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# Analysis of Robotic Process Automation in Supplemental Nutrition Assistance Program:

## Three Case Studies

### Final Appendices



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# Analysis of Robotic Process Automation in Supplemental Nutrition Assistance Program: Three Case Studies

## Final Appendices

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# Appendix A. Technical Notes

Appendix A contains additional details on the methods used to conduct the study.

## A. Research Questions and Objectives by Data Source

***Table A.1. Research Objectives and Questions by Data Source***

| Research Objectives and Questions | | Data Sources | | | | |
|---|---|---|---|---|---|---|
| | | Exploratory Research and Literature Review | Discussions With FNS HQ and Regional Office | Key Informant Interviews (Three per State) | Administrative Data Analysis | Cost-Benefit Analysis |
| Objective 1: Describe how RPA can be and is being used in SNAP administrative operations, service delivery, and measuring program outcomes. | 1. In general, how have RPA and other computerized automation technologies been used in public assistance programs to improve operations, service delivery, and outcomes? | ● | ● | | | |
| | 2. What are specific examples of how RPA from other public assistance programs and private businesses could be applied to SNAP operations and service delivery? | ● | ● | | | |
| | 3. Are there special considerations and challenges FNS should consider when using RPA in SNAP operations and services? | ● | ● | ● | | |
| | 4. How does or could the use of RPA in SNAP differ from its use in other public assistance programs? | ● | ● | ● | | |

| Research Objectives and Questions | | Data Sources: Exploratory Research and Literature Review | Discussions With FNS HQ and Regional Office | Key Informant Interviews (Three per State) | Administrative Data Analysis | Cost-Benefit Analysis |
|---|---|---|---|---|---|---|
| Objective 2: Describe, across the study States, the key features, motivations for selecting, opportunities, challenges, costs, and benefits of their relevant RPA projects. | 1. What are the key features of the RPA projects in the study States? How do these differ among the States? | | ● | ● | | |
| | 2. What are the specific parameters used by the bots' algorithms in RPA projects, and what processes are they automating and how? | ● | | ● | | |
| | 3. What categories and levels of administration (e.g., IT staff, caseworker management, agency leadership) are best placed to effectively implement and manage an RPA project? | ● | ● | ● | | |
| | 4. What were the key contextual factors (e.g., time, place, history) surrounding implementation of the RPA projects? What were the challenges of implementation? | ● | ● | ● | | |
| | 5. What were the specific motivations of and institutional support for the State agency behind implementation of the RPA project? How did caseworkers and employees react? | | ● | ● | | |

| Research Objectives and Questions | | Data Sources: Exploratory Research and Literature Review | Data Sources: Discussions With FNS HQ and Regional Office | Data Sources: Key Informant Interviews (Three per State) | Data Sources: Administrative Data Analysis | Data Sources: Cost-Benefit Analysis |
|---|---|---|---|---|---|---|
| Objective 2 (continued) | 6. How was the implementation of RPA and bots expected to affect SNAP operations and service delivery? Have these expectations manifested? How? | | ● | ● | | |
| | 7. Are there barriers to developing quantitative measures of success, such as employee training requirements, regulatory framework, or internal processes? | ● | ● | ● | | |
| | 8. To what extent have more complex algorithms been used for predictive analysis to reduce, enhance, or change the way labor is used in administrative processes? | ● | ● | ● | | |
| Objective 3: Quantify and assess the impacts, costs, and benefits of RPA projects on SNAP State administrative processes. | 1. What are the quantitative impacts, costs, and benefits of RPA projects on SNAP outcomes, such as increased program access, lower time burdens for applicants, or simplified application processes? | | | ● | | |
| | 2. What quantifiable benefits do the States expect from the use of bots in their RPA projects? Do the States track the data and variables needed for this? If not, what data and variables would need to be collected for quantification? | | | ● | | |

| Research Objectives and Questions | | Data Sources: Exploratory Research and Literature Review | Data Sources: Discussions With FNS HQ and Regional Office | Data Sources: Key Informant Interviews (Three per State) | Data Sources: Administrative Data Analysis | Data Sources: Cost-Benefit Analysis |
|---|---|---|---|---|---|---|
| Objective 3 (continued) | 3. What are the investment and administrative costs for the RPA project? To what extent are these one-time versus recurring costs? | | | ● | | ● |
| | 4. How does the use of bots affect caseworker time use/savings, including training costs and barriers? How is this saved time, if any, being used? | | | ● | ● | ● |
| | 5. How and to what extent do RPA projects increase or decrease payment error rates or potentially misapply policy generally? | | | ● | ● | |
| | 6. What modifications could help ensure better measurement of the effects of RPA in future implementations? | | | ● | | |
| Objective 4: Assess whether and how RPA projects could be designed to scale across SNAP caseload categories and made interoperable with other administrative processes within and between SNAP State agencies. | 1. What types of RPA projects or programs are best suited for introduction to SNAP State operations, and how would these projects be categorized? | ● | ● | ● | | |

| Research Objectives and Questions | | Data Sources: Exploratory Research and Literature Review | Discussions With FNS HQ and Regional Office | Key Informant Interviews (Three per State) | Administrative Data Analysis | Cost-Benefit Analysis |
|---|---|---|---|---|---|---|
| Objective 4 (continued) | 2. What are the key features that make the RPA projects and bots scalable to other agencies, States, or SNAP service providers? How can interoperability across these different management systems be built in from the start? | ● | ● | ● | | |
| | 3. What modifications, if any, would be needed to scale the changes? | ● | ● | ● | | |
| | 4. What are the specific challenges of utilizing bots in SNAP State administrative processes? Do these challenges translate across other Federal programs the State agency may manage as well? | | ● | ● | | |
| | 5. How can FNS and State agencies best maximize the benefits and minimize the costs associated with RPA and bots? | | ● | ● | | ● |

HQ = headquarters; RPA = robotic process automation

## B. Administrative Data

Analyses varied by State because of differences in RPAs, expected outcomes, and availability of administrative data. The following sections describe the overall approach and State-specific procedures.

### 1. Identifying Outcomes

During initial meetings with State staff, the study team asked State staff about hypothesized outcomes related to the implementation of their RPA. The study team then developed and shared a draft logic model that included these outcomes and a list of data needed to assess the outcomes. Each State provided feedback about the fit of each outcome and data availability, which the study team incorporated into an initial data request.

### 2. Data Sources

The study team collected case-level administrative files and summary reports from each State. Data sources and requested elements varied by State. Table A.2 summarizes the data sources provided by each State.

***Table A.2. Administrative Data Sources Provided by Three Study States***

| State | File Name | Description |
|---|---|---|
| Connecticut | RPA Data | Case-level datafile that included case and RPA characteristics, such as recertification request and processing dates, for RPA and non-RPA recertification cases between January 2021 and January 2023 |
| | RPA Data Pilot | Case-level datafile that included case and RPA characteristics, for RPA cases received during the pilot period; included estimated eligibility worker time saved (the pilot study was not limited to SNAP and also included cases processed by the RPA for Medicaid and cash assistance) |
| | Monthly SNAP renewal tasks | Count of online recertifications received each month between June 2020 and August 2021 |
| | Count of RPA-assisted tasks closed during month | Count of RPA tasks closed for each month between December 2020 and August 2021 |
| Georgia | RPA Data | Case-level datafile that included case and RPA characteristics, such as recertification request and processing dates, for all RPA recertification cases between October 2020 and May 2021 |
| | Non-RPA Data | Case-level datafile that included case characteristics, such as recertification request and processing dates, for non-RPA alternate recertification cases between May 2020 and May 2021 |
| | Cumulative 2021 GA RPA Reporting Template | ▪ Monthly summary data<br>▪ RPA performance December 2019–February 2020 and January 2021–May 2021; data included summary of recertification requests received and processed<br>▪ Quality control and error rate from November 2020 through May 2021 |

| State | File Name | Description |
|---|---|---|
| Georgia (continued) | Error Rate Report for Active Cases – All Cases | Monthly error rates for all active cases from October 2020 through May 2021 (also included breakouts for cases above and below error tolerance threshold) |
| | FY 2021 BOTS Cumulative Report – Negative Findings | Case-level QC findings for all negative cases processed by RPA |
| | FY 2021 BOTS Cumulative Report – Positive Findings | Case-level and summary QC findings, including payment errors for all active cases processed by RPA |
| | QC Analysis of QC Error Causes – All Cases | Summary of source of QC errors, October 2020 through May 2021 |
| | QC Benefits Error Report All Cases | Detailed payment errors from overall QC sample (active cases) from October 2020 through May 2021 |
| | QC Regular Sample | Detailed payment errors from overall QC sample from May 2020 through May 2021 |
| New Mexico | UpdateBOT cases | Case-level file for SNAP cases with address changes processed by UpdateBOT between December 2021 and December 2022 |
| | Customer Satisfaction | Customer responses to satisfaction questions on cases processed by RPA |
| | Productivity Standards Outcome and Time to Completion Statistics | Summary of eligibility worker time spent on various case-related tasks, including measures of eligibility worker time spent on task; file covered tasks completed April 2019–May 2020 (prior to RPA implementation) |
| | Time Customer Spent With Live Agent Chat | Record of time spent by live agents on live chats; included start time, end time, and duration; provided for each chat; included chats from January 2022 through December 2022 |
| | UpdateBOT Data | Summary reports of cases processed by UpdateBOT, including number of notifications, notifications approved timely, notifications approved untimely, notifications denied because of ineligibility, and notifications denied because State could not determine eligibility; notifications stratified by households with and without older individuals or individuals with disabilities; provided data from July 2021 through April 2022 |
| | BabyBOT Data | Summary reports of cases processed by BabyBOT, including number of notifications, notifications approved timely, notifications approved untimely, notifications denied because of ineligibility, and notifications denied because State could not determine eligibility; notifications stratified by households with and without older individuals or individuals with disabilities; provided data from January 2021 through June 2022 |

## 3. Data Cleaning and Analytic File Preparation

The study team cleaned the raw case-level datafiles to prepare analytic files. Unless otherwise noted, the summary files were used as provided by the State. Data preparation varied across the three States because of differences in the file structures and available data.

### *Connecticut*

The study team imported the Connecticut RPA file into Stata and cleaned all records. Cleaning steps included renaming variables, reformatting variables (e.g., updating date codes), and creating variable and value labels. Based on guidance from the State staff, two separate variables were used to create a new variable identifying each case's level of RPA use (i.e., full, partial, none). The days to decision outcome variable was created using the application date and the eligibility worker processed date. Other indicator variables, such as those flagging cases that could be dropped in sensitivity analyses, were created. Variables not needed for the analysis were removed from the file.

### *Georgia*

The study team imported the RPA and non-RPA case-level files into Stata and cleaned all records. Cleaning steps included removing duplicate cases, renaming variables, reformatting variables (e.g., updating date codes), and creating variable and value labels. Cleaning procedures were the same across the two files, except for any cleaning steps related to RPA-specific variables (e.g., processing dates for the RPA). For the RPA file, a flag was created to identify each case as an RPA case; for the non-RPA file, a flag was created to identify each case as a non-RPA case. The majority of cases in the file were alternate recertifications (i.e., recertification cases not requiring an interview), although the RPA file included some standard recertifications. Waivers issued in response to the COVID-19 public health emergency allowed interviews to be waived during certain months across the study period; the RenewalBOT was used on some of these recertifications. The study team dropped all standard recertifications to ensure the sample was consistent over time (i.e., in case the time spent on alternate renewals varied from other renewals). The days to decision dependent variable was created using the application date and decision date available in the file. The study team also created an indicator dichotomizing household size into households of one and larger households to use in subgroup analyses. Indicator variables flagging cases that could be dropped in sensitivity analyses were also created. Variables not needed for the analysis were removed from the file. The cleaned RPA and non-RPA files were merged to create a final analytic file.

The study team also used the RPA-specific and overall quality control (QC) sample files for active cases to produce RPA and overall payment error rates. The study team imported the case-level error rates for RPA cases, cleaned the data, and constructed necessary variables. Cleaning included formatting the date, replacing the error amount from missing to zero for cases with payment errors, and constructing an indicator for cases with an error amount above the QC error tolerance threshold ($39 during the study period). The study team collapsed the case-level data to estimate a monthly error rate for RPA cases. Data from two files were used to construct a comparable non-RPA error rate. The case-level QC error report for all cases (QC Benefits Error Report All Cases) contained over- and underissuance amounts but did not contain cases that did not have a payment error. To create a payment error rate, the study team used the Error Rate Report for Active Cases file, which included the full sample size. After formatting the data, the study team merged the issuance data with the monthly total number of cases and collapsed the file to the monthly level. Payment error rates were estimated as the number of cases with an error greater than the error tolerance divided by the total number of cases observed in the month. Lastly, the monthly QC error rate among RPA cases was merged with the monthly QC error rate from all cases into a final analytic file.

