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

Final Report

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Glossary

Alternate renewal: a recertification that does not require an interview (used in Georgia)

BabyBOT: RPA use case that adds a newborn to their mother's Medicaid case (used in New Mexico)

Benefit-cost ratio: monetized benefits of an RPA divided by the costs; a ratio greater than 1 indicates the RPA's benefit outweighs the cost

Business exception: a defined error that occurs when the RPA cannot continue working a case

Chatbot: a type of natural language processing that imitates human conversation; because they do not automate processes, chatbots are not considered an RPA

Interrupted time series: an analysis approach that compares the dependent variable (outcome such as processing timeline, backlog) measured prior to implementation with the dependent variable postimplementation

Robotic process automation (RPA): a software program, usually requiring little code, that can be used to automate, repetitive, rule-based processes

Recertification: the requirement for SNAP households to recertify or renew their benefits periodically to continue receiving SNAP

RenewalBOT: RPA use case that helps process online recertifications that do not require an interview (used in Georgia)

Renewal RPA: RPA use case that helps process online recertifications (used in Connecticut)

UpdateBOT: RPA use case that updates a client's address or authorized representative (used in New Mexico)

Executive Summary

In 2022, the Supplemental Nutrition Assistance Program (SNAP) provided food assistance to an average of 21 million households per month. To issue benefits to new applicants and recertify beneficiaries, SNAP State agencies must verify financial (e.g., income, certain assets) and nonfinancial (e.g., identity, household size, disability status) eligibility criteria. Staff also complete several other administrative tasks, from entering address changes to logging interim change reports of SNAP unit circumstances. Some of these tasks involve repetitive data entry actions. Recently, States have begun adopting robotic process automation (RPA) technology to automate repetitive and rule-based processes with the aim of improving customer service, increasing productivity, and reducing errors (Federal RPA Community of Practice [CoP], 2020a; Fishman & Eggers, 2019).

Current use of RPA among SNAP State agencies ranges from updating addresses to tasks as complex as assisting with processing a SNAP recertification. The U.S. Department of Agriculture's (USDA) Food and Nutrition Service (FNS) has supported the adoption of RPA and seeks further knowledge about implementation benefits and challenges. This study helps fill this knowledge gap through case studies of three States with differing RPA use cases. Specifically, the study was designed to meet four objectives:

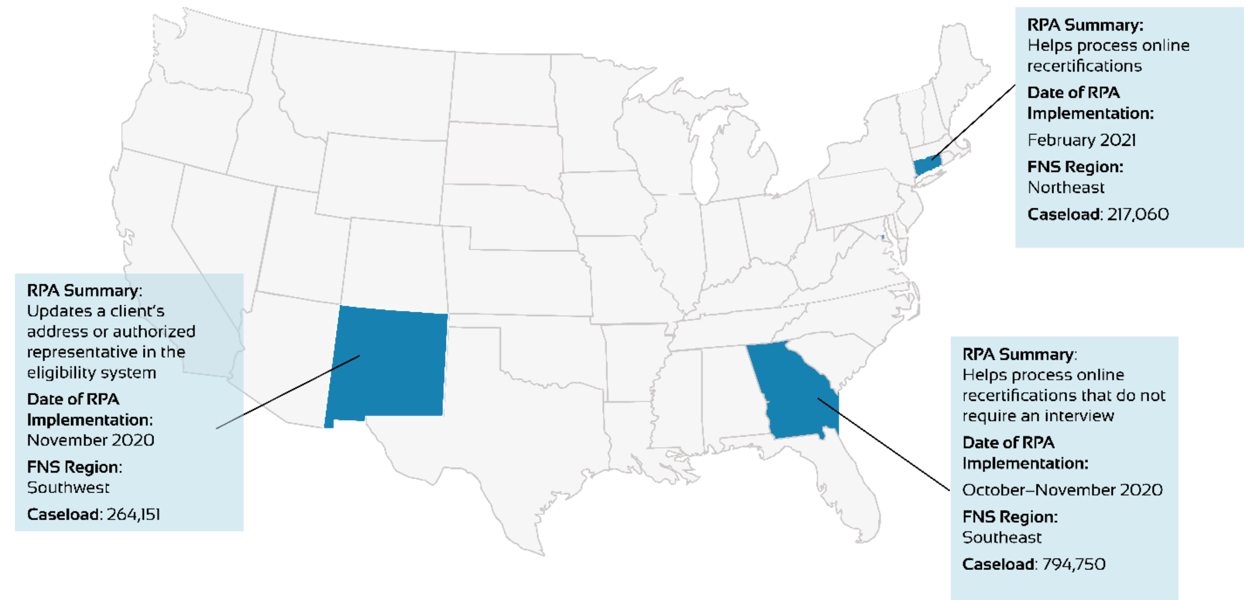
Study Objectives

1. Describe how RPA can be and is being used in SNAP administrative operations, service delivery, and measuring program outcomes.
2. Describe, across the study States, the key features, motivations for selecting, opportunities, challenges, costs, and benefits of their relevant RPA projects.
3. Quantify and assess the impacts, costs, and benefits of RPA projects on SNAP State administrative processes.
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.

A. Methods

This project drew primarily on case study methods to assess RPA use in three States: Connecticut, Georgia, and New Mexico (see figure ES.1). The States reflect a variety of RPA types, FNS regions, caseload sizes, and implementation dates.

Figure ES.1. State Agencies Selected for Study Participation



RPA = robotic process automation

[a] Fiscal year 2021 State average household participation; see https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

The study team collected and analyzed qualitative and quantitative data outlined in figure ES.2.

Figure ES.2. Data Collection and Analysis Components

Qualitative Data	Quantitative Data
• Literature review and interviews with FNS Regional Office staff to provide initial findings on RPA use • Semi-structed interviews with SNAP State agency and frontline staff to understand development, implementation, and continued operation of State's RPA project and challenges and successes of RPA use	• Case-level administrative data and any applicable aggregate-level reports from 6 months before and 6 months after RPA implementation • Cost workbooks to identify all costs and activities associated with development, implementation, and ongoing maintenance of RPA

Note: RPA = robotic process automation

B. Use of RPA

This study profiled two types of RPA.[1] Connecticut and Georgia use similar RPAs that help process online recertifications. New Mexico uses an RPA to help process case updates (i.e., address changes and changes to the authorized representative). Both types of RPA use information provided by clients through an online renewal form, a webchat, or when speaking

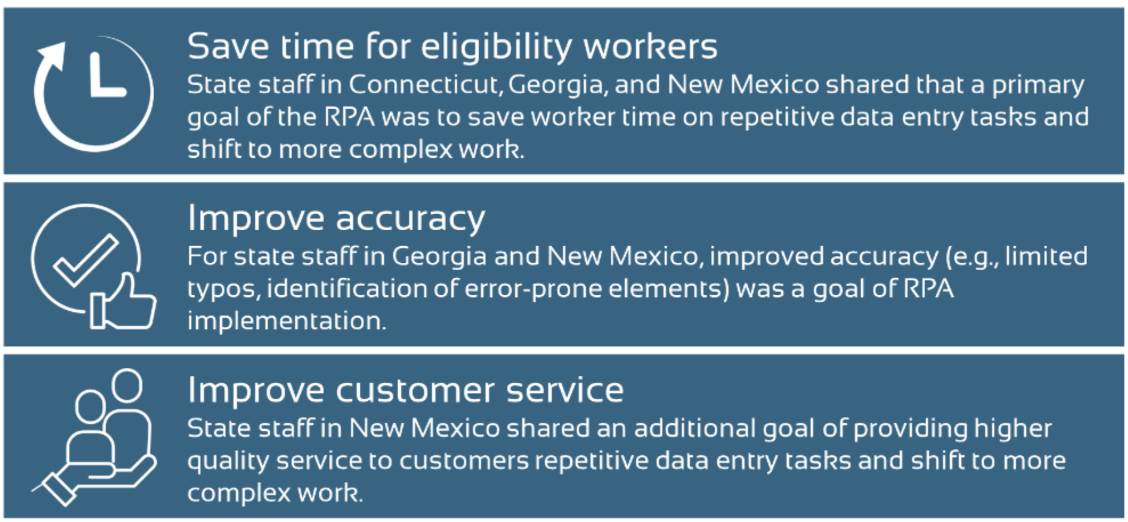
[1] At the time of the study, Georgia was using six RPAs in addition to the one profiled in the study. New Mexico was using five additional RPAs.

with a call center worker to update data within the State's integrated eligibility system. The benefits of using an RPA to update information are clear: The technology cannot make any typographical errors or skip screens, and the information entered exactly matches what the client provided. All three RPAs create new tasks for workers and prepare case notes documenting their actions. In Georgia and Connecticut, the RPA is also able to perform interface checks.

C. Motivations and Barriers to RPA Implementation and Use

Connecticut, Georgia, and New Mexico implemented their RPAs to improve business processes, help staff eliminate backlogs, and improve customer service. Figure ES.3 presents the goals of each State's RPA project.

Figure ES.3. Goals of State RPA Projects



Note: RPA = robotic process automation

1. Barriers

RPA implementation was not without its challenges. In each State, staff had to become familiar with the new technology. Though RPA code may be relatively simple, integrating the software into a State's complex SNAP eligibility system can be complicated. Multiple rounds of testing were required before launch. Each State continues to monitor and test the RPA regularly because any change to the eligibility system may require an update to the RPA code.

Two States faced challenges coordinating with their RPA vendor. At the time of the study, State staff in Connecticut were required to coordinate routine RPA maintenance, testing, and operations with the vendor and were dependent on the availability of contractor staff. New Mexico uses different vendors for the RPA implementation and the eligibility system, and State staff must serve as intermediaries between the two vendors. However, Georgia shared that in-house capability enables the State to be nimble in its operations and saves costs compared with working with an outside party for routine maintenance.

Lack of worker trust in RPA can dampen its benefits. This issue arose in Connecticut and Georgia. States should ensure they provide sufficient RPA training before launching the technology. Training should be offered in several formats (e.g., webinar, written materials). Allowing workers to observe the actions the RPA performs can help establish trust between the new technology and staff. Creating videos of the RPA and sharing them with staff may also be beneficial.

D. Impacts of RPA on Administrative Outcomes, Costs, and Benefits

1. Time Savings

Information collected during interviews with State and frontline staff in Connecticut and Georgia indicates RPAs that help process online recertifications can save time and enable workers to complete more tasks. However, respondents noted that the time savings are minimal.

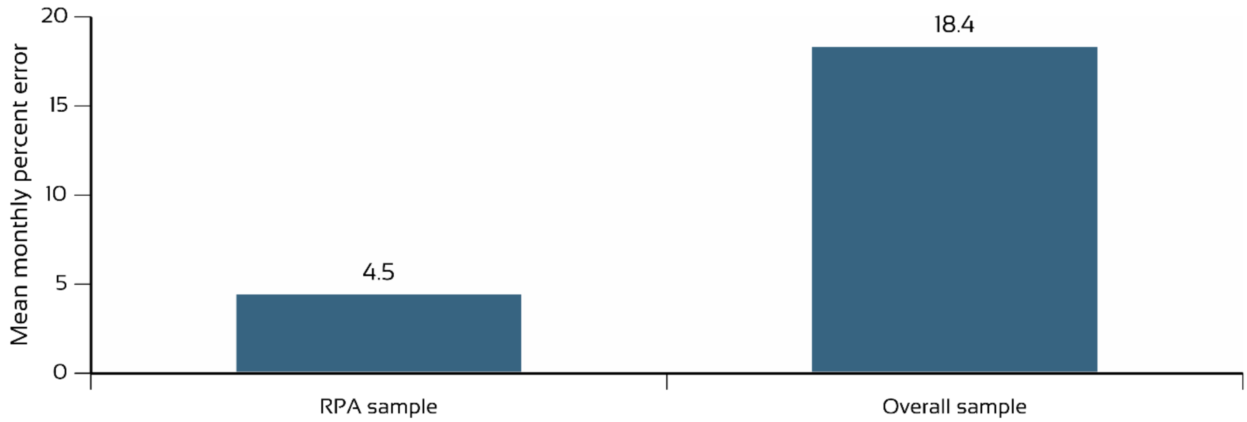
Quantitative findings from Connecticut and Georgia do not suggest RPAs reduced time to certification decision. The number of days to decision was higher for cases processed by RPA in Connecticut. In Georgia, RPA implementation was associated with a statistically nonsignificant increase in days to decision. However, the inability to precisely quantify time savings was the result of data limitations: The study team did not have access to worker productivity data, and days to decision may not be sensitive enough to capture productivity changes. Additional confounding factors, such as lack of staff trust in the RPA, pandemic-related staffing shortages, and increased caseloads, likely influenced the analysis.

