHAs: Informants expressed positive outlooks for the future of eCR. While there is much work to do before these benefits are fully realized, they foresee an array of improvements in efficiency, case detection, decision making, and other aspects of the work of PHAs.

Limitations of the Qualitative Study

The qualitative study was designed to explore the perceptions by public health professionals who work with and use eCR data, with a focus on their perceptions of its utility and impacts within their specific work. The study was not intended to produce generalizable findings about eCR's value. Within this scope, there are some limitations. Specifically:

- The number of individuals and their responsibilities related to eCR varied across the PHAs participating in the interviews. This structural and functional diversity may have influenced the types of insights shared, as individuals had different levels of exposure to and responsibility for eCR-related activities.
- Most of those interviewed had only worked at the PHAs as of the introduction of eCR and therefore could not comment on how eCR had impacted practice or workflow at the PHAs from before eCR was adopted through the time of interview.
- Although all interviewees were asked the same questions, their interpretations of the questions and the aspects of eCR they emphasized in their answers varied substantially. The high degree of variability in how they responded to the question prompts made it challenging to identify clear themes across the PHA groups.

Overall Conclusions

The results from the quantitative portion of this study, which indicate that eCR provides high quality data, were also confirmed in the qualitative discussions with eCR users in six PHAs. The PHA informants described eCR data as generally being richer than other sources, which is consistent with the high levels of completeness found in the quantitative analysis. The quantitative analysis of timeliness revealed a large range in time differences between eICR and ELR arrival times and found that the proportion of eICRs arriving before the corresponding ELR varied substantially between the two PHAs in the study. Interviewees also described significant variation in when eICRs and ELRs arrived; for example, some participants in the qualitative portion of the study reported observing eICRs arrive days earlier than the corresponding ELRs for certain HCO providers (although their comments were not limited to the conditions included in the quantitative study). Finally, interviewees from the PHAs also confirmed the importance of eCR data with the high sensitivity and PPV—which were attributes found in the quantitative portion of the study. Several interviewees described how eCR data had helped their PHA identify cases that might not have been caught through other reporting methods and indicated that they appreciated having thorough eICR data available, as it improved the efficiency of case investigations.

Overall, the qualitative portion of the study supports the broad, positive findings from the quantitative study. In instances where interviewees from the PHAs describe problems or shortcomings with eCR data, they also provide a deeper insight into why these issues may occur. In many cases,

shortcomings with eCR data are not inherent to the eCR system but reflect problems that are specific to individual HCOs or EHR providers within a PHA's jurisdiction. Additionally, some interviewees noted that PHA staff who were not yet as familiar with eCR data were less likely to use it, while also predicting that use would continue to increase in the future as eCR functionality and training expands within their PHA.

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Appendix A: Significance Tables

Tables 1-A, 1-B, and 1-C show the chi-square (χ^2) values and the corresponding p -values aligning with Tables 2-6 in the report. Table 1-A compares the completeness values between report types for each data element within each state, and Tables 1-B and 1-C compare the completeness values between conditions for each data element within each report type.

Table 1-A. eCR and ELR Completeness Significance Comparison

Data Element	CDPHE		UTDHHS	
	χ^2	p	χ^2	p
Patient ethnicity	4000	<.001	639.80	<.001
Patient race	7200	<.001	817.01	<.001
Patient area code	4300	<.001	2.00	0.15
Patient phone no.	5200	<.001	2.00	0.15
Patient street	265.77	<.001	33.71	<.001
Patient city	667.12	<.001	205.19	<.001
Patient state	675.54	<.001	198.72	<.001
Patient zip code	785.49	<.001	149.94	<.001
Facility name	5.66	0.02	N/A	N/A
Facility street	3000	<.001	85.92	<.001
Facility city	1900	<.001	13.02	<.001
Facility state	1900	<.001	2.17	0.14
Facility zip code	1200	<.001	54.32	<.001
Lab name	19.97	<.001	N/A	N/A
Reference range	3200	<.001	1986.05	<.001
Specimen source	4100	<.001	1100	<.001
Specimen type	1200	<.001	-	-
Test name	448.02	<.001	4.15	0.04
Observation ID	N/A	N/A	6800	<.001
Result	N/A	N/A	N/A	N/A
Test status	N/A	N/A	N/A	N/A
Admission date	4400	<.001	9200	<.001
Discharge date	4400	<.001	2000	<.001
Report Date	4700	<.001	N/A	N/A
Pregnancy ind.	-	-	410.13	<.001

Notes: The N/As show data elements with missing or equivalent values, which could not be tested. High chi-square values exceeding range of Stata results display are estimated.