### *New Mexico*

The study team imported the UpdateBOT case file into Stata and cleaned the file. This process included renaming variables, reformatting variables (e.g., updating date codes), and creating variable and value labels. Variables were created to examine changes in RPA processing time by month. ZIP Code data were cleaned to provide five-digit ZIP Codes; ZIP Code values with fewer than five digits were deleted from the analytic file. Variables not needed for the analysis were removed from the file. The study team also imported and cleaned the chat time file using the same procedures.

## 4. Data Analysis

Data analysis was tailored to each State based on expected outcomes and available data. For all States, the study team prepared descriptive statistics for cases processed by the RPA across the period of data provided by the State; in Connecticut and Georgia, descriptive statistics for the non-RPA cases were also produced. Monthly statistics were plotted to examine trends over time. Additional State-specific analyses are discussed below.

### *Connecticut*

Connecticut provided case-level data for RPA and non-RPA cases from January 2021 through December 2023[1]; no preimplementation case-level data were provided.

Connecticut identified two intended outcomes associated with the recertification RPA: increased number of recertifications processed daily and decreased eligibility worker time spent on recertifications.

The study team examined the number of recertifications processed each month using the summary caseload statistics provided by the State. These statistics included the overall number of recertifications processed and the number of RPA tasks completed.

To examine change in eligibility worker time spent on recertifications, the study team used an ordinary least squares (OLS) regression model to examine the association of days to decision (i.e., the number of days between the State's receipt of the renewal form and an eligibility worker's final decision on the case) and RPA use. The following model was used:

$$Days_i = \beta_0 + \beta_1 PartialRPA_i + \beta_2 NonRPA_i + Z_i\gamma + \varepsilon_i$$

—where $Days_i$ is the outcome of interest (days to decision); $\beta_0$ is the intercept; $PartialRPA_i$ is an indicator set to 1 if an RPA partially processed the case (e.g., encountered a business exception leading to an eligibility worker needing to process pieces of the case); $NonRPA_i$ is an indicator set to 1 if the case was processed solely by eligibility workers; $Z_i$ is a vector of covariates that included an indicator for earned income on the case and an indicator for

[1] There were fewer recertification cases in the case-level files than anticipated based on the monthly summary files provided by Connecticut. The reason for this discrepancy is unknown.

unearned income on the case; and $\varepsilon_i$ is an error term. The primary coefficients of interest are $\beta_1$ and $\beta_2$ which respectively indicate the difference in mean days to decision between partial RPA and non-RPA cases and cases fully processed by the RPA. The model was weighted by the number of cases in each of the three RPA categories (full RPA, partial RPA, and non-RPA); the study team included all months between March through December 2022. January and February 2022 were excluded because the project was still in its initial implementation phase, and January 2023 was excluded because the study team did not receive a full month of data.

The study team intended to repeat the regression analysis for eligibility worker time spent on the case, which would offer a more fine-grained measure of time savings. However, the data included an unexpectedly large number of long processing times. Both State staff and the study team were concerned about the validity of the data; Connecticut's eligibility system tracks staff time spent on a task but does not discount time spent on breaks (e.g., overnight hours could be added to cases where a worker begins to process the task but does not complete the task before leaving work). The analysis was not conducted.

### *Georgia*

Georgia identified two primary outcomes: time saved and improvement in payment error rates. Georgia could not provide eligibility worker time spent on task but provided data that enabled the study team to calculate the days to decision for each case (i.e., the number of days between the State's receipt of the renewal form and the eligibility worker's final decision on the case). To assess time saved, the study team used preimplementation and postimplementation data on the average days to decision to conduct an interrupted time series analysis. An ITS model leverages observations over time to determine whether an intervention changed the outcome of interest (Bernal et al., 2017). The study team estimated the following equation for this analysis:

$$Y_t = \beta_0 + \beta_1 T + \beta_2 X_t + \beta_3 (T - T_0) X_t + \varepsilon_t$$

—where is $Y_t$ is the outcome of interest, the average number of days to decision in month t. $T$ represents the number of months since the start of the study, and $T_0$ is a constant equal to the month number when the RPA was implemented. The indicator $X_t$ represents whether the RPA was implemented; the variable is set to 0 prior to implementation and to 1 after implementation. The interpretation of estimated parameters varies from OLS regression. $\beta_0$ represents the intercept or mean number of days to decision in the first month of observation. is the slope or change in monthly average days to decision over time prior to RPA intervention. This model assumes the preimplementation slope would continue over time without $\beta_1$ intervention. $\beta_2$ is the initial level change in average monthly days to decision associated with implementing the RPA. For example, if the RPA implementation caused a decrease in the number of days to decision, $\beta_2$ would be less than zero. The coefficient $\beta_3$ the postimplementation slope or change in average monthly days to decision over time following RPA implementation, and $\varepsilon_t$ is an error term. The study team dropped May 2020 from the analysis because of unusually high average days to decision; the team was concerned this outlier could be related to pandemic-related changes. The ITS was conducted for all cases and used weighted monthly mean days to decision. The study team also repeated the analysis to determine if the association of RPA implementation with days to decision was different in single-member households compared with larger households.

QC data were only available in the postimplementation period, making an ITS impossible. The study compared the monthly payment error rates for the RPA sample and the overall QC sample using a univariate OLS weighted regression model.

#### *New Mexico*

Because of data limitations, all analyses in New Mexico were descriptive. The study team examined trends in UpdateBOT mean processing time and use (i.e., number of address changes processed by the RPA) across the study period. The study team also examined monthly mean time spent in a live chat to provide insight on the potential customer time saved because of the UpdateBOT. New Mexico provided the ZIP Code for address changes. The study team plotted counts of UpdateBOT by ZIP Code across the State to examine the geographic variation in RPA use. The study team also examined trends in disposition and types of cases processed by the UpdateBOT and BabyBOT (see appendix C).

## C. Cost Data

For each State, the study team collected RPA cost data and estimated the total cost of implementing and maintaining the RPA. Using administrative data and information collected during the interviews, the study team calculated RPA benefits when possible. The study team then used the benefits and cost data to conduct a cost-benefit analysis. The analyses varied in each State depending on the quality and availability of data.

### 1. Cost Data Requested and Received

The study team sent a tailored cost workbook to each State to systematically capture data on nonrecurring and recurring costs associated with the RPA. When necessary, the State answered clarifying questions. In general, the cost workbook collected the following data:

- **Staff time**: The cost workbook collected the time spent by staff on RPA preimplementation, implementation, and ongoing maintenance activities. Activities could include proposal writing, developing the RPA specification, or testing the RPA. Each activity was associated with a staff position representing the workers involved in the activity.
- **Staff salary**: The study team requested the average salary information, including fringe benefits, for all positions where staff contributed to relevant RPA activities. States also provided the salary information for eligibility workers who directly worked on cases assisted by the RPA.

- **Other direct costs**: The study team asked for all other direct costs to be documented, such as software costs, licenses, and amounts paid to contractors to support the development and maintenance of the RPA.
- **Indirect costs**: The study team inquired about indirect costs associated with the RPA.

Each State sent a completed cost workbook. Connecticut and Georgia provided the requested information for their full study period, June 2020–August 2021 and May 2020–May 2021, and information on startup efforts that occurred before the study period. Because Georgia implemented several RPAs in a short time, the State estimated the attributable direct costs (the development contract and the annual license and server costs) to the RenewalBOT; the full direct costs benefited all of Georgia's RPAs. The inability to fully and accurately separate costs for each individual RPA introduced imprecision.

Unlike Connecticut and Georgia, New Mexico's cost workbook collected information for multiple RPAs. New Mexico could not separate the costs associated with the UpdateBOT from other RPAs. The design and development of the RPAs were part of a larger technology contract. As a result of staff changes, New Mexico was unable to provide preimplementation or implementation costs. Reported costs began August 20, 2021, almost a full year after the implementation of the UpdateBOT.[2]

All States estimated some or all the reported time spent on RPA implementation and ongoing maintenance activities instead of reporting actual time spent. Since the States completed the cost workbooks retroactively, the estimated times include recall error.

## 2. Data Cleaning

The study team cleaned the cost data and compiled the information in an Excel workbook for each State. Activities were monetized by multiplying staff time by the corresponding average salary. Based on the description and the date the cost was incurred, the activities and other direct costs were classified into the following categories: preimplementation, implementation, and recurring costs. The study team forecasted the recurring costs to represent 12 months of costs; recurring costs were either scaled up to represent a year (e.g., multiplying the total recurring cost by two if the State provided 6 months of recurring cost data) or were projected by assigning future months the cost of the final reported month. Since New Mexico only provided costs beginning in August 2021, all of New Mexico's costs were assumed to be recurring costs.

## 3. Analysis

The study team presented a cost analysis and, when possible, conducted a cost-benefit analysis.

[2] New Mexico implemented UpdateBOT in November 2020.

### Connecticut

The study team reported the preimplementation, implementation, and recurring costs associated with Connecticut's RPA. In addition to the main cost, a Monte Carlo simulation provided a lower and upper bound on the costs. The Monte Carlo randomly adjusted the estimated costs and average salaries by ±5 percent and ±10 percent. The Monte Carlo simulation relied on a uniform distribution and performed 10,000 simulations; the resulting maximum and minimum costs created the range where the true cost likely falls. Because Connecticut provided exact contract costs for its other direct costs, the analysis used those costs as provided.

The simulation addressed two cost data concerns. First, the Monte Carlo simulation accounted for the imprecision in the estimated time spent on activities. Second, Connecticut provided average salaries for each staff position. Several employees with the same staff position may have contributed to the efforts. The variation of the hourly wage and fringe benefits accounted for the possibility that employees' compensation differs from the average.

The study team calculated a benefit-cost ratio that monetized the potential benefits of time saved by eligibility workers on recertification cases. The cost-benefit analysis required the following inputs:

- **Time saved by eligibility worker per case**: In Connecticut's RPA pilot, eligibility workers reported how long it took them to process a case that was already worked by the RPA and how much time they believe it would have taken them to process the same case in the absence of the RPA. Using this information, the study team constructed the measure of time saved. Based on the pilot data, eligibility workers saved an average of 9.4 minutes per case. The interquartile range of time saved was 5.0 and 11.0 minutes. The study team converted the time saved from minutes to hours. Since the analysis relied on the pilot data, time saved on partial and full RPA cases could not be differentiated.
- **Eligibility worker salary**: The analysis used eligibility worker hourly salary, including fringe benefits, from the cost workbook.
- **Number of RPA cases**: Connecticut provided the number of cases processed by the RPA in the "Count of RPA-assisted tasks closed during month" administrative file. The study team excluded pilot data months, which resulted in case count information for 7 months (February 2021–August 2021). The total case count was rescaled to represent 1 year of RPA cases; the analysis assumed the RPA would process the same average number of cases in future months.
- **Total cost of the RPA**: The cost analysis provided the total estimated RPA cost.

The study team combined the inputs to estimate the benefit-cost ratio:

$$\frac{Benefit}{Cost} = \frac{Time\ saved \times Salary \times RPA\ cases}{Total\ cost\ of\ RPA}$$

A ratio greater than 1 indicates the benefits of the RPA outweigh the cost of the RPA. The study team also estimated the benefit-cost ratio using the interquartile range instead of the average time saved from the pilot data; this provided a feasible range for the RPA benefit.

The benefit-cost ratio compared the costs and benefits of the RPA after 1 year of implementation. The analysis assumed the recurring costs and benefits would be constant in future years. The study team also calculated a benefit-cost ratio for 5 and 10 years after implementation using the present value formula[3] and a discount rate of 3.11 percent.[4]

### *Georgia*

The study team reported the preimplementation, implementation, and recurring RPA costs in Georgia. The study team conducted a sensitivity analysis on the cost estimate using a Monte Carlo simulation with a uniform distribution that performed 10,000 simulations, allowing estimated costs and salaries to be adjusted by ±5 percent and ±10 percent. Since Georgia estimated direct costs instead of providing exact costs, the Monte Carlo simulation also adjusted direct costs.