Results suggest New Mexico's RPA, which helps process address changes, helps save time for clients. With the RPA, clients can submit an address change via webchat on their own time or through a quick conversation with call center staff. In the past, a client may have waited over 2 hours to speak with an eligibility worker; administrative data indicate clients spend an average of 10 minutes in a live chat. It takes the RPA, on average, only 4 additional minutes to update the address within the eligibility system.

2. Accuracy

Georgia State staff shared that one goal of the RPA was increased accuracy. Staff noted the RPA cannot make typos or other data entry errors, and the red flags it leaves help provide insight to workers on the most error-prone aspects of a case. An analysis of quality control administrative reports found that recertifications processed using an RPA had lower payment error rates (see figure ES.4).

Figure ES.4. Mean Monthly Error Rate for RPA and Overall QC Samples, Georgia

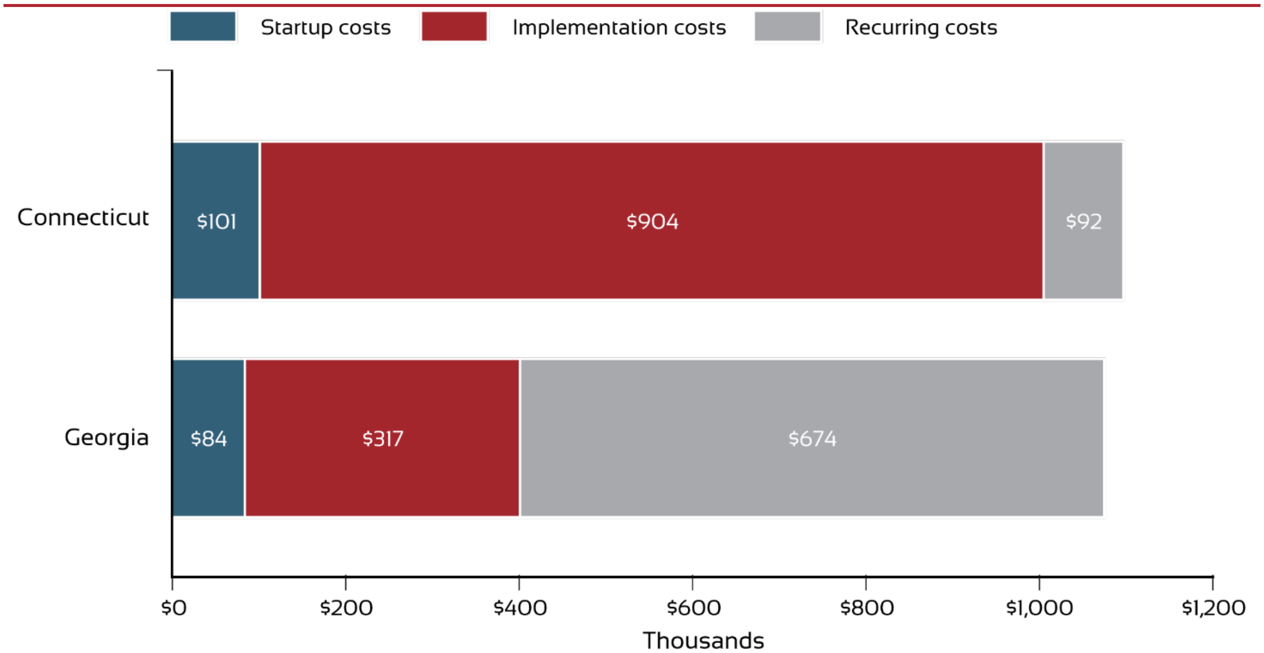


Note: Difference is significant at $p < 0.001$.
QC = quality control; RPA = robotic process automation
Source: Insight tabulations of Georgia administrative QC reports

3. Costs

In Connecticut and Georgia, the study team estimated the total costs of the RPA after 1 year of implementation to be about $1.1 million in each State (see figure ES.5). New Mexico was only able to provide information on recurring costs (e.g., digital worker licenses, monitoring and evaluation); 1 year of these recurring costs total to approximately $217,000.

Figure ES.5. Total Cost of Connecticut and Georgia RPA (in Thousands of Dollars)



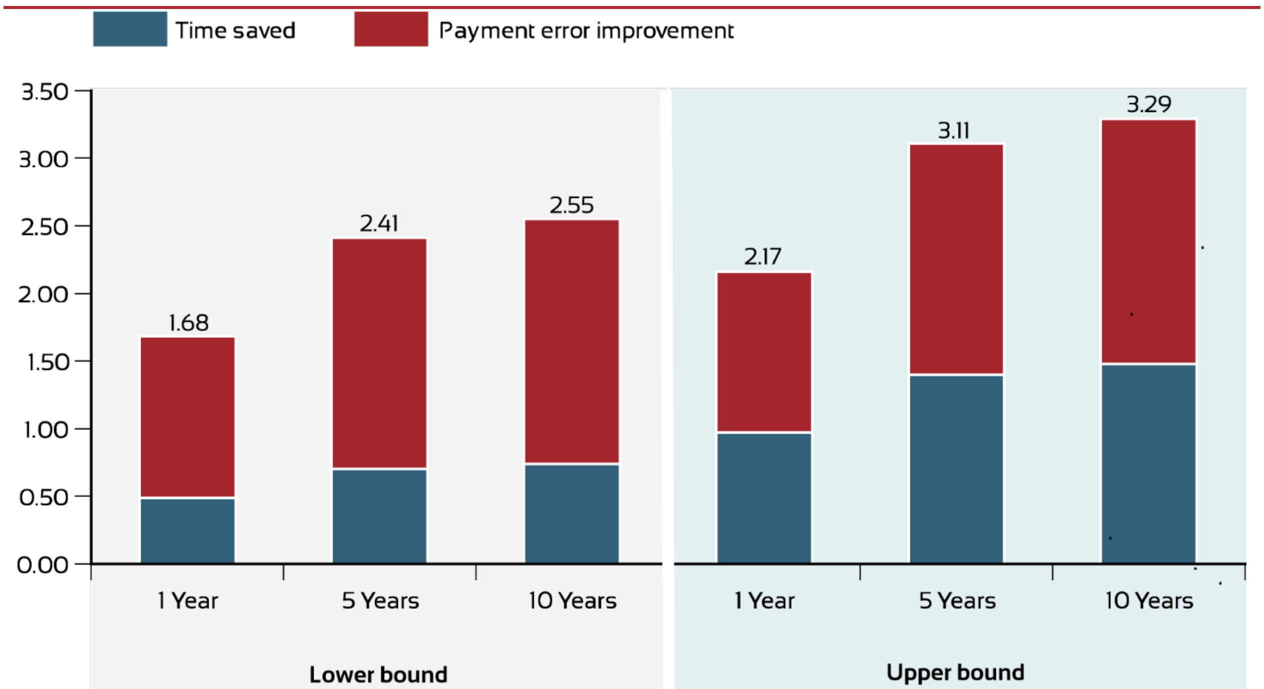
Note: Startup activities include preimplementation meetings and coordination, development of RPA specifications, and grant writing and proposal efforts. Implementation costs include the RPA vendor contract and training. Recurring costs include monitoring and evaluation, ongoing reporting, and ongoing RPA maintenance for 1 year.
RPA = robotic process automation
Source: Insight tabulations of Connecticut and Georgia cost workbooks

4. Benefits

The study team also conducted cost-benefit analyses in Connecticut and Georgia. Connecticut's RPA helps process Medicaid and cash assistance cases in addition to SNAP; the cost-benefit analysis includes the benefit to all these programs. Ultimately, the benefits of Connecticut's RPA did not exceed the costs, even projecting 10 years after implementation. To break even, Connecticut's RPA would need to process 10 times as many cases each year (about 127,000 across all programs), or eligibility workers would need to save 1.6 hours per case, more than the average time spent on a case. During the study period, Connecticut's RPA only processed a third of the online SNAP renewals the State received. If Connecticut were to increase the RPA's capacity through the procurement of additional licenses, the State would likely see an increased benefit. The analysis likely underestimates the potential benefits of the RPA because the study team was only able to monetize eligibility worker time saved (e.g., reductions in errors are not monetized).

In Georgia the study team was able to monetize both eligibility worker time saved and an improvement in the payment error rate. Georgia's RPA benefits exceeded the costs within 1 year of implementation (see figure ES.6). Although the improved error rate yields a larger benefit, time saved by eligibility workers alone nearly exceeds the costs when assuming an average savings of 10 minutes per case.

Figure ES.6. Results of Georgia Cost-Benefit Analysis



Note: A ratio greater than 1 indicates the RPA's benefit outweighs the cost. In the lower bound and upper bound estimates, the study team assumes an eligibility worker saves an average of 5 minutes per RPA case in the lower bound estimates and 10 minutes per RPA case in the upper bound estimate.
QC = quality control; RPA = robotic process automation
Source: Insight's estimation using data from Georgia's cost workbook, staff interviews, and administrative QC reports

E. RPA Scalability

Though many States could benefit from similar RPAs as those used by the three study States, scaling these projects across States is not simple. RPA must be developed with a specific eligibility system in mind, incorporating the exact location of specific elements on each screen. Staff also shared that potential large-scale benefits of an RPA in SNAP were limited by SNAP regulations. Unlike other benefit programs, such as Medicaid, SNAP regulations state that a merit worker must make the final decision on every case. Because a worker still needs to review any updates made to a SNAP case by an RPA, the sheer number of tasks assigned to a worker does not diminish, though they may not need to spend as much time on each task.

Respondents observed that limited information is available to guide States in selecting and implementing an RPA. To better enable States to make decisions regarding RPA implementation, FNS may consider providing additional guidance to States on the following issues:

- **Definition of RPA.** Several Regional Office staff noted they (and States in their regions) had limited experience with RPAs. Providing a clear definition of this technology and explaining how it differs from (and interacts with) other technologies (e.g., chatbots, batch processing, barcoding, other automated system processes) could help States and Regional Offices identify opportunities for RPA.
- **Clear guidelines on acceptable uses of RPAs in SNAP.** Several respondents noted that standardized information from FNS could help guide RPA implementation efforts and improve compliance with complex policies. For example, a list of allowable RPA projects could simplify design and FNS approval processes.
- **Consistent metrics to measure RPA efficacy.** States noted difficulties in providing FNS with requested data. Some respondents felt the requested elements were hard to quantify. Another State noted it was challenging to accommodate FNS reporting requirements because the scope was outside the data the State typically collects or not fully reflective of the benefits of the RPA. FNS may consider working with States to develop a consistent set of metrics for future RPA projects. FNS may also want to consider other data collection approaches, such as random moment time studies, to observe RPA outcomes.

Chapter 1. Introduction and RPA Background

In 2022, the Supplemental Nutrition Assistance Program (SNAP) provided food assistance to an average of 21 million households per month. To issue benefits to new applicants and recertify beneficiaries, SNAP State agencies must verify financial (e.g., income, certain assets) and nonfinancial eligibility criteria (e.g., identity, household size, disability status). Staff also complete several other administrative tasks, from entering address changes to logging interim change reports of SNAP unit circumstances. Some of these tasks involve repetitive data entry actions. Recently, States have begun adopting robotic process automation (RPA) technology to automate repetitive and rule-based processes with the aims of improving customer service, increasing productivity, and reducing errors (Federal RPA Community of Practice [CoP], 2020a; Fishman & Eggers, 2019).

Current use of RPA among SNAP State agencies ranges from updating addresses to tasks as complex as assisting with processing a SNAP recertification. The U.S. Department of Agriculture's (USDA) Food and Nutrition Service (FNS) has supported the adoption of RPA in efforts to increase efficiency and improve service delivery and seeks further knowledge about implementation benefits and challenges. This study helps fill this knowledge gap through case studies of three States with differing RPA use cases. Specifically, the study was designed to meet the following four objectives:

Study Objectives

1. Describe how RPA can be and is being used in SNAP administrative operations, service delivery, and measuring program outcomes.
2. Describe, across the study States, the key features, motivations for selecting, opportunities, challenges, costs, and benefits of their relevant RPA projects.
3. Quantify and assess the impacts, costs, and benefits of RPA projects on SNAP State administrative processes.
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.