Table 1-B. CDPHE Completeness by Condition Significance Comparison

Data Element	eCR		ELR	
	χ^2	p	χ^2	p
Patient ethnicity	46.76	<.001	93.53	<.001
Patient race	2.06	0.15	448.93	<.001
Patient area code	109.25	<.001		
Patient phone no.	109.66	<.001	0.14	0.71

Data Element	eCR		ELR	
	χ^2	p	χ^2	p
Patient street	137.94	<.001	21.55	<.001
Patient city	1.72	0.19	5.77	0.02
Patient state	1.72	0.19	5.99	0.01
Patient zip code	4.81	0.03	11.95	<.01
Facility name	1.07	0.30	0.60	0.44
Facility street	4.82	0.03	2.10	0.15
Facility city	0.29	0.59	25.40	<.001
Facility state	1.07	0.30	25.34	<.001
Facility zip code	0.29	0.59	70.87	<.001
Lab name	1.07	0.30	N/A	N/A
Reference range	N/A	N/A	23.13	<.001
Specimen source	1700	<.001	1000	<.001
Specimen type	N/A	N/A	21.66	<.001
Test name	18.89	<.001	N/A	N/A
Observation ID	N/A	N/A	N/A	N/A
Result	N/A	N/A	N/A	N/A
Test status	N/A	N/A	N/A	N/A
Admission date	2.28	0.13	N/A	N/A
Discharge date	85.82	<.001	N/A	N/A
Report Date	1.07	0.30	N/A	N/A
Pregnancy ind.	-	-	-	-

Notes: The N/As show data elements with missing or equivalent values, which could not be tested. High chi-square values exceeding range of Stata results display are estimated.

Table 1-C. UTDHHS Completeness by Condition Significance Comparison

Data Element	eCR		ELR	
	χ^2	<i>p</i>	χ^2	<i>p</i>
Patient ethnicity	37.98	<.001	2.19	0.34
Patient race	170.32	<.001	0.34	0.84
Patient area code	97.38	<.001	34.60	<.001
Patient phone no.	97.38	<.001	34.60	<.001
Patient street	369.28	<.001	86.47	<.001
Patient city	1.76	0.42	3.06	0.22
Patient state	1.76	0.42	4.00	0.14
Patient zip code	6.80	0.03	3.20	0.20
Facility name	N/A	N/A	N/A	N/A
Facility street	10.36	0.01	4.82	0.09
Facility city	N/A	N/A	0.26	0.88
Facility state	N/A	N/A	0.47	0.79
Facility zip code	N/A	N/A	11.85	<0.01
Lab name	N/A	N/A	N/A	N/A
Reference range	84.76	<.001	335.97	<.001
Specimen source	1100	<.001	N/A	N/A
Specimen type	-	-	-	-
Test name	0.74	0.69	N/A	N/A
Observation ID	51.77	<.001	135.63	<.001
Result	N/A	N/A	N/A	N/A
Test status	N/A	N/A	N/A	N/A
Admission date	N/A	N/A	2.07	0.36
Discharge date	253.62	<.001	68.15	<.001
Report Date	N/A	N/A	N/A	N/A
Pregnancy ind.	144.17	<.001	N/A	N/A

Notes: The N/As show data elements with missing or equivalent values, which could not be tested. High chi-square values exceeding range of Stata results display are estimated.

Appendix B: Interview Protocol

- Welcome
 - Introductions
 - Reminder about overall purpose: The purpose of this interview is to learn (1) your agency's use of eCR data, (2) your perceptions of eCR's usefulness, and (3) how it affects the work of your agency.
 - We are recording
1. Describe your roles at your public health agency in relation to eCR.
 - Job title, how they interact with eCR
 2. Walk us through what happens after eICRs are received by your agency.
 - Follow up as needed to find out:
 - the status of eICR ingestion
 - the flow and processing of the data
 - the form in which users (epidemiologists, PH nurses, etc.) receive the information
 3. Compared to manual reports and ELR, how are eICR data different?
 - How does eCR data compare in terms of timeliness and completeness?
 4. How are eCR data used by your agency?
 - Prompt for specific examples (e.g., tracking reporting by HCOs, case investigations, dashboard, reporting, decision making)
 - For the use(s) identified:
 - What eICR data elements are especially useful to you? Why? How do you use the information?
 - If there are eICR data elements you are not currently ingesting or using, can you identify them and give us an idea of why?
 - From a public health follow-up perspective, are there gaps in the information in eICRs? If so, what are they?
 5. How has your work changed because of eCR? (Prompt for specific examples)
 - Follow up if needed: Has it changed how you do surveillance? (Prompt for specific examples)
 6. What has been the most significant impact of eCR in your PHA so far?
 7. What are your agency's next steps for eCR?
 - Plans for implementation
 - Plans for use
 - Prompt for timeframe(s)
 8. What are your long-term goals for eCR?
 - How do you define success for eCR in your PHA?
 9. In the future, what do you expect to be the benefits or opportunities with eCR in your PHA?
 10. What challenges or limitations do you anticipate?
 - Prompt for past experience if needed

Appendix C: Original Guidelines for Study Participation

The following information was shared with PHAs that expressed interest in participating in the study. Final decisions for study participation were made following direct discussion with PHA representatives. Despite the criteria, no interested PHA was able to provide manual report data.