The study team calculated a benefit-cost ratio that monetized two potential benefits: time saved by eligibility workers on recertification cases and improvements in the payment rate. The cost-benefit analysis required the following inputs:

- **Time saved by eligibility worker per case**: The administrative data on time spent on an RPA and non-RPA cases contained infeasible values. Since Georgia did not provide reliable data on time saved, the benefit-cost ratio was estimated using two values, 5 minutes and 10 minutes saved. In an interview with frontline staff, a worker stated the RPA saved an average of 5 minutes on a case. Based on Connecticut's pilot data, the study team believed 10 minutes to be a feasible amount of time saved. Better data would have provided a more exact estimate of the benefit of time saved.
- **Payment error rate improvement**: The study team estimated the payment error rate improvement between the RPA QC sample and the overall QC sample using administrative data. The team defined an error as an incorrect payment of $39 or more; a payment error could represent either an overpayment or underpayment. The total number of RPA cases multiplied by the payment error rate improvement represents the number of cases where a payment error was avoided as a result of the RPA. Cases with an avoided payment error were assigned a savings value of $39, the QC threshold. This assumption results in a conservative estimate because the misallocation of dollars saved by avoiding a QC error may be substantially higher; $39 is a lower bound.

[3] The present value equals the future value divided by (1 + the discount rate) raised to the t power, where t is the number of years postimplementation.

[4] The discount rate reflects time value of money obtained from the 30-year Treasury Security from 2022 (Federal Reserve Bank of St. Louis, 2003). The study team monetized costs and benefits using 2022 wages and, therefore, does not need to apply an inflation discount when estimating the present value. This assumes a constant real value in future years.

- **Eligibility worker salary**: The cost workbook provided eligibility worker hourly salary, including fringe benefits.
- **Number of RPA cases**: The "RPA Data" administrative file contained the number of cases processed by the RPA. The study team excluded the implementation month, which resulted in case count information for 7 months (November 2020–May 2021). The total case count was scaled up to represent 1 year of RPA cases; this assumes the RPA would process the same average number of cases in future months.
- **Total cost of the RPA**: The cost analysis provided the total estimated cost.

The study team estimated the following equation for the cost-benefit analysis:

$$\frac{Benefit}{Cost} = \frac{(Time\ saved \times Salary \times RPA\ cases) + (Payment\ rate\ improvement \times Threshold \times RPA\ cases)}{Total\ cost\ of\ RPA}$$

A ratio greater than 1 indicates the benefits of the RPA outweigh the cost of the RPA. The benefit-cost ratio was also calculated for 5 and 10 years postimplementation using the present value formula and a discount rate of 3.11 percent.

### *New Mexico*

The study team summarized the recurring cost for all of New Mexico's RPAs and chatbots. Time spent on activities was monetized using the reported salary and fringe benefits for each staff position. All of New Mexico's costs were assumed to be recurring. The recurring costs represent only a partial annual cost because New Mexico was unable to provide cost information for non-State employees. Non-State employees contribute to the ongoing testing, maintenance, and reporting of the RPAs and chatbots. New Mexico provided the annual license cost for 20 RPA "digital workers."

## D. Limitations

Key administrative and cost data limitations follow:

- **Administrative data availability.** All three States were not able to provide all requested data because of data system limitations. Connecticut could not provide case-level preimplementation data. Neither Georgia nor New Mexico could provide productivity data (i.e., time spent by eligibility workers on tasks). Although Connecticut did provide productivity data, the data were not reliable and were not used in the study. New Mexico could not provide a control group (e.g., data on cases that did not have address changes), preimplementation data on address changes, or data on several proposed outcomes (e.g., returned mail). New Mexico had identified improved customer satisfaction as a downstream outcome of RPA use. The State was only able to provide satisfaction survey data for seven cases that had an address change, so the study team did not analyze these data.

- **Missing cost values.** No State was able to provide information on indirect costs. New Mexico's cost workbook lacked preimplementation and implementation costs because of staff turnover. Georgia and New Mexico implemented several RPAs within a short period, and New Mexico's RPA contract was part of a larger technology. Georgia estimated the contract costs associated with the RPA, while New Mexico was unable to disentangle the RPA costs.
- **Implausible date values.** In Connecticut and Georgia, some dates had implausible values (e.g., RPA cases with application dates in 2019; eligibility worker processing date prior to the renewal form submission date; decision dates over 6 months after the recertification request date). In Connecticut, the study team used the eligibility worker processing date in place of the decision date because of the high level of unexpected values for the decision date; the decision date likely reflects the most recent decision date on the case, not the date associated with the RPA action. Although the study team dropped cases with implausible values, some uncertainty remains in the dates that were used.
- **Capturing RPA benefits.** Connecticut and Georgia's cost-benefit analysis underestimate the true benefits of the RPA because of data limitations. In Connecticut, the analysis only monetized the benefit of worker time saved and had to use self-reported productivity data from the pilot period. In Georgia, the study team monetized both worker time saved and improvements in the payment error rate. Georgia was unable to provide productivity data, so the study team relied on interview data. Overall, the cost-benefit analyses would have benefited from better worker productivity data and data on other benefits.
- **COVID-19-related challenges.** Operations during the study period were also influenced by the COVID-19 pandemic. More individuals were eligible for SNAP because of the economic downturn, leading to increased demand from customers. The States experienced staffing challenges, a transition to remote work, and SNAP policy changes that shifted recertification timing or whether someone may have needed to update their address. Disentangling the effects of the pandemic is impossible because of the timing of the RPA implementation.

# Appendix B. Data Collection Instruments

Appendix B contains the data collection instruments used for the study.

# Appendix B1. SNAP State Agency Staff Interview Protocol

My name is *[name]*, and I'm a researcher at Insight Policy Research (Insight). Insight is conducting a study for the U.S. Department of Agriculture's Food and Nutrition Service (USDA FNS) on the use of robotic process automation (RPA, or bots) in SNAP. The study seeks to document the benefits, challenges, and efficacy of RPA use among SNAP State agencies and assess whether and how RPA projects can be designed to scale across State SNAP agencies. *[Interviewer note: The protocol uses the terms "bot" and "bots" throughout, but "RPA" can be used interchangeably.]*

We are conducting interviews with staff in *[State]* and two other States to collect information from a range of stakeholders involved with RPA planning and implementation. I want to start by thanking you for taking the time to speak with us today. Your perspective and insights will be very helpful to the study.

Your participation in this interview is voluntary, and your responses will be kept confidential, except as otherwise required by law. The information you provide us today will be summarized and combined with information gathered from other people we interview in a report that will be shared with FNS and the public. You will not be named in this report or any other project deliverables; however, the specific States we are studying will be identified. You may refuse to answer any question, and you may stop the interview at any time.

I expect our conversation today will take up to 2 hours. Do you have any questions for me about the project in general or what we will be discussing today?

Do I have your permission to record the conversation? You may stop the recording at any time.

*[Confirm permission before recording starts.]*

## A. Background

I'd like to learn about your role and responsibilities at *[name of office]*.

1. What is your current job title or position?
2. How long have you been in this position?
3. What are your primary responsibilities?
4. What was your role in implementing [State's] RPA project?

## B. Use of Bots in State

First, I would like to learn more about *[State's]* bot. I will first share our team's understanding of the bot and then provide you the opportunity to add additional details and clarifications.

Based on our understanding, *[State's]* bot performs the following functions: *[interviewer to provide description based on knowledge from exploratory research, Regional Office interviews, or State recruitment calls]*.

1. Is there anything we are missing? Does this description accurately capture the purpose and key functions of the bot? What else should we know about the bot's functionality? *[Interviewer note: Work with respondent to correct the bot description as needed. Once process is complete, briefly summarize the revised bot description for the respondent to confirm before moving on to other interview questions.]*

## Exercise

*[Interviewer note: Request the respondent provide a diagram/flowchart describing the bot process in advance of the interview. If the State did not submit a diagram in advance of the interview, ask the respondent to share their screen while creating the diagram in Microsoft Word **or** create the diagram as the State staff talk through the process during the interview.]*

1. Could you please walk us through the steps your bot takes to complete its task? What specific parameters does the bot use? What processes are being automated and how? *[Interviewer note: Insert relevant probes in advance of interview based on received diagram. Ask respondents to explain the system(s) the bot interfaces with, whether human interaction is required at any point in the process, how the bot responds to an inconsistency between reported information and matched data, and whether the bot or a human eligibility worker makes the final eligibility decision.]*

2. Does your State use bots in other public benefit programs (e.g., Medicaid, Temporary Assistance for Needy Families [TANF])?
    a. If yes, could you please provide a short summary of the other bots?
        i. Were any components of the SNAP bot first used in another public benefit program? If yes, how did you ensure the bot would comply with SNAP policy? *[Probe for merit worker regulations, known information policy.]*
    b. If yes, do the bots supporting other public benefit programs interface with SNAP? *[Interviewer note: Ask respondent(s) to provide additional detail on how the bots interact across programs, if at all. For example, if the State uses a Medicaid bot to update address information, is the address change also made to the SNAP case?]*

3. On average, how much time does it take for the bot to complete the task?

4. Is there a limit on the number of eligible cases the bot can process? What is this limit? Are there other reasons the bot wouldn't process every eligible case?

5. Has your State ever needed to turn the bot off? If yes, why?

## C. Bot Decisionmaking

I would also like to learn more about how your State decided to implement bots.

1. Why did your State decide to implement the SNAP bot? *[Probe for limited resources/staffing, pitch from IT vendor, heard about use in another State.]*
    a. How did *[State]* ensure all staff were on board? What, if any, initial concerns did staff voice?
    b. Who or what helped facilitate the decisionmaking process?
    c. Were there any initial internal challenges or concerns your State had to overcome? If yes, please describe.
2. Who was involved in the decisionmaking process? Was this the right group of people? Should anyone else have been involved?
    a. Did you consult other agencies or offices in your State when deciding whether to implement your bot (e.g., legal department, human resources)?
    b. *[If not already answered]* Did you consult with other States using a similar bot?
        i. If yes, why? What did you learn?
3. How did your State agency determine which SNAP process(es) to automate?
    a. Was there precedent to automate this process? Did another program (e.g., TANF, Medicaid) or another SNAP State agency implement a similar bot?
4. After the final decision to implement the bot was made, what came next?
    a. Could you tell us more about the bot procurement process? *[Probe for competitive RFP, approached by current eligibility system vendor, number of vendors State spoke to.]*
        i. What activities were included in the procurement process? *[Probe for firm evaluation criteria, budget and timeline development, State approval.]*
        ii. How long did the procurement process take?
        iii. Were any FNS funds used? *[Probe for Process Technology and Improvement Grants (PTIG), reinvestment funds.]*
            (1) *[If PTIG]* Could you tell us more about the grant application process? *[Probe for time needed, staff responsible.]*
5. To what degree did your State work with the FNS Regional or National Office during the bot decisionmaking or development phases?
    a. What guidance did your team receive from FNS? *[Probe for regulatory approvals, policy guidance.]*

b. Was there any additional guidance that would have been helpful that FNS was unable to provide? Please explain.

c. Is your State required to submit any additional reporting about the bot on an ongoing basis? Please explain.

d. Was your State required to submit a Major Change notification to FNS? If yes, what did that process look like?

e. Did FNS raise any concerns about the bot?

   i. If yes, what were the concerns? How did your State alleviate FNS's concerns?

## D. Bot Development, Implementation, and Testing

Now I'd like to learn a bit more about how the bot was developed, implemented, and tested.

1. Did your State develop the bot internally, or did you partner with an information technology (IT) firm?

   a. *[If developed internally]* Were members of your team able to develop the bot, or did you need to hire additional staff members to develop the bot?

   b. *[If partnered with an IT firm]* Which firm?

      i. *[If not already answered]* Did the IT firm approach your State, or did your State approach the firm?

   c. Outside of the IT department, who else was involved in developing your bot? *[Probe for department head, human resources, policy staff, local office staff.]*

2. Once *[State]* decided how to move forward with the bot, what were the next steps in the coding process?

   a. How often did the bot development team members meet during the process?

   b. Was there an assigned project manager? If yes, could you provide more information on their role?

   c. What, if any, challenges were encountered in developing the code for the bot? What worked particularly well?