A. RPA Background

RPA is a software program, usually requiring little code, that can be used to automate, repetitive, rule-based processes. RPA programs, sometimes referred to as bots, mimic routine actions (e.g., mouse clicks in a web-based SNAP eligibility system) that would otherwise be completed by a human worker (Federal RPA CoP, 2020a; Fishman & Eggers, 2019). RPA is well suited for rule-based processes because the rules can be programmed into the software to limit errors. Broadly, an immediate goal of RPA is often to reduce the time staff spend on time-consuming, repetitive tasks, providing more time for more complex tasks. By extension, RPA may also standardize decision-making and reduce human errors, processing, wait times, and costs to employers and customers (Fishman & Eggers, 2019).

RPA is distinct from artificial intelligence (AI) technologies which, instead, analyze and learn from data and simulate human intelligence to complete complex tasks. An example of AI technology is natural language processing, where the AI learns to interpret human language. In contrast, RPA is based on a concrete and unchanging set of rules (CFB Bots, 2018). RPA and AI can be combined to leverage the benefits of both types of technologies. For example, an RPA can be paired with a chatbot, which applies AI technology to imitate human conversation. A chatbot on a website can interact with a customer to collect information, and then the RPA can perform a specific task to process the information (McGloin, n.d.-a; McGloin, n.d.-b; Munroe, 2017).

B. Benefits and Limitations of RPA

While RPA can provide potential benefits to users, it has limitations associated with implementation (see table 1.1). Broadly, RPA can improve workforce efficiency and reduce errors. States can often implement an RPA more quickly than a change to their eligibility system. However, because RPA works quickly, programming errors can affect many cases in a short timespan; robust testing and quality assurance protocols are critical. Unlike AI, RPA technology lacks the ability to handle exceptions or grey areas, so it requires thorough testing on diverse datasets. Thus, it may be difficult to scale across States, where even small differences in policies can create exceptions not included in the original tests. Lastly, because RPA replicates human processes, States may need to examine internal processes prior to automation to avoid introducing bias in RPA implementation.

Table 1.1 Benefits and Limitations of RPA Technology

Benefits	Limitations
▪ RPA can improve workplace efficiency and enable staff to work on higher order activities (e.g., speaking with clients rather than data entry) ▪ RPA can improve accuracy for routine activities (e.g., RPA cannot make a typo) ▪ RPA is relatively quick and inexpensive to implement ▪ RPA may reduce costs by processing data more quickly and efficiently than a worker	▪ RPA may magnify errors; robust testing and QA procedures are needed ▪ RPA replicates human inputs into other software, which may have their own errors ▪ Few regulations and guidelines exist on use of RPA in FNS programs ▪ RPA cannot handle exceptions or adapt to changes without thorough testing and revisions to code ▪ RPA may have data privacy and security concerns (e.g., handling of PII)

Note: PII = personally identifiable information; QA = quality assurance; RPA = robotic process automation
Sources: Chief Innovations Officers Council, n.d.; Desouza & Krishnamurthy, 2017; Federal RPA CoP, 2020a; Federal RPA CoP, 2020b; FedScoop, 2021; Fishman, 2015; Management Concepts, 2021; McGloin, n.d.-b; Mulvaney, 2018; Rehr & Munteanu, 2021; Shein, 2018; StateScoop, 2021; Wood, 2020; Wright & Bott, 2017

C. Use of RPA in the Federal Government

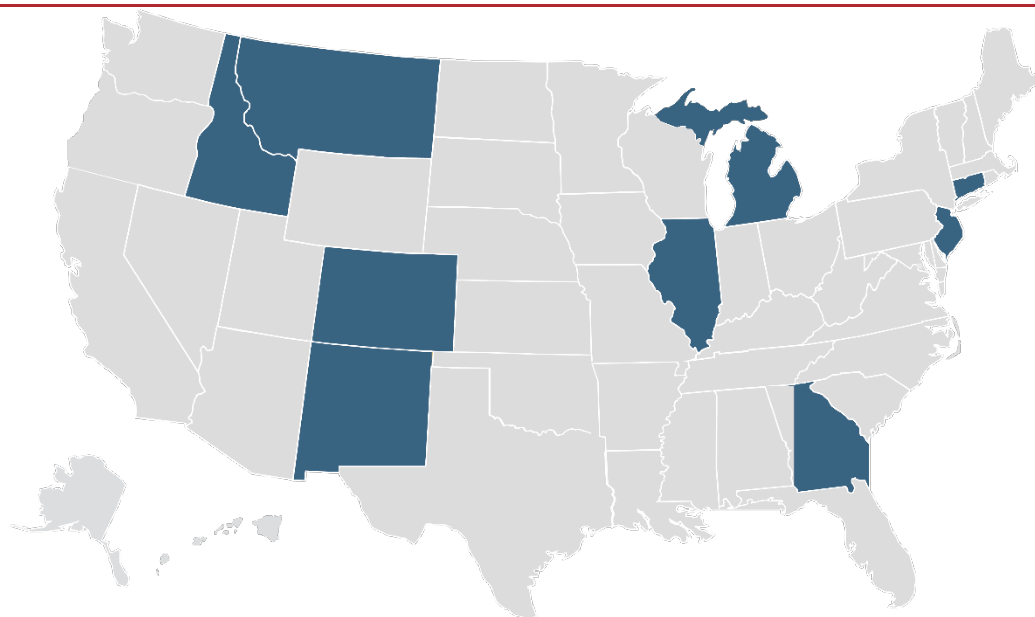
Several Federal and State agencies have deployed RPAs to support government staff and streamline program operations (Desouza & Krishnamurthy, 2017). A survey of Federal and State operations executives conducted in November and December 2020 found 66 percent of Federal and 40 percent of State respondents reported their agency used RPA technology (FedScoop &

StateScoop, n.d.). The most common uses of RPA in the public sector include data collection and processing, document management, identity verification, support of workflow transitions (e.g., routing documents between offices), and call center support (Rehr & Munteanu, 2021).

D. Use of RPA Among SNAP State Agencies

As of January 2022, nine States were using RPA in SNAP administration: Colorado, Connecticut, Georgia, Idaho, Illinois, Michigan, Montana, New Jersey, and New Mexico (see figure 1.1). Use of RPA technologies among SNAP State agencies includes assisting with recertifications and periodic reporting, updating addresses, entering case notes, sending missed interview notices, and updating reporting related to SNAP Employment and Training participation.[2] These tasks are particularly well suited for RPA because each has a straightforward logic. For example, in Georgia, the RPA inputs information from a client's SNAP renewal form into the eligibility system by following the system's built-in driver flow.

Figure 1.1. RPA Use Among SNAP State Agencies



Note: RPA = robotic process automation

[2] Depending on the task, an RPA may only be able to assist with part of a process. For example, for recertifications, an eligibility worker will still need to make the final determination and review the steps taken by an RPA.

1. Considerations for RPA Use Within an Integrated Eligibility System

Many State agencies use integrated eligibility systems that help workers determine eligibility for several Federal programs, including SNAP, Medicaid, and Temporary Assistance for Needy Families (TANF). The use of integrated eligibility systems adds both opportunity and complexity to adopting RPA used in other assistance programs (e.g., Medicaid) for SNAP. While some of the RPA projects used in Medicaid could likely be scaled and implemented in the SNAP context, changes to RPA actions would be needed to ensure compliance with SNAP regulations. For example, some States use RPA to automatically enroll a newborn in Medicaid; this RPA could not be directly copied from Medicaid to SNAP without adding a step for an eligibility worker to approve the change.

2. SNAP Regulations Related to RPA Use

SNAP State agencies must also consider two regulations when implementing RPA. First, SNAP regulations require that a worker make the final decision on every case.[3] To comply with this regulation, RPA cannot authorize, deny, or change benefit status but can be used to organize and edit information to “stage the case” for an eligibility worker. Second, RPA must comply with policy on what action the State takes when the information is questionable, unclear, or considered known to the State agency from another program administered by the same State agency.[4] This complex decision tree could increase the potential points at which errors could arise in an RPA, especially if an RPA functions within an integrated eligibility system. Household income, for example, is calculated differently for Medicaid than for SNAP; new income information reported in Medicaid would need to be interpreted differently in SNAP to understand whether any action is needed.

E. Study States

Three States participated in the study: Connecticut, Georgia, and New Mexico. The States reflect a variety of RPA types, FNS regions (Northeast, Southeast, and Southwest), and caseload sizes. For instance, Georgia’s caseload is approximately three times the size of Connecticut’s or New Mexico’s.[5] Georgia and New Mexico implemented their RPAs in 2020, while Connecticut implemented its RPA in 2021.

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[3] 7 C.F.R. § 272.4

[4] For further information, see https://www.fns.usda.gov/snap/recipient/reporting-state-agency-requirements.

[5] Fiscal year 2021 State average household participation; see https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap

Connecticut has implemented one RPA use case to automate aspects of the State's online renewal process. The RPA imports data from the online renewal form into the State's eligibility system and checks certain interfaces. Once the RPA finishes its work, it reclassifies the task for the worker and leaves case notes. The worker then makes the final determination on the case.

Georgia has implemented seven RPA use cases. The study team focused on the RenewalBOT. This RPA imports data reported by the applicant on their online SNAP renewal form; extracts data from other interfaces, PDFs, and the eligibility system; and documents error-prone elements for the eligibility worker to follow up on. The other six RPA use cases complete tasks ranging from sending notices to TANF participants to documenting SNAP work requirements.

New Mexico has implemented five RPA use cases. The study team focused on the UpdateBOT, which updates a client's address or authorized representative in the eligibility system. Other RPAs automate processes to add a newborn to an existing case (BabyBOT), reset a password, and move comments from the State's call center system to its eligibility system documenting SNAP work requirements.

F. Impetus for the Study

RPA is a relatively new technology in SNAP case management. While FNS has approved RPA implementation in a handful of States on a case-by-case basis, no clear guidelines exist on acceptable use cases within SNAP operations. Although States have shared information about their experiences with RPA at conferences and in informal conversations, little information is publicly available on the use of RPA among SNAP State agencies across the country and the expected costs, benefits, and returns on investment.

The remainder of this report presents case studies of RPA use in three States: Connecticut, Georgia, and New Mexico. The case studies discuss important considerations for developing and implementing RPA projects, associated outcomes, and the costs and benefits of the technology. The report concludes with a discussion of the considerations for future use of RPA in SNAP, including facilitators to implementation and operations gleaned from interviews with the study States, relevant challenges, and considerations for scalability.

Chapter 2. Study Methods

The project employed a case study methodology to understand and assess the use of RPA in SNAP in Connecticut, Georgia, and New Mexico. The study team interviewed State and local office staff and collected administrative and cost data from each State. Prior to data collection, the study team also conducted a literature review and interviewed FNS Regional Office staff to develop an initial understanding of the extent of RPA use among SNAP State agencies. Table 2.1 presents the study objectives and data sources used to address them. Appendix A provides a crosswalk of data sources and research questions for each objective.

Table 2.1. Study Objectives by Data Source

Study Objective	Literature Review	Interviews With Federal Staff	Interviews With Key Informants	Administrative Data	Cost Data
Describe how RPA can be and is being used in SNAP administrative operations, service delivery, and measuring program outcomes	●	●	●		
Describe, across the study States, the key features, motivations for selecting, opportunities, challenges, costs, and benefits of their relevant RPA projects	●	●	●		
Quantify and assess the impacts, costs, and benefits of RPA projects on SNAP State administrative processes			●	●	●
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	●	●	●	●	●

Note: RPA = robotic process automation

A. Literature Review and Interviews With Federal Staff

The project team conducted a literature review and interviewed FNS Regional Office staff. The literature review focused on documents provided by FNS and internet searches for grey[6] and academic literature about RPA. The documents received from FNS provided initial findings regarding the use of RPA in SNAP. Grey and academic literature provided data on the use of RPA in the private and public sectors and the benefits, limitations, and challenges associated with the technology.