To participate in the **Completeness** analysis, your PHA must meet the following criteria:

- Be receiving eICRs into a system (test is OK) for one or more of the selected condition(s) (*gonorrhea, hepatitis C Infection, syphilis*) and able to extract data from them
- Be receiving ELRs and manual reports for the same selected condition(s) (one or more of *gonorrhea, hepatitis C Infection, syphilis*)
- Maintain and be able to differentiate data from eCR, ELR, and manual report sources
- Be able to provide a current (e.g., May, June, & July or similar 2024 period) three-month sample of data from all three sources (eICRs, ELRs, and manual reports)
- Be willing and able to do at least one of the following:
 - Provide raw line level (individual level) data from a sample of eICRs, ELRs, and manual reports that are deidentified to remove personal information (PII) OR
 - Calculate the percentage of fields in the sample of each report type (eICR, ELR, manual) that contain data that meets validation criteria (i.e., correct format or type of data, not a missing or invalid code)

To participate in the **Timeliness** analysis, your PHA must meet the following criteria:

- Meet the Completeness criteria above
- Receive and maintain date and timestamps for the earliest arrival of all eICRs, ELRs, and manual reports in comparable formats (i.e., all record time and dates to same detail levels)
- Be willing and able to do at least one of the following:
 - Provide information (e.g., an ID code) that will allow raw line level data for eCRs, ELRs, and manual reports to be matched (i.e., to find and compare different sources of data for the same incidence/report/encounter) OR
 - Provide line level data that has already been matched across eICR, ELR, and manual report OR
 - Match eICR, ELR, and manual report data internally and calculate differences in the earliest receipt date/time for eICR, ELR, and manual reports

To participate in PPV/sensitivity analyses, your PHA must meet the following criteria:

- Be receiving eICRs into a **production environment of a surveillance system** for one or more of the selected conditions (*gonorrhea, hepatitis C Infection, syphilis*)
- Use eCR for public health surveillance (i.e., making case determinations)
- Have the ability to determine all data sources (i.e., eICR, ELR, manual report) associated with a case
- Have the capability of tracing confirmed cases back to the original (first) source of the reported case (i.e., be able to identify whether the original trigger of the case was an eICR, ELR, or manual report)
- Be willing and able to do at least one of the following:
 - Provide line level case data from your surveillance system with associated eICR, ELR, and manual report data OR
 - Calculate the portion of confirmed cases per the numerator and denominator calculations provided in the plan document

Appendix D: Validity Criteria

Table 2-A summarizes the validity criteria used to recode each data element, by line, in data provided by UTDHHS. Data from CDPHE were aligned with the data criteria of UTDHHS.

Table 2-A. Validity Criteria

Data Element (common report name)	UTDHHS system name	Validity Rule Description
Patient ethnicity	Patient_ethnicity	Contents = "2135-2", "2186-5", "H", "N", "U", "UNK"
Patient race	Patient_race	Contents = "2028-9", "2054-5", "2076-8", "2106-3", "1004-1", "2058-6", "2131-1", "1002-5", "A", "W", "O", "I", "B", "UNK", "U"
Patient area code	Patient_phone_area_code	Number of characters = 3
Patient phone no.	Patient_phone	Number of characters = 7
Patient street	Pat_adr_street	Pattern check for contents starting with at least one number and contains at least one word
Patient city	Pat_adr_city	Pattern check for contents starting with letter characters
Patient state	Pat_adr_st	Contents = one of 51 valid system postal codes
Patient zip code	Pat_adr_zip	Contents = valid five-digit code in U.S. zipcode database (in R)
Facility name	Diagnostic_name	Contents = not missing
Facility street	Dx_street	Pattern check for contents starting with at least one number and contains at least one word
Facility city	Dx_city	Pattern check for contents starting with letter characters
Facility state	Dx_state	Contents = one of 51 valid system postal codes
Facility zip code	Dx_zip	Contents = valid five-digit code in U.S. zipcode database (in R)
Lab name	Lab_name	Contents = not missing
Reference range	Ref_range	Contents = not missing
Specimen source	Specimen_source	Contents = not missing
Specimen type	N/A	N/A
Test name	Test_name	Contents = not missing
Observation ID	Lab_order_id	Contents = not missing
Result	Test_local_result_value	Contents = not missing
Test status	Test_status	Contents = not missing
Admission date	Admit_date	Contents = not missing
Discharge date	Discharge_date	Contents = not missing
Report Date	Report_date	Contents = not missing
Pregnancy ind.	Patient_pregnancy	Sex = F; Age 15-50; Contents = not missing

Note: Specimen type data validity was "contents = not missing" for CDPHE only; missing in UTDHHS data.