3. What testing did *[State]* conduct before the bot went live? *[Probe for focus groups, testing among staff, use case testing, release with quick-turnaround feedback and updates.]*

   a. Who was involved in testing?

   b. How long did the testing process take? Was it an iterative process?

4. During the testing process, how did you ensure the bot would correctly apply SNAP policy (i.e., align with Federal regulations)?
    a. How did the team address policy errors that arose during the testing phase?
5. *[IT staff **only**]* Does the SNAP bot include any quality assurance features? If yes, can you explain how those functions operate?
6. When did the SNAP bot launch? Have there been any issues or errors with the bots since launch? If yes, please describe.
7. What training did *[State]* provide to staff in advance of the bot launch? What did the training entail?
    a. Have there been any ongoing trainings to account for new hires or bot updates?
    b. Who led the training? What position do they hold?
    c. What do you see as the most important or helpful aspects of these trainings?
8. What feedback did you receive from frontline staff (e.g., eligibility workers, clerical staff) after the bot launched?
    a. Have perceptions among frontline staff changed in the months/years since implementation?
9. *[IT staff **only**]* Does *[State]* use or plan to use artificial intelligence, machine learning, or predictive analytics in SNAP operations? *[Probe for chatbots.]*
10. When you reflect on the process of developing and implementing the bot, what challenges did *[State]* encounter? *[Probe for policy-related challenges, errors as a result of the bot, unclear guidance from FNS, difficulties with relationship with IT firm.]*
    a. How were these challenges addressed?
11. What worked well related to bot development, implementation, and testing? *[Probe for staffing, project management, IT firm partnership.]*
    a. What advice or recommendations would you provide to other States interested in developing and implementing a bot?
    b. What issues are most important for States to keep in mind when considering bots?

## E. Outcomes

Next, I'd like to ask some questions about measuring the impact of bots.

1. What were the intended outcomes of the SNAP bot? *[Probe for faster application processing, lower error rates, improved timeliness, decrease in backlog.]*

a. To your knowledge, did the bot have any effect on additional outcomes in the longer term (i.e., not immediately after implementation)? If yes, for which outcomes? *[For example, it may take several months for the backlog to decrease as a result of the time saved by the bot.]*

b. *[If not answered]* What effect, if any, has the bot had on payment error rates?

c. Did the bot have any unexpected outcomes, either positive or negative?

2. How did your team measure progress toward these outcomes? *[Probe for comparing preimplementation and postimplementation data.]*

    a. What barriers, if any, did your team encounter when developing quantitative measures of these intended outcomes? *[Probe for employee training requirements, regulatory frameworks, internal processes.]*

        i. Are there any data/metrics regarding the bot that you would like to see but currently do not have access to?

3. Does *[State]* continue to monitor the efficacy of the bot? What metrics are reviewed? How often are these examined?

4. What are the key performance indicators associated with the bot?

    a. What data does your State collect about the bot?

5. In addition to quantitative outcomes, are there any qualitative outcomes associated with the bot? *[Probe for staff satisfaction, bot providing staff more time to work on higher order tasks.]*

    a. What tasks are eligibility workers able to complete now that the bot handles simpler and more repetitive tasks?

    b. How, if at all, have employee responsibilities shifted because of bot implementation? *[Probe for eligibility workers now having more time to spend on complex tasks]*

## F. Benefits and Costs

Next, I want to discuss the benefits and costs associated with bots. Thank you for completing your cost workbook ahead of this interview.

1. In your opinion, what are the benefits associated with implementing the bot?

2. To what extent was the cost of the bot a factor in your decision to implement it? What were the primary cost drivers? *[Probe for contractor costs, staff time, hardware costs.]*

    a. What are the recurring costs associated with the bot?

3. In your opinion, do the benefits of the bot outweigh the costs? Why or why not?
    a. If not, do you anticipate your opinion may change in the long term?
    b. Has your State completed a cost-benefit analysis or any other cost-related analysis of the bot? If yes, could you tell us more about it? What were the results?
4. Next, I want to walk through the cost workbook you completed. *[Interviewer note: Tailor the probes before the interview and after reviewing the cost workbook. Sample probes are listed below. If you did not receive the cost workbook before the interview, let the respondents know you may send followup questions via email after you receive the workbook.]*
    a. We noticed no time was spent on *[task]*. Is this correct?
    b. Based on our conversation, it appears the following individuals were involved in the bot implementation process but are not included in the cost workbook: *[insert individuals].* Could you provide us the missing information?
    c. Where there any other direct costs in addition to *[insert costs listed in workbook]*?
    d. Did State staff track the time they spent on this project, or are the hours provided estimates?
    e. How did you determine the average time spent on the RPA/non-RPA task?

## G. Scalability

Finally, I would like to talk about how bots can be scaled. In this context, "scale" refers to expanding the use of your State's bot across other benefit programs in your State, such as Medicaid or TANF, or to SNAP agencies in other States.

1. Now that your State has been using the bot for *[length of time]*, have you encountered any additional challenges? If yes, please describe. If no, can you tell us why you think operations have proceeded smoothly?
    a. Are there any factors specific to SNAP policy or administrative processes that present a particular challenge to using bots in SNAP?
    b. *[If State uses bots outside of SNAP]* How do the challenges experienced in implementing the SNAP bot compare with those associated with bots that support other programs?
2. Is your State considering expanding the use of its current SNAP bot? *[Probe for running bot more frequently, expanding caseload affected by the bot.]*
    a. If yes, what aspects of the bot are easy or beneficial to scale?
        i. What changes, if any, would need to be made to scale the bot effectively?

ii. Is your State considering scaling your bot beyond SNAP to other programs now or in the future? If yes, what changes would need to be made to the bot to facilitate use in other programs?

3. *[IT staff **only** if State uses bots outside of SNAP]* How would the SNAP bot need to be adapted to interface with other public benefit programs (e.g., Medicaid, TANF)?

4. Is your State considering implementing additional SNAP bots? *[Probe for bots to handle periodic reporting with no changes, initial processing of applications.]*
   a. If yes, which bots? Why?

5. What information or support, if any, would be helpful to receive from FNS to facilitate bot scalability?

6. What considerations should future SNAP bot developers keep in mind when designing bots to promote scalability?
   a. What types of bots are best suited for use in SNAP?
   b. What challenges are associated with using bots in SNAP?

7. What suggestions do you have for States to maximize the effects of bots while minimizing the costs associated with implementation?

8. Have other SNAP State agencies sought guidance from your team on developing a bot? *[Probe for advice on firms, technical details, outcomes.]*
   a. If yes, how did those conversations begin?
   b. If yes, what advice did you share with the SNAP State agencies?
   c. If yes, to your knowledge, what were the outcomes of those conversations?

## H. Wrap-Up

Thank you for answering our questions.

1. Thinking generally, what information about bots and the use of bots in SNAP would be most important for us to know?

2. Is there anything else you would like to share about the use of bots in SNAP?

3. Is there anything we should have asked you about these topics but did not?

4. May we follow up with you by email or phone if we have further questions?

That completes our questions for you. Thank you very much for speaking with us.

# Appendix B2. Frontline Staff Interview Protocol

My name is *[name]*, and I'm a researcher at Insight Policy Research (Insight). Insight is conducting a study for the U.S. Department of Agriculture's Food and Nutrition Service (USDA FNS) on the use of robotic process automation (RPA, or bots) in SNAP. The study seeks to document the benefits, challenges, and efficacy of RPA use among SNAP State agencies and assess whether and how RPA projects can be designed to scale. *[Interviewer note: The protocol uses the terms "bot" and "bots" throughout, but "RPA" can be used interchangeably.]*

We are conducting interviews with staff in *[State]* and two other States to collect information from a range of stakeholders involved with RPA planning and implementation. I want to start by thanking you for taking the time to speak with us today. Your perspective and insights will be very helpful to the study.

Your participation in this interview is voluntary, and your responses will be kept confidential, except as otherwise required by law. The information you provide us today will be summarized and combined with information gathered from other people we interview in a report that will be shared with FNS and the public. You will not be named in this report or any other project deliverables; however, the specific States we are studying will be identified. You may refuse to answer any question, and you may stop the interview at any time.

I expect our conversation today will take approximately 1 hour. Do you have any questions for me about the project in general or what we will be discussing today?

Do I have your permission to record the conversation? You may ask me to stop the recording at any time.

*[Confirm permission before recording starts.]*

## A. Background

I'd like to learn about your role and responsibilities at *[name of office]*.

1. What is your current job title or position?
2. How long have you been in this position?
3. What are your primary responsibilities?

## B. Use of Bots in State Description of State's Bot

First, I would like to learn more about the bot *[State]* has implemented. *[Interviewer note: If necessary, the interviewer should provide a definition of RPA. For the purposes of this study, we are considering RPA to be synonymous with a bot. RPA/bots automate simple processes, such as mouse clicks or keystrokes. Chatbots are distinct from RPA and are not the focus of this study.]*

1. First, I would like to share with you our understanding of the bot, based on information we received from our interview with staff at the SNAP State office. *[Interviewer shares summary of the bot.]*
    a. Are there any errors in the workflow we described? If yes, please explain.
    b. Are there other ways you use the bot? If yes, please explain.
    c. Outside of what we just discussed, are there any other key features of the bot?
    d. How long have you been using the bot?
    e. Has it had any updates since implementation? If yes, what were the updates?

## C. Bot Development, Implementation, and Testing

Now I'd like to learn more about your experience during the bot development process.

1. Why do you think *[State]* decided to implement the bot?

2. Were you, or any of your frontline staff colleagues, consulted during the development of the bot? If yes, please describe. *[Probe for attended design meetings, tested bot prior to implementation.]*

3. *[If not answered in previous question]* Were you involved in testing the bot prior to implementation?
    a. If yes, what did testing entail?
    b. How long before the bot went live did testing occur? Has there been any ongoing testing of the bot that you are aware of?

4. Did you attend any bot trainings before it was implemented? If yes, please describe.
    a. Have you attended any additional bot trainings since then? If yes, please describe.
    b. Who conducted the training? What was their position?
    c. Now that you have used the bot, do you think anything was missing from the training? If yes, what should have been included?
    d. What about the training worked particularly well or was most informative?

5. When you first started using the bot, how easy was it to use? Why?
    a. What was challenging about it?

6. What were your initial reactions to using the bot? How did other caseworkers react?

7. Thinking broadly, were there any challenges to developing and implementing the bot? If so, what were they (e.g., policy-related challenges)?
    a. How were these challenges addressed?
8. What worked well related to bot development, implementation, and testing (e.g., staffing, project management, use of contractor)?
    a. What advice or recommendations would you provide to other States' teams interested in developing and implementing a bot?

## D. Current Bot Use

1. Would you be able to walk us through how you typically use the bot in your workday? *[Probe for how regularly they interact with the bot and what interaction entails. For example, is there an application that needs to be opened or a button that needs to be pressed, or does the bot run in the background?]*
    a. On a scale of 1 to 5, how difficult is it to use the bot? Why? What makes it [*easy/challenging*]?
    b. Have there been any continued challenges to using the bot (e.g., bot errors, slower processing time, reduced customer satisfaction)? If yes, can you describe them?
        i. Have steps been taken to address these challenges? If yes, can you please describe them?
        ii. Have the challenges been resolved? Why or why not?
2. How, if at all, did the bot change your interactions with participants?
3. How, if at all, has the bot changed the tasks you perform each day?
    a. Has the bot saved you time? If yes, why?
    b. Has the bot enabled you to spend more time on complex tasks, rather than simple or repetitive ones? If yes, why? Which tasks?
        i. Do you now spend more time per complex case, or can you get through a larger number of complex cases per workday than in the past? Please describe.
    c. Do you think the bot has had a similar effect for colleagues doing the same or similar work? Why?

## E. Outcomes

The next questions focus on how to measure the impact and outcomes of the bot.

1. In general, do you think the bot has been helpful? Why or why not?

2. What have been some of the benefits of implementing the bot? *[Probe for how it has impacted SNAP operations and/or service delivery, such as faster case processing times, reduction in errors, more staff available for other tasks.]*
   a. Did the bot work as expected?
   b. Did it have any unexpected outcomes, either good or bad?

## F. Future of Bots in SNAP

Next, I'd like you to think about bots in SNAP more generally.