Documents Received From FNS

- Process and Technology Improvement Grant (PTIG) applications
- Major Change Documents and FNS approvals
- RPA Pilot Data Reports
- Results from FNS survey of RPA use
- RPA environmental scan

The study team also conducted 1-hour interviews with staff in each of the seven FNS Regional Offices to further explore the use of RPA in SNAP. Interview topics included (1) the use of RPA among States in the region; (2) RPA development processes, including the role of FNS in State implementation efforts; (3) RPA outcomes; (4) availability of existing State data on RPA outcomes; and (5) the future of RPA use in SNAP, including challenges and considerations. The study team used findings from these interviews to inform the State selection process.

B. Key Informant Interviews

1. Data Collection

The study team conducted in-depth semi-structured virtual interviews with State and frontline staff (e.g., eligibility workers, supervisors; see appendix B for the protocols). Interviews occurred between August and November 2022, and topics included (1) the use of RPA in the State; (2) RPA decision-making; (3) RPA development, implementation, and testing; (4) outcomes; (5) benefits and costs; and (6) scalability. The study team also collected additional relevant documentation from States, such as RPA manuals and training materials (e.g., video recordings of RPA). Table 2.2 describes the interviews completed with each State.

Table 2.2. Interviews Completed by State

State	Interviews Completed
Connecticut	■ Two interviews with SNAP State agency staff – One interview with policy and data systems staff – One interview with quality assurance and testing staff ■ Three interviews with SNAP frontline staff
Georgia	■ One interview with SNAP State agency staff, including policy and data systems staff ■ Three interviews with SNAP frontline staff

[6] Grey literature is literature produced by government agencies, not-for-profit entities, or private enterprises that is outside of commercial publication channels (e.g., books or peer-reviewed journals). Grey literature includes theses and dissertations, conference papers and proceedings, reports (e.g., white papers, working papers, internal documentation), government documents, datasets/statistics, policies/procedures, blog posts, and social media (North Central University, 2021).

State	Interviews Completed
New Mexico	▪ Two interviews with SNAP State agency staff – One interview with policy and data systems staff – One interview with quality assurance and testing staff ▪ Two interviews with frontline staff ▪ One interview with Medical Assistance Division staff knowledgeable about BabyBOT

2. Analysis

The study team synthesized data from documents and interviews to provide a comprehensive description of each State's RPA projects and determine primary limitations and considerations for RPA scalability and future use in SNAP. Following the interviews, the study team reviewed and abstracted information from transcripts and supporting documents. The study team summarized takeaways and met regularly to discuss common and distinct insights gathered from each interview. This process helped identify cross-cutting themes related to RPA successes and challenges.

C. Administrative and Cost Data

1. Data Collection

Administrative data. The study team sent an administrative data request and variable list to each State requesting data from 6 months prior and 6 months after RPA implementation (see appendix B). Connecticut and Georgia provided case-level data for recertifications assisted by the RPA[7] and high-level RPA summary reports. New Mexico provided case-level data for the UpdateBOT and aggregate reports for both UpdateBOT and BabyBOT. Table 2.3 summarizes the data each State submitted (see appendix A for additional details).

Table 2.3 Administrative Data From Study States

State	Timeframe	Data Received
Connecticut	December 2020–December 2022	▪ Case-level data on recertifications, including RPA and non-RPA cases (i.e., cases processed entirely by eligibility workers) ▪ Additional summary files: total number of cases processed per month and number of RPA tasks closed
Georgia	May 2020– May 2021	▪ Case-level data on recertifications, including preimplementation period ▪ Additional summary files: QC data and FNS reports
New Mexico	July 2021–December 2022	▪ Case-level data on cases processed by UpdateBOT December 2021–December 2022 ▪ Additional summary files: description of cases processed by UpdateBOT (July 2021–April 2022) and BabyBOT (January 2021–June 2022); separate files of time spent on live agent chats and customer satisfaction

Note: QC = quality control; RPA = robotic process automation

[7] The RPA runs data matches, enters data, and creates tasks for eligibility workers. Eligibility workers determine eligibility for each case.

Cost data. To identify all costs and activities associated with the development, implementation, and ongoing maintenance of the RPA, the study team developed and sent each State a cost workbook (see appendix B). States used the workbook to report time spent by staff on relevant tasks (e.g., developing RPA specifications, testing), staff salaries, and other direct costs (e.g., contracts, licenses) associated with the RPA. Upon receipt of the completed cost workbooks, the study team reviewed the data and sent any clarifying questions to the State via email. All States provided a completed cost workbook, but New Mexico was unable to provide startup and implementation costs.

2. Analysis

Administrative data. The study team used the administrative data to assess RPA outcomes. Table 2.4 describes the analytic approach for each State (see appendix A for further details).

Table 2.4. Administrative Data Analysis Approach, by State

State	Approach
Connecticut	▪ Examined monthly trends in number of recertifications processed daily following RPA implementation ▪ Used ordinary least squares regression to compare (1) eligibility worker time spent on recertification requests and (2) number of days to decision with and without RPA assistance following RPA implementation
Georgia	▪ Examined monthly trends in recertifications processed and days to decision pre- and postimplementation for RPA and non-RPA cases ▪ Used interrupted time series analysis to compare mean days to decision pre- and postimplementation ▪ Examined differences in payment error rates between RPA and non-RPA cases postimplementation
New Mexico[a]	▪ Examined monthly trends in UpdateBOT tasks following implementation ▪ Examined variation in RPA use across geography and household type ▪ Explored trends in case disposition and timeliness for UpdateBOT

Note: RPA = robotic process automation

[a] New Mexico provided summary data for the BabyBOT. The study team presents trends in BabyBOT use, case disposition, and timeliness in appendix C.

Cost data. The study team used the data from the State cost workbooks to estimate the total cost of each RPA project. When possible, the team also conducted a cost-benefit analysis. Table 2.5 describes the analysis for each State (see appendix A for further details).

Table 2.5. Cost Data Analysis Approach, by State

State	Approach
Connecticut	1. Estimated total RPA costs; used sensitivity analysis to adjust for uncertainty in costs 2. Used case-level RPA pilot data[a] to estimate and monetize one RPA benefit: amount of time saved per case; calculated benefit-cost ratio
Georgia	1. Estimated total RPA costs; used sensitivity analysis to adjust for uncertainty in costs 2. Used QC summary files and information gathered from interviews with frontline staff to estimate and monetize two RPA benefits: decreased errors and eligibility worker time saved; calculated benefit-cost ratio
New Mexico	1. Examined recurring State staff and RPA license costs associated with all RPAs and chatbots; analysis excluded contractor staff costs and other direct costs

Note: QC = quality control; RPA = robotic process automation

[a] In the pilot data, which contain information on Medicaid, SNAP, and TANF cases processed by the RPA, workers reported the time it took to process a case after the RPA and the time they thought it would have taken without the RPA.

D. Study Limitations and Considerations

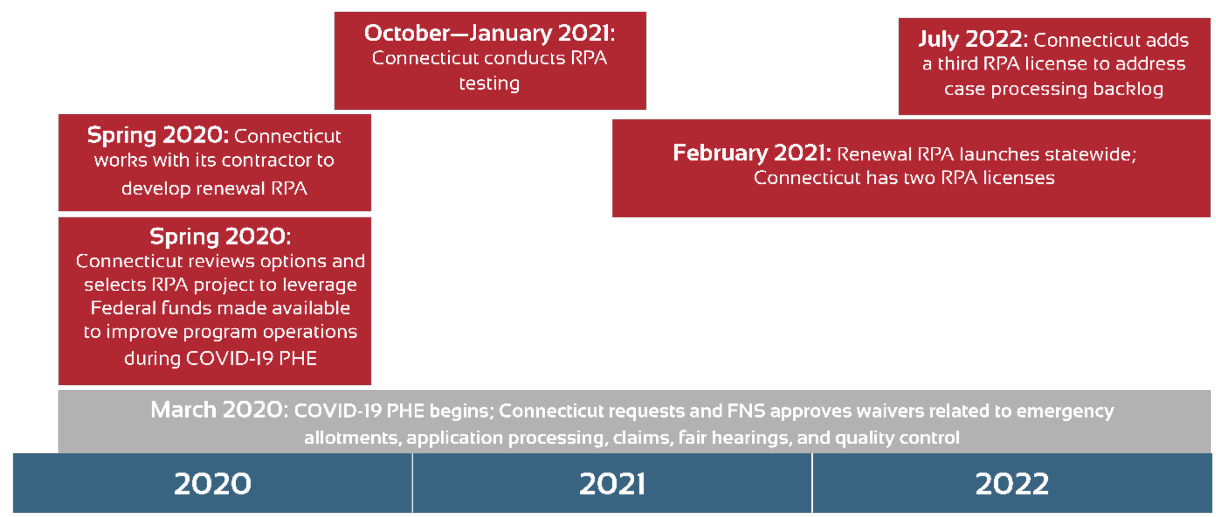
Because the project uses a case study design to assess the use and impact of RPA in three States, findings are not generalizable and reflect only the experiences of these States. Other States that choose to implement RPA may have different outcomes and costs. The study has other limitations that warrant consideration:

- All three study States implemented their RPA in 2020 at the height of the **COVID-19 public health emergency (PHE)**. At that time, States were using a variety of COVID-19 waivers offered by FNS to ensure continued operations; the use of these waivers may have affected RPA implementation, program operations, and outcomes.
- Most implementation activities took place in 2020, approximately 2 years prior to data collection. Respondents were asked to **retroactively estimate their time spent on RPA implementation activities**. The study team conducted sensitivity analyses to account for the potential recall bias.
- All three States encountered **challenges providing historical data.** The dates the State agency received a client's SNAP renewal form and made the final determination sometimes reflected the most recent date for each case rather than the dates associated with the RPA task. Because RPA data (e.g., time spent on task) were not recorded in the State's integrated eligibility system, Connecticut and New Mexico also encountered challenges linking RPA data and the eligibility system.
- Georgia and New Mexico implemented RPA as part of larger technological updates, leading to **challenges disentangling RPA-specific costs** from other contract costs.

Chapter 3. Use of RPA in Connecticut

In February 2021, Connecticut implemented an RPA to assist with online SNAP, Medicaid, and cash assistance (e.g., TANF) renewal tasks, referred to as the renewal RPA. This RPA updates a client's case in Connecticut's eligibility system based on information received on the online renewal form and conducts certain interface checks. Figure 3.1 presents a timeline of RPA implementation activities and other key dates.

Figure 3.1. Connecticut Renewal RPA Development and Implementation Timeline

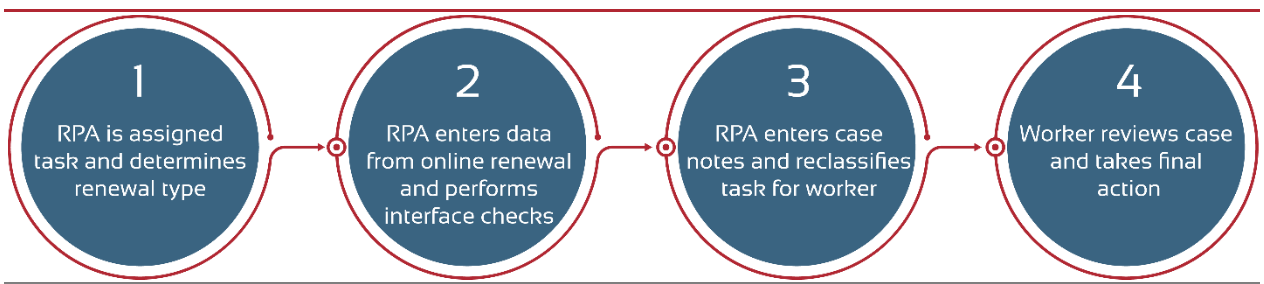


Note: PHE = public health emergency; RPA = robotic process automation

A. RPA Features

At the time of the study, Connecticut had three licenses for its renewal RPA. From June 2020 to August 2021, the RPAs ran Monday through Friday, excluding holidays. In January 2022, the State extended RPA runtimes to 7 days a week from 7 a.m. to 7 p.m. All three RPA licenses follow the same process (see figure 3.2); a description of this process follows.

Figure 3.2. Connecticut RPA Process



Note: RPA = robotic process automation

1. As the first step in the process, Connecticut's task management system assigns the RPA an online renewal. Using information from the renewal form, the RPA determines whether the case is a "change" or "no-change" renewal.[8]
2. The RPA then inputs participant data from the renewal form into the State's integrated eligibility system, ImpaCT. The RPA also runs internal and external interface checks (e.g., Equifax) to confirm information reported by the client or elsewhere in ImpaCT.
3. When the RPA completes its work, it creates a task for an eligibility worker to review the RPA's actions and make a final determination on the case. The RPA can create four categories of tasks: no-change requiring review, no-change requiring resolution, change requiring review, and change requiring resolution. Eligibility workers only need to verify the RPA's work for "review" cases; however, "resolution" cases require eligibility workers to follow up with a client or take other actions to resolve discrepancies. The RPA also adds a task comment that lists next steps for the worker and a separate case note to document the interface check results.
4. Finally, an eligibility worker reviews the RPA-generated task. For a "resolution" case, the worker addresses the issue(s) the RPA identified. The worker then makes the final benefit determination and enters a case note.

If the RPA encounters an error in the interface check, the RPA logs the error in the case notes and continues processing the case. Once the RPA's review is complete, the task is marked as "return to work pool," and the eligibility worker manually completes the interface check during their review. The RPA may also encounter one of several defined business exceptions, which requires human intervention. The most common business exception occurs when the RPA is unable to locate the household in the State's eligibility system and, therefore, cannot initiate the renewal.

B. Development and Implementation

In spring 2020, Connecticut asked its IT contractor, Deloitte, to present RPA use case scenarios for the State's consideration that would streamline operations and support State staff and participants. Ultimately, the State developed its renewal RPA using COVID-19 relief funding available to support State process improvement efforts.

Connecticut's RPA project team included a SNAP policy expert, a Medicaid expert, an interface program specialist, and a project manager, who worked directly with the IT contractor. The project team also worked with the policy division, field operations division, and legal department throughout the development and implementation process. Respondents noted that the core project team had the correct people to ensure the RPA aligned with Federal regulations and followed all applicable policies.

[8] Change renewal cases include revisions to participant information (e.g., employment status, address) from the previous benefit authorization. No-change renewal cases include the same participant information as the prior benefit authorization.

The IT contractor programmed the RPA during the summer of 2020 using technology from the RPA vendor, UiPath. State staff noted that using a contractor familiar with the State's eligibility system eliminated the learning curve and created consistency across projects and systems. State staff also discussed the importance of working collaboratively and iteratively with the contractor, especially when staff may be unfamiliar with RPA technology and unaware of what issues may arise. Together the teams developed an RPA design document, which outlined each action the RPA takes when working a case. The teams also used the document to track issues encountered during RPA testing. The document quadrupled in size throughout development and testing, showcasing the iterative nature of the development process.

During the development phase, Connecticut had to decide where to host the RPA—either on internal servers or external servers maintained by the IT contractor. At the time of the study, the IT contractor hosted Connecticut's RPA, but the State shared it was planning to transition to a new State-controlled environment. This transition, which occurred in February 2023, enabled State staff to operate and test the RPA directly and removed the need to coordinate with the IT contractor for routine RPA testing, maintenance, and operations. According to State staff, these hosting and licensing changes reduced costs associated with the RPA.[9]

At the time of the study, State staff reported Connecticut was using only one RPA, the renewal RPA. However, they expressed interest in exploring other RPAs, such as the BabyBOT. State staff noted that an RPA acceptable use policy, published by FNS, could support States in scaling RPA projects if it clearly outlined permitted technologies, technologies that require additional FNS approval, and technologies that are not allowed.

1. Testing

Three members of Connecticut's quality management (QM) team supported RPA testing. These staff were knowledgeable about internal testing procedures and SNAP policy. The QM team engaged in several rounds of testing from October 2020 to January 2021. The testing approach included two phases: manual tests and dry runs of the RPA. During the manual testing phase, the QM team had to manually create specific testing scenarios. For example, to test a reported income change, the team needed to create a scenario that included an income change without adjusting any other data. The IT contractor then conducted the test, and the QM team reviewed the results. During the dry run phase, the IT contractor identified 20 renewals submitted by clients to run the RPA against in the production environment. The QM team reviewed the output data and case notes to ensure the RPA worked properly.

QM team members noted several challenges with the testing process. It was time consuming to create testing scenarios, and the team was short-staffed, which was particularly challenging given the short turnaround for this project. However, staff noted that the two-pronged testing approach worked well. In the future, they recommend extending the testing timeline and

[9] Because the transition did not occur during the study period, the cost savings are not reflected in the cost analysis (see section E).

connecting the testing and development teams early in the project to help mitigate any challenges.

The RPA project team also conducted two RPA pilots, one in December 2020 for no-change renewals and the other in January 2021 for change renewals. Staff decided to pilot the no-change renewals first because they were simpler. The State recruited teams of frontline staff (e.g., eligibility workers, supervisors) to serve as testers. Testers completed a virtual RPA training prior to the pilot. For each pilot case, testers reviewed the actions taken by the RPA and the case notes. They also recorded in an Excel document how long it took to process the renewal and how much time they thought it would have taken in the absence of the RPA.[10] Pilot testers discovered issues with case note formatting, procedures for handling utility expenses, and challenges documenting child support payments. These issues were resolved prior to the full RPA launch in February 2021.

Since the RPA launch, the RPA project team has made minor modifications to the RPA, such as revising task handling logic. Each time ImpaCT is updated—regardless of the magnitude of the update—the QM team must conduct a round of regression testing to ensure the RPA continues to work as expected. Until the RPA was moved onto an internal server, the QM team had to coordinate with the IT contractor to complete these routine testing procedures. State staff noted this issue as a challenge because Connecticut did not have full control of RPA operations and was dependent on the contractor's availability and resources.

2. Training

The RPA project team did not directly offer additional staff training opportunities when the RPA launched. The project team shared information about the technology through a series of emails and materials (e.g., the State's RPA guide). Staff were also told to reach out to their colleagues who were involved in the pilot testing with any questions.

> Some people thought [the RPA] was just a worker not processing their work.
>
> *—Frontline staff*

Interview respondents acknowledged not offering additional training was a misstep. Both State and frontline staff noted that eligibility workers were confused about the new technology, and some workers thought the RPA was a fellow staff member who was shirking their work and not processing cases correctly. To address confusion, the RPA project team held staff training meetings and developed additional training materials in 2022, after the technology launched. The Connecticut team noted the need for staff training at the time of RPA launch was a key lesson learned.

C. Outcomes

RPA implementation had two primary goals: decreasing the time staff spend on recertification tasks and increasing the number of recertifications processed daily. The renewal RPA also had

[10] Connecticut shared the Excel file containing data from the pilot with the study team.

one unintended beneficial outcome. Frontline staff reported the format of the case notes left by the RPA was simple and provided the eligibility worker all the necessary information. Other Connecticut teams are interested in adopting this format and reference it as the standard for case notes.

1. Time Savings

> I would say [the RPA] is probably 95 plus percent accurate.… [The RPA] helps streamline the process bit and maybe save[s] a couple of minutes in the research phase … instead of the research taking half an hour, maybe it took 25 minutes [with the RPA].
>
> *—Frontline staff*

State staff expected the RPA to decrease the time spent processing a no-change renewal. While frontline staff thought the RPA does save them time, they noted any time savings are minimal. Specifically, one interview respondent reported the RPA decreases case processing time for no-change renewals, participants with stable incomes, and large households; however, those time savings decrease when eligibility workers need to refer to or rerun interface checks. Another interview respondent noted that the straightforward cases, where the RPA saves time (e.g., no change renewals, stable incomes), only compose 20 percent of the average eligibility worker's caseload. Self-reported pilot data suggest eligibility workers expected to save an average of 9 minutes on a case worked by the RPA compared with a case they had to fully process.

One respondent noted an eligibility worker's time is spent differently on cases worked by the RPA compared with those processed manually. An eligibility worker's review of an RPA case is passive because the worker is checking the RPA's actions. A manual case requires the eligibility worker to actively review all pages of the renewal form and navigate many screens in the ImpaCT system. An interview respondent also suggested RPA-worked cases have fewer errors than cases processed solely by eligibility workers**.**

Quantitative assessment

Connecticut provided administrative case records from January 2021 through January 2023. The records included cases processed by the RPA and those processed entirely by eligibility workers.[11] Connecticut could not provide cases from the preimplementation period. The data included a measure of eligibility worker time spent on each case; however, because of data quality concerns,[12] the study team could not reliably compare the time eligibility workers spent on RPA cases with time spent on non-RPA cases.

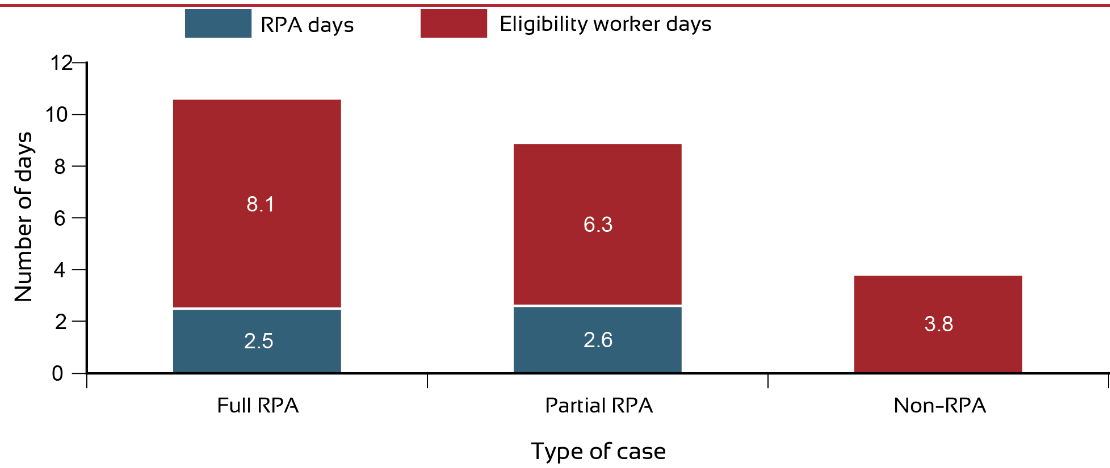
The administrative case files also included the date the recertification request was received and the date the eligibility worker issued the certification decision; the study team used these two

[11] The case-level files had fewer RPA and non-RPA recertifications than the total number of recertifications processed by Connecticut. The study team used case-level files for the time analyses and the summary data for the caseload analysis below because of the relative strengths of each dataset.
[12] The data included many missing values and implausibly long times spent on the task (e.g., 6 percent of cases with reported time were recorded as taking 23–24 hours). About 7 percent of RPA cases with reported eligibility worker times took over 23 hours; 4.2 percent of non-RPA cases took longer than 23 hours.

variables to calculate the number of days to decision. The study team compared the mean number of days to decision for recertifications processed by the RPA and cases processed by eligibility workers (non-RPA). RPA cases were further stratified by whether the RPA was able to completely process the recertification (full RPA) or only partially completed its assigned tasks (partial RPA).[13] During the first 2 years of implementation, full RPA recertifications took an average of 10.5 days to complete, partial RPA cases took an average of 8.9 days, and cases processed entirely by eligibility workers took 3.8 days (see figure 3.3). For both full and partial RPA cases, on average, the RPA completed its task about 2.5 days after the State received the renewal. On average, eligibility workers made the final decision 8.1 days after the case was processed by the RPA for a full RPA case and 6.3 days after for a partial RPA case.

The difference between RPA and non-RPA cases remained similar through December 2022. The longer time spent on full RPA cases contrasts with the State and study team's hypothesis that the RPA would reduce time. The reasons for these differences are not clear and may be related to eligibility workers doublechecking the work completed by the RPA. Another explanation may be that the RPA processes cases received during the previous 3 days. While, ideally, eligibility workers would pull and complete the RPA task as soon as the RPA has finished, it is not always possible and could extend the number of days to decision. The tasks in an eligibility worker's task queue depend on caseload, staffing, and assignment configurations (i.e., which tasks are prioritized), which could lead to a worker pulling RPA-generated tasks later than other more highly prioritized tasks.