1. Thinking broadly, do you have suggestions for other SNAP processes where a bot could be useful?
   a. What would help SNAP eligibility workers? How would it help?
   b. What could help other SNAP State or local office staff? How would it help?
   c. What could help SNAP participants? How would it help?
2. Do you think the State's current bot could be scaled to handle a larger number and variety of cases? Why or why not?
3. To your knowledge, is your State considering implementing any other bots?
   a. If yes, how do you feel about that?
4. In general, what concerns do you have about the use of bots in SNAP?
   a. Are there certain bots or applications you think would not be useful or could even be harmful to the program?

## G. Wrap-Up

Thank you for answering our questions.

1. Thinking generally, what information about bots and the use of bots in SNAP would be most important for you to know?
2. Is there anything else you would like to share about the use of bots in SNAP?
3. Is there anything we should have asked you about these topics but did not?
4. May we follow up with you by email or phone if we have further questions?

That completes our questions for you. Thank you very much for speaking with us.

# Appendix B3. Analysis of Robotic Process Automation in SNAP: Preliminary Administrative Data Request for <STATE>

## A. What is the purpose of this administrative data request?

This document provides instructions and requirements for submitting program and cost data as part of the *Analysis of Robotic Process Automation (RPA) in SNAP* study. The purpose of the study is to assess the impact of RPA on SNAP operations, including costs and benefits of RPA implementation. Three States representing three diverse RPA uses have been selected to participate in the study.

The following sections provide detailed instructions for preparing and submitting the data extract, including guidance on which records to include in the file, a specific list of variables needed, the format for the file, procedures for handling missing data, data confidentiality, and the process for submitting data.

Insight Policy Research (Insight) is the contractor for this study. A representative from Insight will arrange a consultative discussion with State staff familiar with the State data systems to discuss the administrative data to be provided.

## B. What is the timeline for submitting the data submission?

Data should be submitted no later than <DATE>.

## C. What should be in the files?

Data submissions should include two files. The first will cover 13 months of program data, including 6 months of preimplementation data, the implementation month, and 6 months of postimplementation data in one file. Data will be provided at the case level for each case where an RPA action could be taken. Each case should have a unique identifier. The data should also include an identifier for the SNAP office. The office variables will only be used to control for differences across sites and individual caseworkers. Additional variables will describe the complexity of the case (e.g., types of reported income).

The second file will include summary data for each study month, including the count of cases processed, payment error rates, and the case and procedural error rate (CAPER).

## D. What is the preferred file format for submissions?

Preferred file formats are comma-separated values (.csv), text (.txt), or Microsoft Excel (.xlsx), although other formats are acceptable. Please discuss alternate formats with Insight.

## E. What variables should be included?

Table A provides a list of the variables that should be included in the monthly participant file. Table B provides a list of the summary variables that should be included in the monthly summary file.

If codes are used to identify information (e.g., type of income, local office), please submit a crosswalk of these codes and their descriptions with your file.

## F. How should missing versus nonparticipating data be handled?

Missing values should be indicated by a BLANK space. Please do NOT fill unknown values with zeros. Zero should ONLY indicate an actual zero value, such as an error rate equal to 0 (no errors made).

For all indicator variables, a value of "1" should represent "yes," and a value of "0" should represent "no."

For date variables, please provide 8-digit character strings, filled with 0s for single-digit months or days (e.g., May 1, 2019, should be entered as 05012019).

## G. How will Insight ensure privacy of State data?

These data will be stored on network drives protected using the security mechanisms of Insight's network operating system. Insight headquarters are located in a secured building, and all servers are in a controlled-access area. Insight will set up a secure file transfer protocol (SFTP) site specifically for this project to enable secure transmittal of all datafiles. Only Insight's project team and designated SNAP State agency personnel will have access information for this site. All data from State agencies will be transmitted to Insight via SFTP, which will encrypt electronic data in transit to Insight's servers. These data, once received, will remain encrypted until all identifying information is removed. State agencies should also refrain from sending any personally identifying information (PII), including names or social security numbers, or other data beyond the data elements requested by Insight.

## H. How should the files be submitted?

To protect the data, please submit the files using Insight's SFTP system that encrypts both commands and data, preventing passwords and sensitive information from being accessed during transmission. Instructions for using this system will be sent separately.

## I. Questions or concerns?

If you have any other questions or concerns, contact Dr. Courtenay Kessler at ckessler@insightpolicyresearch.com or 703.504.9498.

*Table B3.1. Potential Participant and Household Variables*

| Data Element(s) Requested | Variable Name | Description | Data Format | Code/Categories Examples |
|---|---|---|---|---|
| Participant ID | SNAP_ID | SNAP participant's ID provided by the State to identify individual SNAP participants within a household | Numeric | Example: 111 |
| Household ID | HH_ID | Household ID provided by the State to identify individual SNAP households | Numeric | Example: 11111 |
| Date Case Action Initiated | CASE_DATE | Date of case action initiated (e.g., recertification submitted) | Numeric/ Date | Example: 05012019 |
| Date(s) of All Case Actions | ACTDATE_1 - ACTDATE_X | Dates for all case actions taken | Numeric/ Date | Example: 05012019 |
| All Case Actions | ACTION_1 – ACTION_X | All actions on case | String/Code | Examples: Client notice sent, final decision |
| Current Status | STATUS | Current SNAP status | String/Code | Example: Active |
| Household Size | HH_SIZE | Count of SNAP household members | Numeric | Example: 1, 7 |
| Type(s) of Income | INC_TYPE1- INC_TYPEX | Type of income recorded | Code | Examples: SSI, Earned Income |
| Type(s) of Target Task | TASK1-TASKX | Type of task completed by the RPA | Code/String | Examples: Copy text, None |
| Date(s) of Target Task | TASKDT1- TASKDTX | Date of target task | Numeric/ Date | Example: 05012019 |
| Time RPA Spent on Task | TASKTM1- TASKTMX | Time spent on task | Numeric | Example: 2 minutes<br>As a substitute, start and end time of task can also be provided as two separate variables (e.g., 10:15am–10:17am) |

Note: This table provides sample requested variables and will be tailored to each State, pending data availability, after the introductory data discussions.

*Table B3.2 Potential Monthly Summary Variables*

| Data Element(s) Requested | Variable Name | Description | Data Format | Code/Categories Examples |
|---|---|---|---|---|
| Month | MONTH | Month of observation | Date (YYYYMM) | Example: 202201 |
| Cases Processed | CASES_N | Count of RPA cases processed, both preimplementation and postimplementation | Numeric | Examples: 1234, 9876 |
| Payment Error Rate | PER | Payment error rate (percentage) | Numeric | Examples: 7.54, 10.21 |
| Case and Procedural Error Rate (CAPER) | CAPER | Case and procedural error rate (percentage) | Numeric | Examples: 22.43, 32.10 |

Note: This table provides sample requested variables and will be tailored to each State, pending data availability, after the introductory data discussions.

# Appendix B4. Cost Workbook

| Type of Activity | SNAP Staff Activities | Activity Description |
|---|---|---|
| **RPA and Control Tasks (Eligibility Worker Activities)** These activities are tasks that were replaced by the RPA or that were selected to be similar to RPA tasks. More detail will be added once the RPA is selected. | <RPA TASK> | Task that eligibility workers previously completed that is now done by an RPA. Examples include updating case files from periodic request forms or helping process recertifications for certain types of cases. |
| | <CONTROL TASK> | Task that eligibility workers complete that is similar to the RPA task (but is not completed by the RPA). Insight will work to identify this task, as needed, for the administrative data analysis. |
| | Error checking | Eligibility worker tasks related to checking for errors related to the RPA task (preimplementation and postimplementation) |
| | Next step tasks | Eligibility worker tasks that need to be completed after the RPA task (e.g., making a final decision on the case, reviewing item flagged by the RPA) |
| | Other eligibility worker activity (describe in Notes column) | Other eligibility worker tasks identified as relevant to the procedure during conversations with Insight. Please specify. |
| **Startup Activities** These are activities that occurred as part of the RPA development and implementation processes. Activities may be completed by SNAP staff or contractors. | Proposal writing | Efforts related to planning, writing, and editing any grant or funding proposals to support RPA implementation |
| | Policy and program planning efforts around RPA | Activities related to identifying the policy implications and steps needed to implement an RPA (e.g., coordinating with FNS, completing a Major Change notification) |
| | Negotiate contract, license, or RPA purchase | Tasks to identify and finalize an RPA contractor and/or provide ongoing license for the RPA |
| | Develop specifications for RPA | Activities to determine the scope of the RPA, working with the programmer to develop code for the RPA |
| | Coordinate RPA implementation activities with contracted staff | Activities to coordinate, schedule, and direct efforts of contracted staff, including IT staff involved in implementing the RPA |
| | Changes to MIS or other systems | Programming changes needed to the MIS or other systems due to RPA implementation |
| | Testing RPA performance | Startup testing of the RPA; includes tests in production environment and with actual case files |
| | Provide training and TA to eligibility workers | Designing, scheduling, and implementing training on RPA use for eligibility workers. This also includes followup communication and any TA activities. |
| | Preimplementation meetings and coordination | Any meeting and coordination efforts related to the RPA startup |
| | Other preimplementation activities (describe in Notes column) | Other preimplementation activities not described above; please specify |

| Type of Activity | SNAP Staff Activities | Activity Description |
|---|---|---|
| **Ongoing Activities**<br>These are activities that occur on an ongoing basis to maintain RPA use. Activities may be completed by SNAP staff or contractors. | Ongoing RPA maintenance | Any efforts to modify, enhance, or maintain the RPA |
| | Coordinate ongoing RPA activities with contracted staff | Activities to coordinate, schedule, and direct efforts of contracted staff to maintain the RPA |
| | Monitoring and evaluation | Any efforts to assess the performance of the RPA, including errors, time spent on task(s), staff satisfaction, and outcome evaluation |
| | Ongoing reporting | Reporting activities to funders or FNS |
| | Other postimplementation activities (describe in Notes column) | Other postimplementation activities not described above; please specify |

**Note**: RPA tasks, control tasks, next step tasks, States, and dates will all be updated by the Insight study team before the cost workbook is shared with the State.

**Glossary of Terms**

MIS = Management Information System; RPA = robotic process automation; TA = technical assistance

## Analysis of RPA in SNAP

### *Time Tracking Log*

### <State> Version (Month 1–Month 12)

***Instructions:*** *In this time log, please include the average time spent by eligibility workers on <RPA TASK> and <CONTROL TASK> activities and error checking, next steps, and other relevant tasks completed by eligibility workers. We are looking for the average time it takes to complete one task. We understand the average total time per task may be an estimate. See blue section in the Activity Descriptions tab for further information.*

| Task | Average Total Time per Task in Minutes | Is this an Actual or Estimated Time? | Notes |
|---|---|---|---|
| <RPA TASK> | | | |
| <CONTROL TASK> | | | |
| Error checking task | | | |
| Next steps task | | | |
| Other task(s); please describe | | | |
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**Analysis of RPA in SNAP**
***Salary Worksheet***
**<State> Version (Month 1–Month 12)**

| Staffing Position (Include Each Staff Position Listed in Time Log) | Pay Rate (Dollars) | Basis Paid (Select From List) | Fringe Benefit Percentage/ Amount | Fringe Benefits Calculated As: | Notes |
|---|---|---|---|---|---|
| | | [select from list] | | [select from list] | |
| | | [select from list] | | [select from list] | |
| | | [select from list] | | [select from list] | |
| | | [select from list] | | [select from list] | |
| | | [select from list] | | [select from list] | |
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| | | [select from list] | | [select from list] | |
| | | [select from list] | | [select from list] | |

**Note:** Please include average caseworker salary (tasks from blue tab) and specific salaries for staff involved in RPA implementation and maintenance (tasks from green tab). Please also include hourly rates for any contractor staff listed in the time tracking log.

## Analysis of RPA in SNAP

### *Other Direct Costs (ODC) Worksheet*

### <State> Version (Month 1–Month 12)

| Type of Other Direct Cost (e.g., RPA Software Costs or Licensing, Amounts Paid to Outside Contractors for Work on the Project[a], Hardware/Other Infrastructure Costs; Please Describe) | Amount Spent (Dollars) | Notes |
|---|---|---|
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**Note:** If preferred, please report costs by month and indicate as such in the Notes column.

[a] Only list contractor costs not included in the time tracking log and salary worksheet.

**Analysis of RPA in SNAP**
***Indirect Costs Worksheet***
**<State> Version (Month 1–Month 12)**

| Question | Response |
|---|---|
| 1. Does your accounting system assign indirect costs to any of the direct labor and ODC costs listed above? (Yes or No) | |
| 2. If yes, describe how applicable indirect costs are defined and measured. (Hypothetical example: Indirect costs include management, human resources, accounting, information technology services, and building maintenance. They are charged at the rates of 12 percent of labor costs and 2 percent of ODCs.) | |
| 3. If yes, what were the total indirect costs associated with the RPA during the study period (Month 1–Month 12) (in dollars)? | |

# Appendix C. Supplemental Tables

This appendix provides supplemental tables and information for the three study States.

## A. Connecticut

Connecticut provided data for all recertifications between January 2021 and mid-January 2023. The study team dropped January 2023 from the descriptive analyses because of the partial data. Table C.1 summarizes monthly characteristics of the recertifications processed by Connecticut and included in the case-level datafile provided to the study team. Over time, the proportion of cases processed by the RPA has increased. Other household characteristics remained stable over the study period.

***Table C.1. Monthly Summaries of Online Recertifications Processed in Connecticut, January 2021—December 2021***

| Date | *N* | Percentage Processed by RPA | Mean Household Size *N* (SD) | Income Type | | | |
|---|---|---|---|---|---|---|---|
| | | | | Earned Income Only (Percent) | Unearned Income Only (Percent) | Earned and Unearned Income (Percent) | No Income (Percent) |
| January 2021 | 1,456 | 17.6 | 3.50 (2.12) | 16.1 | 13.2 | 63.6 | 7.1 |
| February 2021 | 1,910 | 76.5 | 3.27 (2.04) | 13.3 | 11.4 | 68.8 | 6.5 |
| March 2021 | 2.274 | 47.4 | 3.32 (2.05) | 16.6 | 12.4 | 64.3 | 6.6 |
| April 2021 | 1,011 | 34.6 | 3.18 (1.91) | 15.9 | 19.6 | 58.5 | 6.0 |
| May 2021 | 1,985 | 28.5 | 3.00 (2.01) | 15.4 | 24.0 | 54.4 | 6.2 |
| June 2021 | 2,627 | 51.9 | 3.13 (2.07) | 16.0 | 21.4 | 56.1 | 6.4 |
| July 2021 | 2,666 | 43.5 | 3.60 (2.09) | 12.5 | 12.8 | 70.9 | 3.9 |
| August 2021 | 2,301 | 83.8 | 3.39 (1.99) | 16.2 | 12.0 | 66.0 | 5.8 |
| September 2021 | 2,444 | 79.9 | 3.57 (2.05) | 17.1 | 11.3 | 66.9 | 4.7 |
| October 2021 | 2,998 | 70.5 | 3.47 (2.01) | 16.2 | 12.1 | 66.7 | 5.0 |
| November 2021 | 3,066 | 77.4 | 3.27 (2.06) | 15.2 | 19.2 | 59.7 | 5.9 |
| December 2021 | 3,151 | 83.7 | 3.26 (2.10) | 15.9 | 19.8 | 57.9 | 6.4 |
| January 2022 | 2,243 | 58.0 | 3.12 (2.05) | 16.5 | 23.6 | 54.3 | 5.6 |
| February 2022 | 2,716 | 58.6 | 3.06 (2.12) | 15.1 | 24.2 | 53.7 | 7.0 |
| March 2022 | 2,663 | 55.0 | 3.03 (2.03) | 16.5 | 25.2 | 52.8 | 5.5 |
| April 2022 | 1,672 | 57.7 | 3.00 (2.04) | 14.8 | 30.2 | 49.7 | 5.3 |
| May 2022 | 2,059 | 80.8 | 3.10 (2.05) | 16.2 | 25.0 | 52.9 | 5.9 |
| June 2022 | 2,692 | 85.7 | 3.20 (2.09) | 17.3 | 23.1 | 54.2 | 5.5 |
| July 2022 | 3,015 | 85.4 | 3.31 (2.12) | 14.6 | 22.6 | 58.0 | 4.8 |

| Date | N | Percentage Processed by RPA | Mean Household Size N (SD) | Income Type | | | |
|---|---|---|---|---|---|---|---|
| | | | | Earned Income Only (Percent) | Unearned Income Only (Percent) | Earned and Unearned Income (Percent) | No Income (Percent) |
| August 2022 | 2,069 | 81.4 | 3.23 (2.11) | 13.6 | 23.9 | 57.5 | 5.0 |
| September 2022 | 5,034 | 64.8 | 3.25 (2.04) | 16.2 | 20.2 | 57.4 | 6.2 |
| October 2022 | 2,185 | 74.1 | 3.34 (2.04) | 15.3 | 22.4 | 57.4 | 4.8 |
| November 2022 | 4,023 | 80.7 | 3.37 (2.10) | 18.0 | 18.9 | 57.5 | 5.6 |
| December 2022 | 3,375 | 87.5 | 3.39 (2.09) | 19.6 | 18.1 | 55.9 | 6.5 |
| **Overall** | **61,635** | **67.9** | **3.27 (2.07)** | **16.0** | **19.4** | **58.9** | **5.8** |

RPA = robotic process automation
Source: Insight tabulations of Connecticut administrative data

The study team conducted a sensitivity analysis on the total cost of Connecticut’s RPA to address imprecision in the estimates; table C.2 presents the findings.

***Table C.2. Connecticut RPA Sensitivity Cost Analysis, in Thousands of Dollars***

| Simulation Parameter | Lower Bound | Cost | Upper Bound |
|---|---|---|---|
| ±5 percent | 1,072 | 1,098 | 1,122 |
| ±10 percent | 1,052 | 1,098 | 1,147 |

Note: The Monte Carlo simulation varies the estimated time spent on activities and the workers’ salary using a ±5 and ±10 percent range. The simulation does not alter the one-time contract cost for RPA DDI or the annual RPA maintenance and operations contract cost. Any future contract renegotiations or enhancements to the RPA’s functions would alter the overall RPA cost.
DDI = design, delivery, and implementation; RPA = robotic process automation
Source: Insight tabulation of Connecticut’s cost workbook

The cost-benefit analysis assessed the benefit of eligibility worker time saved by the RPA compared with the total cost. Table C.3 reports the estimated benefit, total cost, and the benefit-cost ratio. A benefit-cost ratio greater than 1 indicates the RPA’s benefit outweighs the cost.

***Table C.3. Connecticut RPA Cost-Benefit Analysis***

| Metrics | | 1 Year Postimplementation | 5 Years Postimplementation | 10 Years Postimplementation |
|---|---|---|---|---|
| Benefit, in Thousands of Dollars | Lower bound: 5 minutes saved per case | 110 | 519 | 965 |
| | Average: 9 minutes saved per case | 58 | 275 | 511 |
| | Upper bound: 11 minutes saved per case | 128 | 605 | 1,124 |
| Cost, in Thousands of Dollars | | 1,098 | 1,440 | 1,814 |

| Metrics | | 1 Year Postimplementation | 5 Years Postimplementation | 10 Years Postimplementation |
|---|---|---|---|---|
| Benefit-Cost Ratio | Lower bound | 0.05 | 0.19 | 0.28 |
| | Average | 0.10 | 0.36 | 0.53 |
| | Upper bound | 0.12 | 0.42 | 0.62 |

Note: The present value of benefits and costs are reported in 2022 thousands of dollars. The benefits represent the monetized eligibility worker time saved based on the annual RPA case count and average worker salary. A benefit-cost ratio greater than 1 indicates the RPA's benefit outweighs the cost.
RPA = robotic process automation
Source: Insight tabulation of Connecticut's cost workbook and administrative pilot dataset

## B. Georgia

Table C.4 presents monthly data on alternate recertifications processed by the RenewalBOT and entirely by eligibility workers (i.e., non-RPA cases).

***Table C.4. Monthly Summaries of Alternate Recertifications Processed by Eligibility Workers and the RenewalBOT Over Time, Georgia***

| Date | Cases Received (*N*) | | Mean Days to Decision | |
|---|---|---|---|---|
| | RPA | Non-RPA | RPA | Non-RPA |
| May 2020 | 0 | 33 | N/A | 42.8 |
| June 2020 | 0 | 8,745 | N/A | 2.0 |
| July 2020 | 0 | 14,895 | N/A | 3.5 |
| August 2020 | 0 | 12,879 | N/A | 2.8 |
| September 2020 | 0 | 43,344 | N/A | 8.3 |
| October 2020 | 13 | 42,500 | 21.5 | 12.5 |
| November 2020 | 664 | 37,937 | 19.2 | 15.1 |
| December 2020 | 11,140 | 24,011 | 23.5 | 16.1 |
| January 2021 | 17,899 | 14,506 | 11.7 | 7.8 |
| February 2021 | 26,241 | 17,501 | 15.2 | 9.3 |
| March 2021 | 31,109 | 14,519 | 21.7 | 15.1 |
| April 2021 | 25,041 | 11,857 | 26.3 | 18.2 |
| May 2021 | 25,448 | 8,822 | 24.1 | 17.7 |
| **Overall** | 137,555 | 251,549 | 20.6 | 11.2 |

Note: RPA cases were processed by the RenewalBOT and certified by eligibility workers. Non-RPA cases were completed entirely by eligibility workers. The RenewalBOT was implemented at the end of October 2020. Mean days to decision is the unweighted mean.
RPA = robotic process automation
Source: Insight tabulations of Georgia administrative data

Table C.5 presents payment error rates for the RPA and overall QC samples.

***Table C.5. Monthly Summaries of Payment Error Rates for the RPA and Overall QC Sample, Georgia***

| Date | Payment Error Rate (Percent) | |
|---|---|---|
| | RPA | QC Sample |
| October 2020 | N/A | 26.9 |
| November 2020 | 6.7 | 23.1 |
| December 2020 | 3.3 | 28.0 |
| January 2021 | 6.7 | 11.9 |
| February 2021 | 0.0 | 16.9 |
| March 2021 | 0.0 | 25.0 |
| April 2021 | 6.7 | 11.7 |
| May 2021 | 9.1 | 14.5 |
| **Overall** | 4.5 | 19.2 |

Note: The RPA sample includes only recertifications processed by the RenewalBOT. The QC sample includes new applications, recertifications, and other change reports. The QC sample may include cases processed by the RenewalBOT.
N/A = not applicable; QC = quality control; RPA = robotic process automation
Source: Insight tabulations of Georgia administrative data

Table C.6 provides an overall summary of the alternate recertifications processed in Georgia during the study period. Non-RPA case characteristics are stratified by whether the case was processed pre- or postimplementation of the RenewalBOT.