Figure 3.3. Mean Days to Decision for Full RPA, Partial RPA, and Non-RPA Cases in Connecticut



N = 54,322

Note: All recertification decisions are issued by eligibility workers. Full RPA indicates cases where the RPA completely processed the recertification case and then assigned the case to an eligibility worker for review or resolution and certification decision. Partial RPA indicates the RPA processed some portion of the recertification but could not complete all tasks because it encountered an error or business exception. Non-RPA cases were initially assigned to and entirely completed by eligibility workers. Cases with missing application date, RPA process date, or eligibility worker date were removed from this analysis.

Source: Insight tabulations of Connecticut RPA data

[13] Appendix A describes how full and partial RPA processing status was determined.

To help explain the differences in days to decision, the study team examined variation in the types of cases assigned to the RPA and eligibility workers. The administrative data also included a measure of SNAP household income type (see appendix table C.1).[14] The study team conducted a regression controlling for SNAP household income type; in this model, full RPA was the reference case. Results suggested that partial RPA recertifications were associated with a 2-day shorter processing period compared with full RPA recertifications; the mean days to decision for non-RPA cases was over 6 days shorter than for full RPA recertifications (see table 3.1). The longer processing period associated with RPA cases was unexpected. Internal processes related to working RPA cases, worker time spent reviewing the cases, or data limitations could explain the findings.

Table 3.1. Regression Results: Association Between RPA Implementation and Days to Decision for Online Recertifications, Connecticut

Parameter		Estimate (SE)	*p*-value
RPA type	Full RPA	Ref.	Ref.
	Partial RPA	-2.20 (0.07)	< 0.001
	Non-RPA	-6.30 (0.07)	< 0.001
Earned income		1.04 (0.06)	< 0.001
Unearned income		0.22 (0.07)	0.001

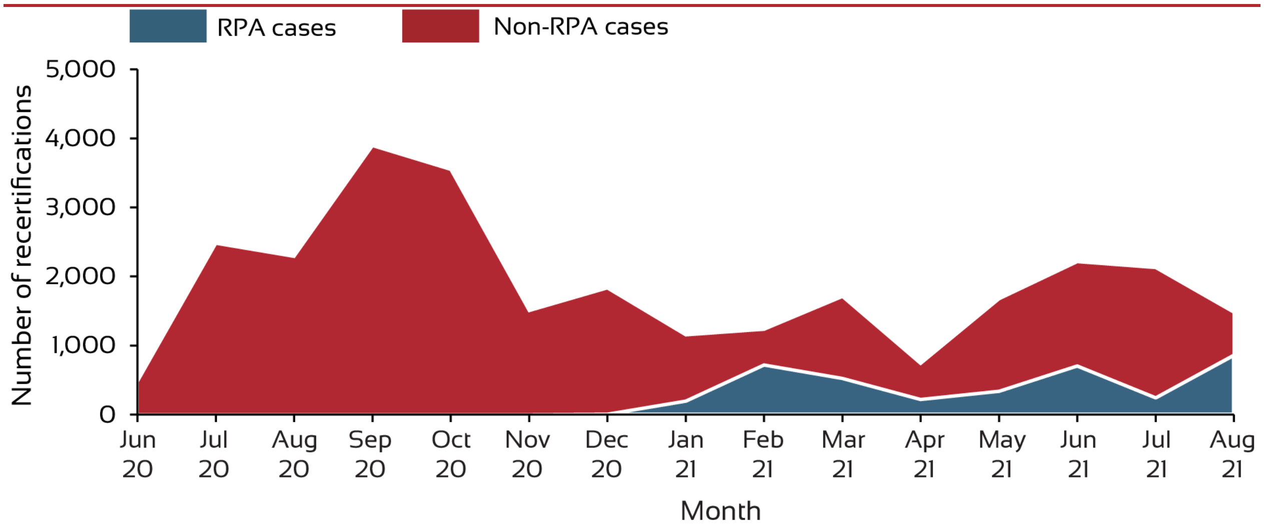
N = 58,269
Note: This model suggests that, on average, recertification cases with earned income take about 1 day longer than cases without earned income. Cases with unearned income also extend the days to decision but only by about a fifth of a day. Compared with full RPA recertifications and controlling for income types on the case, partial RPA recertifications take 2 fewer days to issue a decision; non-RPA cases take 6 fewer days. A *p*-value of 0.05 was set as the cutoff for statistical significance. All independent variables were significantly associated with days to decision.
RPA = robotic process automation; ref. = reference group; SE = standard error
Source: Insight tabulations of Connecticut RPA data

2. Number of Recertifications Processed

State staff expected the introduction of RPA to increase the number of cases that could be processed per day. The COVID-19 PHE presented a challenge to evaluating this outcome. Summary data provided by the State suggest caseloads were variable in the months preceding the RPA implementation (see figure 3.4). In the months following RPA implementation, the percent of SNAP recertifications processed by the RPA ranged from less than 1 percent during the pilot period to 59 percent in February 2021.

[14] A greater proportion of RPA cases had earned income (76 percent) than non-RPA cases (71 percent); more non-RPA cases had unearned income (80 percent) than RPA cases (77 percent). These data suggest potential unmeasured differences between the kinds of cases assigned to the RPA.

Figure 3.4. Number of SNAP Recertifications Received by Connecticut, Before and After RPA Implementation



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

The variation in caseload directly affects the number of cases processed a day. Because the overall recertification caseload appears to have declined following RPA implementation, the number of cases processed each day has also declined. The RPA caseload may also be capped because of the total capacity of Connecticut's three RPA licenses and Medicaid and cash assistance caseloads.

D. Challenges to RPA Use

Eligibility worker mistrust of the RPA proved to be a challenge in Connecticut. Several interview respondents reported manually checking the RPA's actions to ensure the case was processed correctly before proceeding with the next steps identified by the RPA. Any time savings associated with the RPA are potentially diminished if staff are essentially doing "double the work."

> Once I started going through more and more cases, and there weren't errors, and [the RPA] was consistently being accurate, then I kind of developed more … trust.
>
> *—Frontline staff*

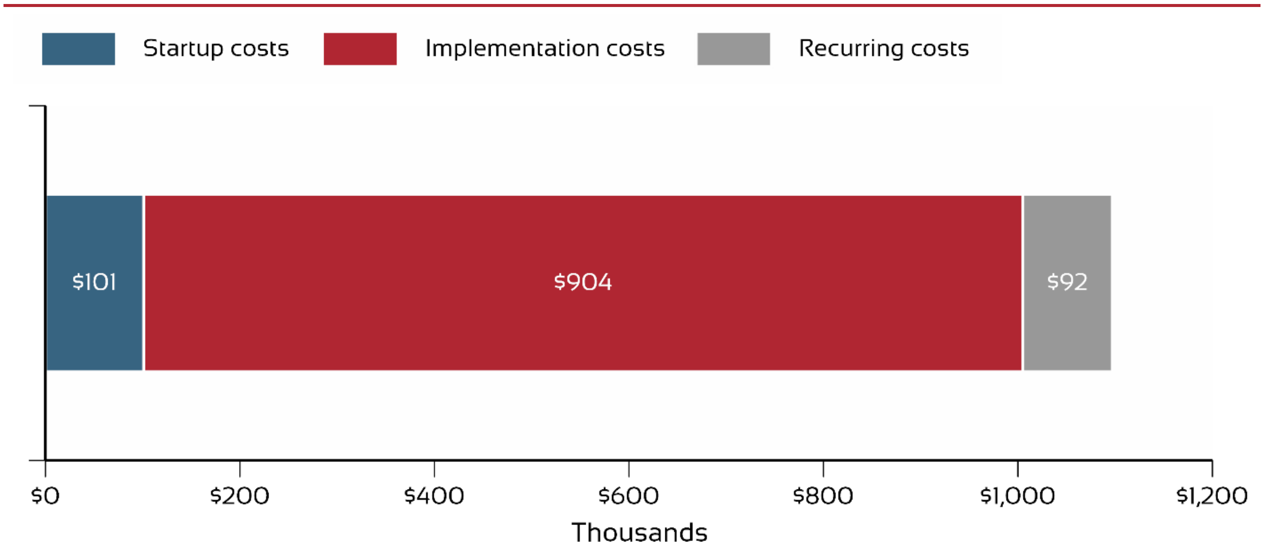
Interview respondents explained why workers may not trust the RPA and how trust issues may have been mitigated. One interview respondent noted that staff distrust may stem from the agency's corrective action procedures. When a case error is identified, the eligibility worker who last authorized the case typically receives a correction. Because frontline staff are unclear on the corrective procedures for cases where the RPA made an error, it may prevent workers from trusting the RPA's work. Interview respondents suggested additional staff training before RPA launch may have mitigated staff trust issues; however, another interview respondent thought staff members' RPA trust challenges would have emerged regardless of prelaunch training.

E. Comparing Costs and Benefits

The availability of Federal funding catalyzed Connecticut's RPA project. The State was interested in the technology previously but did not pursue it until an opportunity to leverage Federal resources emerged.

Connecticut's RPA cost approximately $1.1 million (see figure 3.5). Startup activities, including preimplementation meetings and the development of RPA specifications, accounted for 9.2 percent of the total cost. Implementation costs accounted for 82.4 percent of the total RPA cost. The largest single item cost—the design, delivery, and implementation contract—accounted for nearly 60 percent of the total cost of Connecticut's RPA. The estimated recurring costs, which include vendor contracts for RPA maintenance and quality assurance, are 8.4 percent of Connecticut's total RPA cost. When Connecticut added its third RPA license, the State paid additional implementation costs but no further maintenance costs.

Figure 3.5. Total Cost of Connecticut's RPA, in Thousands of Dollars



Note: Startup activities include preimplementation meetings and coordination, development of RPA specifications, and grant writing and proposal effort. Implementation costs include the design, delivery, and implementation contract; the training of technical assistants and eligibility workers; and the testing of the RPA performance. Recurring RPA costs include monitoring and evaluation, ongoing reporting, and ongoing RPA maintenance for 1 year. See appendix table C.2 for the cost sensitivity analysis.
RPA = robotic process automation
Source: Insight tabulations of Connecticut cost workbook

The study team assessed the costs and benefits of RPA implementation. The team projected the annual recurring RPA costs and monetized the benefits of eligibility worker time saved to produce a benefit-cost ratio. During pilot testing, eligibility workers reported saving an average of 9 minutes per recertification task. Ultimately, the cost of Connecticut's RPA exceeded the benefits, even 10 years postimplementation (table 3.2). For Connecticut's RPA to break even 1 year after implementation, eligibility workers needed to have saved an average of 1.6 hours per case, a duration of time larger than the average length of time spent on a case by a worker. Alternatively, with an average of 9 minutes saved per case, the RPA needed to have processed

10 times as many cases in a year, or approximately 127,000 cases. Lastly, during the study period, Connecticut's RPA only processed a third of the online SNAP renewals the State received. If Connecticut were to increase the RPA's capacity through the procurement of additional licenses, the State would likely see an increased benefit.[15]

However, it is important to note that the presented cost-benefit analysis underestimates the potential benefits of the RPA. The study team was only able to monetize one benefit: eligibility worker time saved. Anecdotal evidence from interviews with State and frontline staff suggests Connecticut's RPA may have other benefits, such as enabling workers to focus on more complex tasks (e.g., interacting with clients) or improving case accuracy; the study team was unable to measure these benefits because of a lack of data. Interview respondents believed the benefits of the RPA outweigh the costs, but the challenges presented by eligibility workers' lack of trust in the technology are an important factor to consider.

Table 3.2. Results of Connecticut Cost-Benefit Analysis

Years Postimplementation	Benefit/Cost Ratio	Sensitivity Analysis: Lower–Upper Bounds
1	0.10	0.05–0.12
5	0.36	0.19–0.42
10	0.53	0.28–0.62

Note: A ratio greater than 1 indicates the RPA's benefit outweighs the cost. The primary ratio assumes an average time saved of 9 minutes per RPA case. In the sensitivity analysis, the study team assumes an eligibility worker saves 5 minutes and 11 minutes per RPA case, the 25th and 75th percentiles reported in the pilot dataset. See appendix table C.3 for the underlying inputs.
Source: Insight estimation using Connecticut cost workbook and administrative pilot dataset

F. Conclusions

Connecticut implemented the renewal RPA to help improve and streamline business processes. Interviews with Connecticut State and frontline staff suggest the renewal RPA does help eligibility workers save time, though respondents noted the time savings are minimal. While quantitative findings do not suggest time savings, this may be a result of data limitations. The study team did not have access to worker productivity data and used days to decision as an imperfect proxy for time savings. During the period of analysis, Connecticut only had two RPA licenses, which also limited the number of renewal tasks the RPA could process.

In a pilot report shared by the State, eligibility workers estimated an average of 9 minutes of time savings per RPA case compared with a non-RPA case. The study team used this estimate to conduct a cost-benefit analysis. Results indicate the costs of the renewal RPA do not exceed the benefits. However, the study team was only able to monetize one benefit (time saved), which means the analysis likely underestimates any benefits associated with the RPA.

[15] During the study period, Connecticut's RPA processed an average of 1,066 cases per month (518 SNAP cases). During the same time period, Connecticut received an average of 1,594 SNAP renewals per month. Increasing the productivity of the RPA could help increase the benefits of the technology.

Interviews with State and frontline staff also revealed two lessons learned and two facilitators to RPA implementation and continued operations in Connecticut.

1. Lessons Learned

- **RPA hosting environment.** When RPA vendors maintain control of the technology after launch, State staff are required to coordinate routine RPA maintenance, testing, and operations with the vendor. In Connecticut, this process meant State staff were dependent on the availability of contractor staff. In February 2023, Connecticut moved the RPA to an in-house server to mitigate this challenge.
- **Staff training and promoting staff trust in the RPA.** RPA training should be offered in several formats before RPA launch to ensure staff receive the most important details and know how to seek further help. All staff should also have access to training materials in multiple forms (e.g., webinars, written materials). Worker buy-in is essential for the successful launch of RPA technology. State staff should consider ways to foster RPA trust from the outset of a project, not only at launch. RPA training may help promote staff trust of the technology, but States should also consider other trust-building measures.

2. Facilitators

- **Detailed RPA requirements document.** Connecticut worked iteratively with its IT contractor to develop a comprehensive RPA requirements document throughout the project lifecycle. The final version of the document outlines each action the RPA takes when processing a case (including screenshots of RPA actions), identifies RPA issues the teams encountered during testing, and lists the defined business exceptions. This document serves as the primary reference for information related to Connecticut's renewal RPA design and functionality. Working collaboratively on the document enabled both the State and its contractor to ensure all potential RPA scenarios were identified and worked through before statewide implementation.
- **Comprehensive RPA testing.** Connecticut's QM team leveraged a two-pronged testing approach (i.e., manual tests and dry run tests) to observe how the renewal RPA performed in specific scenarios and when working with actual client cases. The QM team's approach promoted collaboration between the State and IT contractor teams. Connecticut had three RPA testers dedicated to the project; these QM staff were familiar with the RPA, the technology's intended functionality, and State policies. The QM team noted the availability of staff and other support resources (e.g., testing documents, plans) is crucial to a successful RPA testing initiative.

Chapter 4. Use of RPA in Georgia

In November 2022, Georgia was using seven RPA use cases across its public benefit programs. This chapter focuses on the RenewalBOT, which helps workers process alternate SNAP recertifications that do not require an interview. Georgia had other RPAs to assist with tracking work participation for TANF, issuing notices to TANF participants, conducting preliminary case reads to help supervisors identify errors, and tracking SNAP work requirements. Georgia also developed two RPAs to assist with Medicaid changes and recertifications in preparation for the end of the PHE. Figure 4.1 presents a timeline of RPA implementation activities and additional key dates.

Figure 4.1. Georgia RenewalBOT Development and Implementation Timeline

Note: PHE = public health emergency; RPA = robotic process automation

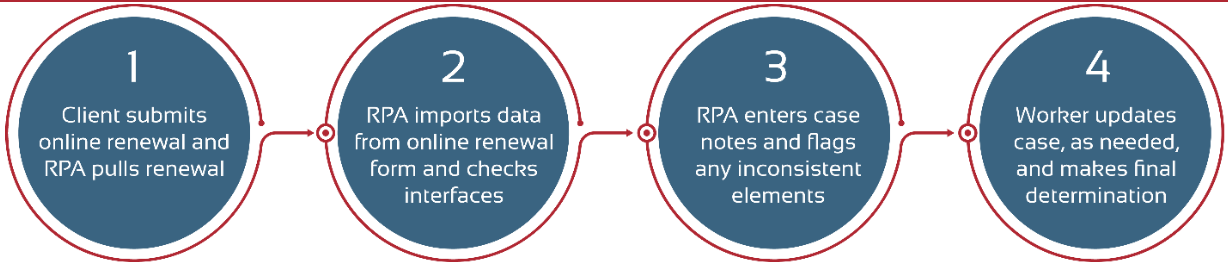
A. RPA Features

> [The RPA] also helps spin our time back from data entry and prework into traditional case management … to [try to] help people substantively work through challenges and barriers that they are facing.
>
> *—State staff*

Georgia's RenewalBOT helps workers process SNAP recertifications that do not require an interview (i.e., alternate recertifications).[16] The RPA has three functions: (1) import data reported on the client's SNAP online renewal form into Gateway, Georgia's integrated eligibility system; (2) check interfaces (e.g., child support [STARS], Medicaid [FDSH], the Work Number, Social Security [SOLQ]); and (3) document case notes and create red flags for inconsistent elements (e.g., income reported in the Work Number but not on the renewal form). Once the RPA finishes its work, the case is added back to an eligibility worker's task queue. The worker reviews the case comments left by the RPA, addresses any red flags, pulls necessary information from interfaces, updates the case, and makes the final determination. Figure 4.2 presents an overview of the process.

[16] In this chapter, the discussion of recertifications processed by the RPA includes only recertifications that do not require a phone interview. These cases are also referred to as alternate renewals in Georgia.

Figure 4.2. Georgia RPA Process

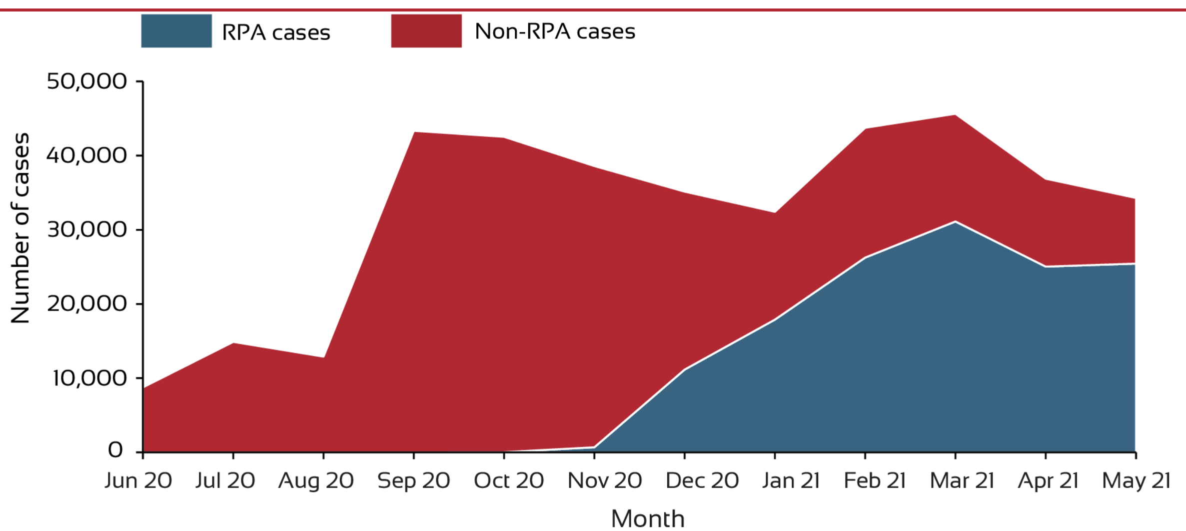


Note: RPA = robotic process automation

During the study period, Georgia had 150 licenses for its RenewalBOT, more than double the number (70) operational during the pilot phase. Multiple licenses enable an RPA to work on the number of cases equal to the number of licenses simultaneously.[17] Georgia's RPA runs 24/7 and takes about 12 to 15 minutes to complete one case, though the duration largely depends on household size.

Since it was launched, RenewalBOT has increasingly handled a higher proportion of alternate recertification cases (see figure 4.3).[18] The total number of alternate recertifications increased in the preimplementation period (before November 2020) but remained relatively consistent in the months following RPA implementation. During the pilot phase (October–November 2020), only about 1 percent of cases were processed by the RPA. Beginning in December 2020, this proportion increased, culminating with RenewalBOT processing nearly three-quarters of all recertifications not requiring an interviews 6 months postimplementation.

Figure 4.3. Number of Alternate Recertifications Processed by the RenewalBOT in Georgia



Note: RPA = robotic process automation
Source: Insight tabulations of Georgia RPA data

[17] While each RPA uses the same code, it can only work one case at a time.
[18] During the COVID-19 PHE, interviews were waived during some periods, and the RPA was able to process standard renewals (i.e., renewals that typically require an interview). This analysis focuses on alternate renewal requests to be consistent over time.

1. Further Use of Technology

Georgia also explored further use of technology in SNAP operations. State staff were considering the use of virtual artificial intelligence call center agents and were working with students at the Georgia Institute of Technology to develop machine learning algorithms to assist with call routing and task assignment optimization. Georgia was also seeking FNS approval to implement an additional RPA, known as an attended RPA, that would work in real-time to assist an eligibility worker with processing a recertification application. Staff also discussed how RPA technology could be better leveraged in the future to allow interconnectivity across different programs (e.g., SNAP and school meals).

B. Development and Implementation

Initially, Georgia decided to implement the RenewalBOT to assist staff with the case backlog. State staff chose to automate aspects of the SNAP recertification process because they believed it would have the largest impact on the backlog; recertifications represent a large volume of worker tasks. A primary facilitator in Georgia's implementation process was buy-in from leadership in the Governor's Office and the Office of Planning and Budget. This support ensured the SNAP agency had the funds to implement the technology and the project did not encounter any delays.

In addition to staff at the Georgia SNAP agency and the Office of Planning and Budget, leadership at the Office of Information Technology was also involved in the decision-making process. Georgia also worked closely with the FNS Southeast Regional Office. After submitting a Major Change Report, FNS staff visited the Georgia SNAP office and received a demonstration of the RPA.

1. Development

Georgia worked with a software company, UIPath, to develop the RPA. The State approached UIPath because the company had the required expertise. Georgia was interested in developing in-house RPA capabilities. Once UIPath developed the initial program, State IT staff took over all ongoing RPA updates and maintenance. Georgia State staff noted the importance of developing in-house RPA competency. Making modifications in-house saves time and money because outside contractors may not be familiar with SNAP eligibility rules and policy. Though IT staff noted they were unfamiliar with RPA technology when it was first implemented, they were quickly able to get up to speed. Staff indicated that making necessary updates and coding new RPA is relatively simple.

> I would definitely advocate that States need to be committed to doing [RPA], to some degree, in-house so that they can continuously make … modifications. Otherwise, every deployment is going to have a cost charge, … a formalized process, or some additional component that you're paying for versus an integrated system where [you] can be more nimble and reactive to real-time situations.
>
> *—State staff*

2. Testing

During the pilot phase, State staff tested several scenarios and configurations within Gateway and reviewed every case the RPA touched to ensure cases contained no errors. Staff in the policy unit, field program operations, and the quality control (QC) unit were all involved in RPA testing. Postimplementation, Georgia continues to monitor the RPAs, conducts daily reads on a sample of cases, and updates the list of business exceptions as needed.

Testing did not reveal any instances where the RPA caused an error, but the team did encounter a variety of business exceptions. A business exception occurs when the RPA cannot continue working a case; the case is then sent back to the worker. One common example of a business exception is needing to add or remove a person from a case. Though the RPA is not able to complete its work on a case when it encounters a business exception, all updates it has made are retained. Georgia maintains a desk guide for workers explaining the possible business exceptions.

3. Training

Ahead of the RenewalBOT's launch in November 2020, all eligibility workers participated in online training through the State's Institute for Online Training and Instructional Systems platform. The training was developed by the State's SNAP policy training unit. The State later shared desk guides with eligibility workers and provided additional one-on-one trainings via videoconference. One frontline worker shared that the training was helpful because it enabled workers to see what the RPA would be doing.