***Table C.6. Overall Summary of Alternate Recertifications Processed by Eligibility Workers and RPA, Pre- and Postimplementation, Georgia***

| Metrics | | RPA | Non-RPA, Preimplementation | Non-RPA, Postimplementation |
|---|---|---|---|---|
| Cases processed (n) | | 137,542 | 79,896 | 129,153 |
| Mean days to decision | | 20.6 (14.4) | 5.8 (7.4) | 14.2 (12.2) |
| Mean household size | | 1.9 (1.7) | 1.9 (1.7) | 1.9 (1.7) |
| Income type (%) | Earned income only | 24.8% | 25.6% | 26.0% |
| | Unearned income only | 39.4% | 35.7% | 37.4% |
| | Both earned and unearned income | 22.6% | 23.1% | 20.9% |
| | No or missing income | 13.1% | 15.6% | 15.7% |

Note: RPA cases were processed by the RenewalBOT and certified by eligibility workers. Non-RPA cases were completed entirely by eligibility workers. The RenewalBOT was implemented at the end of October 2020. In this table, preimplementation refers to May through September 2020. Postimplementation is November 2020 through May 2021.
N/A = not available; RPA = robotic process automation
Source: Insight tabulations of Georgia administrative data

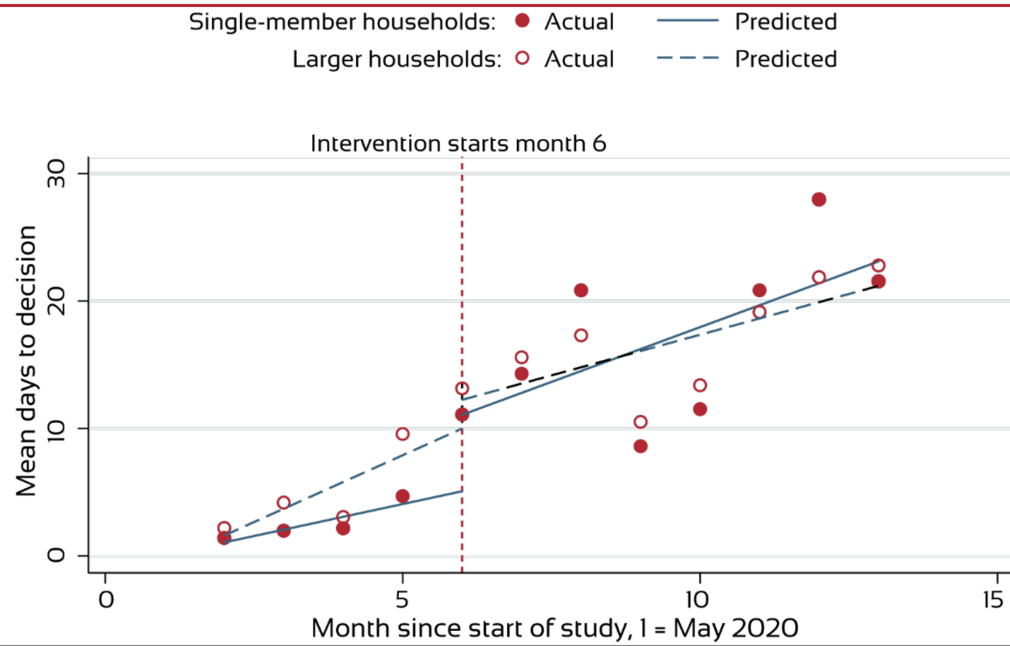
In addition to the interrupted time series (ITS) analysis presented in the main text, the study team also considered a multiple-group ITS that assessed whether the relationship between RPA implementation and days to decision varied by household size. Household size is one of many factors that influence case complexity. Households with one member may be less complex and take less time to process than larger households; the RenewalBOT may have led to greater declines among these less complex cases. Results from the ITS (see table C.7) confirm that cases for one-member households took an average of half a day less to complete than cases for larger households, although this difference was not significant. To assess the existence of a differential effect of the RPA on smaller and larger households, the study team examined whether a difference was present in the preimplementation trend in days to decision between the two groups; the difference between groups was not significant, suggesting the interpretation of subsequent results is valid. Following RPA implementation, days to decision increased monthly for single-member households and larger households. Contrary to the study team's hypothesis, single-member households had a bigger increase in days to decision (1.7 days) than larger households (1.2 days), although this difference was not significant. Figure C.1 highlights the overall increase in days to decision for both groups and the similarity of the trends between the single-member and larger household cases.

***Table C.7. Interrupted Time Series Results: Differences in Days to Decision Among Single-Member and Larger Households Before and After RenewalBOT Implementation in Georgia***

| Parameter | Interpretation | Estimate (SE) | *p*-Value |
|---|---|---|---|
| $B_1$ | Pre trend, or monthly change in days to decision during preimplementation period for larger households | 2.10 (0.74) | 0.012 |
| $B_2$ | Post level change, or change in days to decision associated with implementing RPA in October for larger households | 2.25 (3.20) | 0.493 |
| $B_3$ | Post trend change, or change in slope after RPA implementation compared with preimplementation slope for larger households | -0.82 (0.80) | 0.320 |
| $B_4$ | Difference between larger and single-member households prior to RPA implementation | -0.54 (0.85) | 0.533 |
| $B_5$ | Difference in change in days to decision during preimplementation period between larger and single-member households | -1.10 (0.79) | 0.184 |
| $B_6$ | Difference in days to decision associated with implementing RPA between larger and single-member households | 3.75 (4.33) | 0.399 |
| $B_7$ | Difference in change in days to decision after implementing RPA between larger and single-member households | 1.54 (1.05) | 0.160 |
| $B_1 + B_3$ | Post trend, or monthly change in days to decision during postimplementation period for larger households | 1.28 (0.32) | 0.001 |
| $B_1 + B_3$ | Post trend, or monthly change in days to decision during postimplementation period for single-member households | 1.72 (0.61) | 0.012 |
| Difference | Difference between post trends for larger and single-member households | 0.44 (0.68) | 0.527 |

Note: The estimate column provides the regression coefficient. Larger households include all households with more than one member.
RPA = robotic process automation
Source: Insight tabulations of Georgia administrative data

***Figure C.1. Trends in Days to Decision for Single-Member and Larger Households Before and After RenewalBOT Implementation in Georgia***




HH = household
Source: Insight tabulations of Georgia administrative data

Table C.8 presents the sensitivity analysis conducted for Georgia's RPA cost. The analysis addressed imprecision in the cost estimates and provided a lower and upper bound for the total cost.

***Table C.8. Georgia RPA Sensitivity Cost Analysis, Thousands of Dollars***

| Simulation Parameter | Lower Bound | Cost | Upper Bound |
|---|---|---|---|
| ±5 percent | 1,032 | 1,075 | 1,116 |
| ±10 percent | 991 | 1,075 | 1,159 |

Note: The Monte Carlo simulation varies the estimated time spent on activities, the workers' salary, and other direct costs using a ±5 and ±10 percent range. Any future contract renegotiations or enhancements to the RPA's functions would alter the overall RPA cost.
Source: Insight's estimation using Georgia's cost workbook

The study team monetized two benefits in Georgia—eligibility worker time saved and improvements in the payment error rate. Table C.9 presents the estimated benefits, total RPA cost, and the benefit-cost ratio. The benefits of Georgia's RPA outweigh the costs according to this analysis; the benefit-cost ratio is greater than 1.

*Table C.9. Georgia RPA Cost-Benefit Analysis*

| Metrics | | 1 Year Postimplementation | 5 Years Postimplementation | 10 Years Postimplementation |
|---|---|---|---|---|
| Benefit, in Thousands of Dollars | Total: Lower bound benefit | 1,805 | 8,495 | 15,783 |
| | Error improvement | 1,282 | 6,036 | 11,215 |
| | Time saved, 5 minutes | 522 | 2,458 | 4,568 |
| | Total: Upper bound benefit | 2,327 | 10,953 | 20,351 |
| | Error improvement | 1,282 | 6,036 | 11,215 |
| | Time saved, 10 minutes | 1,045 | 4,917 | 9,136 |
| Cost, in Thousands of Dollars | | 1,075 | 3,521 | 6,185 |
| Benefit-Cost Ratio | Total: Lower bound | 1.68 | 2.41 | 2.55 |
| | Error improvement | 1.19 | 1.71 | 1.81 |
| | Time saved, 5 minutes | 0.49 | 0.70 | 0.74 |
| | Total: Upper bound | 2.17 | 3.11 | 3.29 |
| | Error improvement | 1.19 | 1.71 | 1.81 |
| | Time saved, 10 minutes | 0.97 | 1.40 | 1.48 |

Note: The present value of benefits and costs are reported in 2022 thousands of dollars. Total benefits include the error improvement and eligibility worker time saved. The error improvement represents the lower payment error rate among RPA cases compared with the overall QC sample. Time saved represents the value of savings from eligibility workers spending less time on cases processed by the RPA. A benefit-cost ratio greater than 1 indicates the RPA's benefit outweighs the cost.
Source: Insight's estimation using Georgia's cost workbook, staff interviews, and administrative QC data

## C. New Mexico

The study team conducted additional analyses of UpdateBOT use (section C.1). New Mexico also provided information on several other RPAs used in SNAP and data on the number and duration of live web chats. In particular, several interviews provided qualitative data on the BabyBOT, and State staff provided administrative data on BabyBOT use. Section C.2 summarizes all RPAs used by New Mexico SNAP during the study period, section C.3 includes a more detailed description of BabyBOT implementation and use, and section C.4 provides summary statistics of UpdateBOT, BabyBOT, and live chat use.

### 1. Additional Analysis of UpdateBOT in New Mexico

Table C.10 provides monthly summaries of UpdateBOT use from December 2021 through December 2022, including all months of data provided by New Mexico. Over the course of the study, the UpdateBOT fully completed 53 percent of address change tasks it processed. During March through June, the UpdateBOT had a stark decline in productivity. Although approximately the same number of address changes were processed, no tasks were completed in these months. This pattern is also reflected in the much shorter mean processing times observed in the spring. Starting in July, the proportion of address changes and processing times increased, although mean processing times were shorter than in January 2021 and February 2022. Throughout the observed period, the majority of address changes were for mailing addresses. One interview participant had noted they prioritize making mailing address changes because updating the mailing address more closely ensures mail will arrive to the SNAP participant.

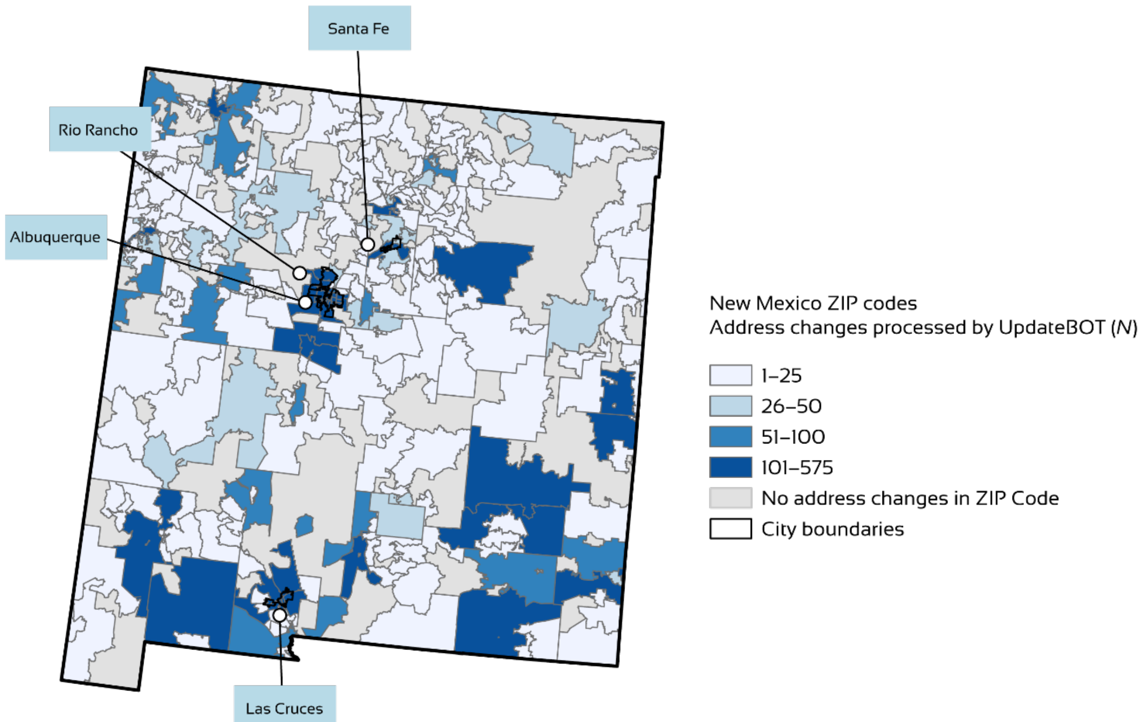
*Table C.10. Monthly Summary of Cases Processed by UpdateBOT, New Mexico*

| Metrics | | Dec 2021 | Jan 2022 | Feb 2022 | Mar 2022 | Apr 2022 | May 2022 | Jun 2022 | Jul 2022 | Aug 2022 | Sept 2022 | Oct 2022 | Nov 2022 | Dec 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cases processed (n) | | 516 | 611 | 565 | 635 | 650 | 897 | 1,819 | 1,887 | 1,576 | 1,459 | 1,405 | 1,368 | 626 |
| Proportion completed (%)[a] | | 78.3 | 76.4 | 16.3 | 0.0 | 0.0 | 0.0 | 0.0 | 69.9 | 65.0 | 65.2 | 69.1 | 67.9 | 67.3 |
| Mean RPA processing time in seconds (SD) | | 455.0 (102.9) | 477.8 (103.7) | 114.7 (193.9) | 18.3 (18.0) | 21.4 (14.3) | 17.7 (13.8) | 16.8 (11.2) | 305.0 (114.0) | 303.9 (101.8) | 327.2 (101.7) | 336.2 (129.0) | 328.6 (93.1) | 380.5 (620.7) |
| Address change type[b] | Residential (%) | 24.5 | 25.4 | 22.5 | 16.2 | 22.1 | 22.9 | 24.9 | 20.1 | 19.0 | 19.1 | 16.2 | 14.6 | 13.1 |
| | Mailing (%) | 75.5 | 74.6 | 77.5 | 83.8 | 77.9 | 77.1 | 75.1 | 79.9 | 81.0 | 80.9 | 83.8 | 85.4 | 86.9 |

Note: Data for December 2022 include only the first 12 days of the month.
RPA = robotic process automation; SD = standard deviation
[a] 13 cases had an undefined completion status and were excluded from the analysis.
[b] 46 cases did not have valid address type codes and were excluded from the analysis.
Source: New Mexico administrative data

The study team mapped the counts of address changes conducted by the UpdateBOT over the study period by ZIP Code (figure C.2). Darker shaded areas indicate larger counts of address changes. Areas with greater RPA use generally correspond to metropolitan areas within the State.

***Figure C.2. Map of UpdateBOT Address Changes in New Mexico***




Note: Final data include 13,152 address changes across 296 ZIP Codes in New Mexico. A total of 828 address changes were made for ZIP Codes outside of New Mexico, which were excluded from the analysis.
Source: New Mexico administrative data

## 2. Overview of Additional New Mexico RPAs

State and frontline staff in New Mexico provided information on six distinct RPA use cases. The study team presented detailed findings regarding the UpdateBOT in chapter 5 of the report. Table C.11 provides an overview of the other five RPA use cases.

*Table C.11. Overview of Additional New Mexico RPAs*

| RPA Name | Description |
|---|---|
| BabyBOT | BabyBOT uses a chat interface to collect information from hospital representatives to add a newborn to their mother's Medicaid case. The RPA enters information collected via the chat about the newborn to the case in ASPEN. The RPA adds case comments to the ASPEN case and uploads the Notification of Birth into the customer's Electronic Case File. If the mother also receives SNAP benefits, the RPA creates a task for an eligibility worker to certify the change. |
| BrainyBOT | BrainyBOT is an internal resource staff can use to receive answers to frequently asked questions about SNAP, TANF, and Medicaid policy; ASPEN and network how-to; and password resets. The RPA uses a combination of suggested responses and a web crawl component to generate answers to staff inquiries. |
| FAQBOT | FAQBOT is an external resource for clients to receive answers to questions about HSD programs. The RPA uses a combination of suggested responses and a web crawl component to generate answers to clients' inquiries. If the question cannot be answered, the chat will be transferred to a live agent, or the client can request a call from an agent. |
| Self-ServiceBOT | Self-ServiceBOT is available to the client via chat function or call center interactive voice response. The client provides identifying information to allow the RPA to look up their case information. The RPA can provide application status or case details, such as appointment times, benefit categories and amounts, or outstanding required verifications. |
| YesNMBOT | YesNMBOT authenticates and collects relevant information from the client to reset their online portal password. If the password is reset, it will return the temporary password to the customer. If the process takes longer than 5 minutes, the client will be transferred to a live agent via chat. The RPA will add case comments in ASPEN. |

ASPEN = Automated System Program and Eligibility Network; HSD = Human Services Department; RPA = robotic process automation

Source: New Mexico Major Change Report submitted to FNS and interviews with staff

## 3. Use of BabyBOT in New Mexico

New Mexico provided detailed information about the implementation of the BabyBOT. The BabyBOT is used by presumptive eligibility determiners (PEDs) to add a newborn to the mother's existing Medicaid case. To add a newborn, the PED accesses a portal in YesNM, the State's online application system. In the PED-facing YesNM portal, PEDs select "add a newborn" on the left side of the screen, which opens a chatbot window. The chatbot guides the PED through a series of questions (e.g., mother's Medicaid ID, infant's name and date of birth). Once complete, the information is sent to the BabyBOT RPA, which then updates the required screens in Automated System Program and Eligibility Network (ASPEN), New Mexico's integrated eligibility system. Once the RPA completes its task, the PED receives an email confirming whether the infant was added to the case. If the BabyBOT is unable to make the update, PEDs can follow up directly with an eligibility worker for manual entry. If an eligibility worker needs to review a case, they can resume where the RPA stopped and do not need to start from the beginning.

### *BabyBOT training*

All PEDs are trained to use the BabyBOT. At the time of the study, only PEDs who interacted with mothers and newborns in medical settings, such as hospitals and birthing centers, had access to the BabyBOT.[5] When the BabyBOT was first implemented, existing PEDs completed an addendum training. For new PEDs, BabyBOT training is incorporated into the 2-day PED certification training. In both trainings, PEDs complete a walkthrough of each necessary screen in ASPEN. They then must pass a comprehension test with a score of 90 percent or higher. Staff shared the importance of having a hands-on training environment where staff could work with the RPA directly. According to interviewed staff, about 50 PEDs routinely use the BabyBOT; only 200 of 760 total PEDs are authorized to use the BabyBOT.

### *BabyBOT testing*

The study team also interviewed Medical Assistance Division (MAD) staff who work with the RPA vendor to oversee and maintain the BabyBOT. MAD staff meet with the RPA vendor at least once a week and with the State's eligibility system vendor every other week. The RPA vendor also provides a daily report of all BabyBOT cases.

The RPA requires continued testing. If a technical issue arises, the RPA vendor offers a solution and provides a document describing the necessary changes. Next, MAD works with State and vendor testing staff to create 8 to 15 testing scenarios in ASPEN and YesNM to evaluate the proposed changes. One example of a test scenario is certifying a Medicaid and SNAP case—the RPA can certify the Medicaid case, but it must stop and create a task for an eligibility worker to certify SNAP because FNS policy does not allow nonmerit staff to certify cases. If all scenarios pass testing, the State approves the changes for production.

### *BabyBOT challenges*

MAD staff described the challenges they encountered with the RPA:

- If a mother receives SNAP in addition to Medicaid, an eligibility worker must certify change in household composition for the SNAP case. At times, the BabyBOT mistakenly assigns a task to an eligibility worker where the SNAP case was previously denied. This is a challenge because it creates unnecessary tasks for eligibility workers, who already have a demanding caseload. MAD staff shared they were working to fix this error to ensure the RPA is not adding a newborn to an inactive SNAP case.
- Because RPAs are programmed to mimic specific mouse clicks within an eligibility system, any change to the screens or layout of the system can affect RPA performance. In 2022, New Mexico had to transition ASPEN, a web-based system, from Microsoft Internet Explorer to Microsoft Edge. State staff noted that this transition affected BabyBOT success rates.

### *BabyBOT outcomes*

The study team interviewed a PED about her experience using the BabyBOT. The PED found the BabyBOT easy to use. She reported the BabyBOT made her tasks "simpler and more

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[5] PEDs are also located in prisons, schools, or other community settings; PEDs in these settings are not authorized to use BabyBOT.

manageable" because she can add a newborn directly to the mother's existing case rather than needing to submit a new application for the newborn. The PED shared she can spend more time on complex cases, including cases that require substantial documentation.

MAD staff felt PEDs' interactions with participants did not change because of the BabyBOT, but they agreed it saved time for both PEDs and eligibility workers. For eligibility workers, having PED staff enter newborns via the BabyBOT is helpful because it minimizes their workload. Generally, eligibility workers only need to certify changes when the case includes SNAP or TANF; the RPA can fully process Medicaid-only cases. Despite the challenges associated with the RPA, MAD staff appreciated the BabyBOT, saying it is "the superior method." In the past, it may have taken workers 30 days to process a new Medicaid application for a newborn, but, as staff noted, the "RPA … can add a baby in 15 minutes. This saves time for the customer who needs Medicaid coverage for their infant now."

Since the implementation, the number of SNAP cases the BabyBOT processed has ranged from 60 to 313 cases and averaged 247 cases per month (see figure C.3 and table C.12). These counts do not include Medicaid-only cases processed by the BabyBOT.

***Figure C.3. Monthly Trends in SNAP Cases Processed by BabyBOT, New Mexico***


Note: The figure includes only SNAP cases processed by BabyBOT. BabyBOT also processes Medicaid cases.
Source: New Mexico administrative data

*Table C.12. Monthly Summaries of SNAP Cases Processed by BabyBOT, New Mexico*

| Date | Number of Cases Processed |
|---|---|
| January 2021 | 244 |
| February 2021 | 197 |
| March 2021 | 296 |
| April 2021 | 285 |
| May 2021 | 271 |
| June 2021 | 313 |
| July 2021 | 326 |
| August 2021 | 343 |
| September 2021 | 305 |
| October 2021 | 228 |
| November 2021 | 221 |
| December 2021 | 241 |
| January 2022 | 197 |
| February 2022 | 60 |
| March 2022 | 187 |
| April 2022 | 217 |
| May 2022 | 258 |
| June 2022 | 264 |

Note: This table includes only SNAP cases processed by BabyBOT. BabyBOT also processes Medicaid cases.
Source: New Mexico administrative data

## 4. Additional RPA Analyses

The study team examined the proportion of cases processed by the UpdateBOT and BabyBOT for households with older individuals or individuals with disabilities based on summary reports provided by New Mexico (table C.13). A recent U.S. Department of Agriculture report (Cronquist & Eiffes, 2022) suggests 18 percent of SNAP households in New Mexico included an older individual, and 18.4 percent of households included an individual with a disability.[6] In comparison, almost a third of cases processed by the UpdateBOT were for households with either an older individual or individual with a disability. Cases where infants were added by the BabyBOT were less likely to have an older individual or an individual with a disability, perhaps because younger households are more likely to add an infant.

[6] The report did not include a measure of either older individuals or individuals with disabilities; direct comparisons are limited by data availability.

*Table C.13. Distribution of Household Types Processed by UpdateBOT and BabyBOT*

| Household Type | UpdateBOT *N* (%) | BabyBOT *N* (%) |
|---|---|---|
| **Total** | 1,917 (100) | 4,453 (100) |
| Households with older individuals or individuals with disabilities | 595 (31.0) | 282 (6.3) |
| Households without older individuals or individuals with disabilities | 1,322 (69.0) | 4,171 (93.7) |

Note: Mean values are based on all months provided by New Mexico. Provided months of data varied for UpdateBOT and BabyBOT.
SD = standard deviation
Source: New Mexico administrative data

New Mexico also provided disposition on cases processed by the UpdateBOT and BabyBOT (table C.14). Over 80 percent of cases processed by the UpdateBOT were approved, half of which met timeliness standards. Seventy percent of BabyBOT cases were approved with timely notification. Only 13 percent were denied either because the case was deemed ineligible or because the State could not determine eligibility.

*Table C.14. Distribution of Case Disposition and Timeliness for Cases Processed by UpdateBOT and BabyBOT, New Mexico*

| Household Type | UpdateBOT *N* (%) | BabyBOT *N* (%) |
|---|---|---|
| Total cases processed (*n*) | 1,917 (100) | 4,453[a] (100) |
| Cases approved, notification timely | 802 (41.8) | 3,110 (70.2) |
| Cases approved, notification untimely | 796 (41.5) | 722 (16.3) |
| Cases denied because of ineligibility | 142 (7.4) | 362 (8.2) |
| Cases denied because State could not determine eligibility | 177 (9.2) | 235 (5.3) |

Note: Mean values are based on all months provided by New Mexico. Provided months of data varied for UpdateBOT and BabyBOT.
[a] Disposition is missing for 24 BabyBOT cases. Proportion of cases by disposition is calculated based on the 4,429 cases with disposition.
Source: New Mexico administrative data

The study team also reviewed the total and average monthly tasks performed by the UpdateBOT, BabyBOT, and live chat (table C.15). Each technology was tracked over a different range of time.

*Table C.15. Tasks Performed by UpdateBOT, BabyBOT, and Live Chat Over Study Period, New Mexico*

| Metrics | Study Period | Total Tasks *(N)* | Average Monthly Tasks Mean (SD) | Range |
|---|---|---|---|---|
| UpdateBOT | December 2021–December 2022[a] | 13,388 | 1,115.7 (520.5) | [516, 1,887] |
| BabyBOT | January 2021–June 2022 | 4,453 | 247.4 (65.8) | [60, 343] |
| Live chat | January 2022 – December 2022[a] | 6,655 | 554.6 (94.3) | [315, 675] |

Note: Tables present unweighted means.
SD = standard deviation
[a] December 2022 data were incomplete and removed from calculating total tasks and the average monthly tasks.
Source: New Mexico administrative data

# Appendix D. References


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