Both State and frontline staff acknowledged some initial mistrust of the RPA. One frontline staff member was concerned the RPA was going to conduct case reviews. The staff member noted feeling relieved upon learning the RPA was designed to help workers and not monitor them or review their work. State staff also noted that showing workers the RPA QC data helped gain workers' trust because they could see an improvement in case accuracy for cases worked by the RPA.

C. Outcomes

According to State and frontline staff, RPA implementation had two primary goals: save worker time and increase accuracy. The RenewalBOT also had one unintended beneficial outcome. Because the RPA works through many cases per day, it can alert IT staff to any errors or defects in the system (i.e., conduct regression testing).

1. Time Savings

State and frontline staff indicated the RPA can help save worker time and ensure Georgia can meet Federal timeliness benchmarks through the following mechanisms:

- The RPA completes much of the repetitive data entry across the 286 screens in Gateway, Georgia's integrated eligibility system (e.g., enters dates, updates addresses). One worker noted the ability to get through more recertification tasks in a day because of the prework the RPA had done; this worker shared that the RPA saved 5–10 minutes per case.[19] The worker used the time saved by the RPA for more in-depth conversations with clients.
- Because the RPA goes through the entirety of Gateway's driver flow, workers can navigate to a specific screen in the system if they need to update information, rather than clicking through all the screens.

However, as one worker noted, RPA time savings may be minimal for some cases. A worker cannot simply approve the recertification without reviewing the case notes, updating income, or resolving discrepancies. For more complex cases, where a call to the client is necessary or additional verification documents are required, a worker must still complete the bulk of the work processing the recertification.

> It's saved a lot [of time] because, normally, when we first enter a renewal, … we have to click on every page in order to go to another page. So if [the RPA] goes in the case before us, that means that [the RPA already] went to every page…. [Now] we can click on the first page, the income page, … without having to go through every single page.
>
> *—Frontline staff*

Quantitative assessment

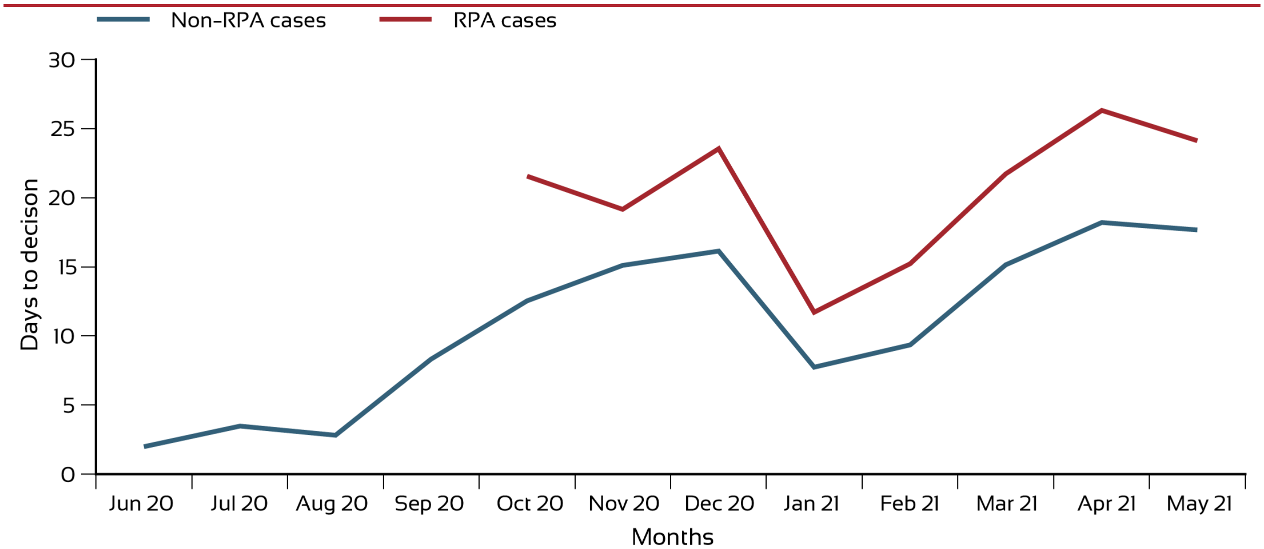
To help determine whether time savings were associated with the implementation of RenewalBOT, the study team examined trends in the number of days to decision among all alternate recertifications (figure 4.4). The team defined days to decision as the number of days elapsed between the time the State received a client's online SNAP renewal form and the time an eligibility worker made the final determination on the case. The number of days to decision began increasing in September, prior to RPA implementation in October. In the 6 postimplementation months, cases processed by the RPA consistently took between 4–8 days longer to complete than cases processed solely by eligibility workers. The average number of days to decision was consistently less than a month for both RPA and non-RPA cases.

Because only 1 year of data was available, it is unclear if the general trend toward increased days to decision changes represents seasonal trends. Waivers, policy changes, and staffing shortages related to the COVID-19 PHE may also have influenced the length of time needed to process a recertification. It is not clear why RPA cases would take more days to process than non-RPA cases. Reasons may include a time lag in when cases processed by the RPA are

[19] Because of a lack of productivity data, the study team was unable to quantitatively assess time saved per case as a result of RPA implementation.

assigned; eligibility workers spending time checking tasks performed by the RPA; a delay in contacting applicants to confirm income or address outstanding questions; or coding issues within the eligibility system.

Figure 4.4. Trends in Days to Decision, RPA and Non-RPA Alternate Recertification Cases in Georgia



Note: The RPA was implemented in October 2020. For monthly sample sizes see appendix table C.4.
RPA = robotic process automation
Source: Insight tabulations of Georgia RPA data

The study team also conducted an interrupted time series design to assess whether the use of the RPA led to a change in time eligibility workers spend on each case. The study team requested data on the amount of time spent by eligibility workers and the RPA on each alternate recertification; however, the State did not collect this information. As a proxy for time spent, the study team assessed changes in the number of days to decision for alternate recertifications. The team hypothesized that if the RPA saves worker time, workers should then be able to process and issue benefits more quickly for RPA recertification cases. This may lead to a faster turnaround time for all recertification cases, including cases processed entirely by eligibility workers, because workers can complete more tasks per day. The study team dropped all standard recertifications to ensure the sample was consistent (i.e., in case the time spent on alternate renewals varied from other renewals).[20] Because of the unusually high mean days to decision in May 2020, the study team removed May from this analysis.

Results from the interrupted time series model suggest the introduction of the RenewalBOT was associated with a statistically nonsignificant 3-day increase in the number of days to decision (table 4.1; figure 4.5). A significant trend in increased days to decision each month was observed in both the pre- and postimplementation periods. Following RenewalBOT implementation, the number of days to decision increased 1.4 days each month, reflecting a

[20] The majority of cases in the file were alternate recertifications. Waivers issued in response to the COVID-19 PHE allowed interviews to be waived during certain months across the study period; the RenewalBOT was used on some of these recertifications.

slower increase than observed preimplementation. The study team also examined whether the effect of the RPA varied by case simplicity by comparing days to decision for households with one member and households with more than one member.[21] Although the trends differed slightly, RenewalBOT implementation was associated with an average increase in days to decision for both household categories (see appendix table C.7).

The increase in the number of days to decision may be the result of extra diligence on the part of eligibility workers in ensuring the RPA completed its tasks correctly. Challenges related to RPA use (RPA overwriting information and not reassigning tasks to a worker's queue; see section D) may also have contributed to an increase in the number of days to decision. Frontline staff noted that trust in the RPA increased over time, and fewer staff were doublechecking the RPA's work; future analyses may want to consider examining trends further into the postimplementation period. The SNAP State agency also reported that staff turnover was a challenge; worker shortages may have increased the number of days to decision for the entire caseload.

The number of days to decision depends, in part, on client action. After reviewing the case, additional information may be required from the client to determine eligibility (e.g., additional documentation). Georgia's policies provide the client the maximum amount of time to respond within the standard of promptness (i.e., by the 30th calendar day following the date of application). The study team was not able to determine whether a case was pending because it needed client or State action; future research should consider this distinction.

As noted above, the study team was unable to directly assess the amount of worker time saved on each renewal task; future research on this outcome would be valuable. It is possible that although the entire recertification process takes additional days (while remaining within SNAP timeliness limits), the overall time spent handling a case has been reduced. That is, it may still take a worker 20 days to get to a renewal task in their queue, but they spend less time per task than before and can complete more tasks throughout the day.

Table 4.1. Interrupted Time Series Results: Days to Decision in Georgia

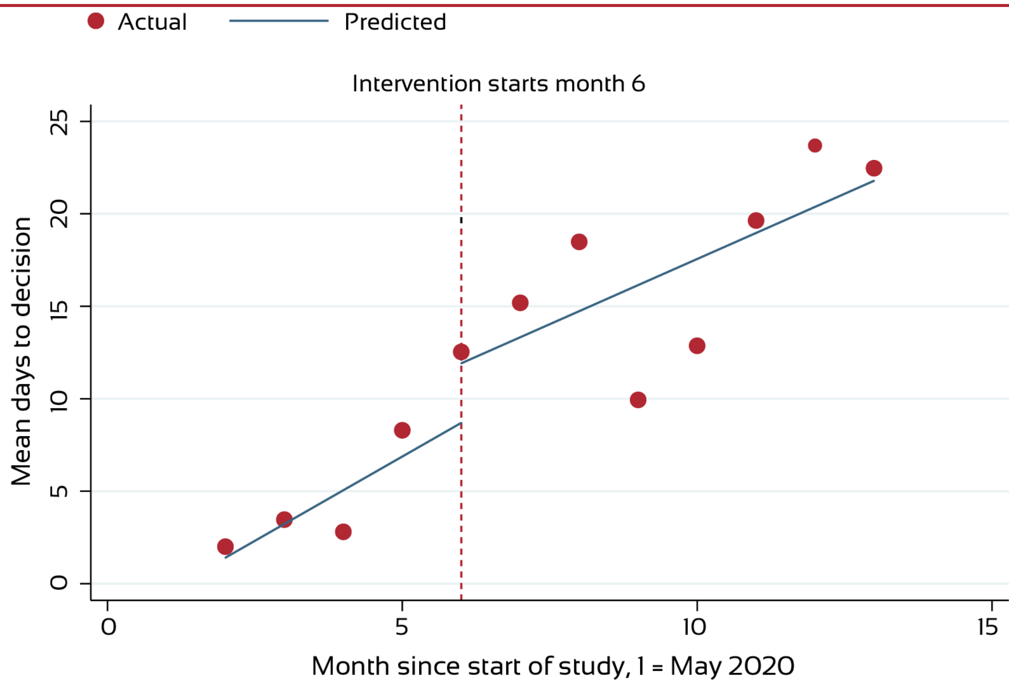
Parameter	Interpretation	Estimate (SE)	*p*-Value
β_1	Pre trend, or monthly change in days to decision during preimplementation period	1.82 (0.63)	0.020
β_2	Post level change, or change in days to decision associated with implementing RPA in October	3.22 (3.00)	0.315

[21] Households with one member are less complex because they generally require fewer income checks.

Parameter	Interpretation	Estimate (SE)	*p*-Value
β_3	Post trend change, or change in slope after RPA implementation compared with preimplementation slope	-0.41 (0.72)	0.584
$\beta_1 + \beta_3$	Post trend, or monthly change in days to decision during postimplementation period	1.41 (0.36)	0.004

Note: The estimate column provides the regression coefficient. Results indicate that during the preimplementation period, days to decision increased by 1.8 days each month. During October, when the RPA was implemented, results suggest that days to decision increased by 3.2 days (post level change), although this difference was not statistically significant. In the postimplementation phase, days to decision continued to increase over time by 1.4 days per month ($p = 0.004$); this number represents a nonsignificant decline in the monthly increase of days to decision (β_3) from 1.8 to 1.4 additional days per month.
RPA = robotic process automation
Source: Insight tabulations of Georgia RPA data

Figure 4.5. Observed and Predicted Days to Decision Pre- and Postimplementation of the RenewalBOT in Georgia



Source: Insight tabulations of Georgia RPA data

2. Increased Accuracy

State staff noted another goal of the RPA was increased accuracy. Red flags and case notes can provide workers with greater insight on where to focus their attention and when to ask the client for additional verification. For example, the RPA will create a red flag if the client's address has changed but they have not reported a change in housing expenses. As one worker explained, they appreciate knowing upfront that a call to the client will be necessary rather than having to work through the entire case to come to the same conclusion.

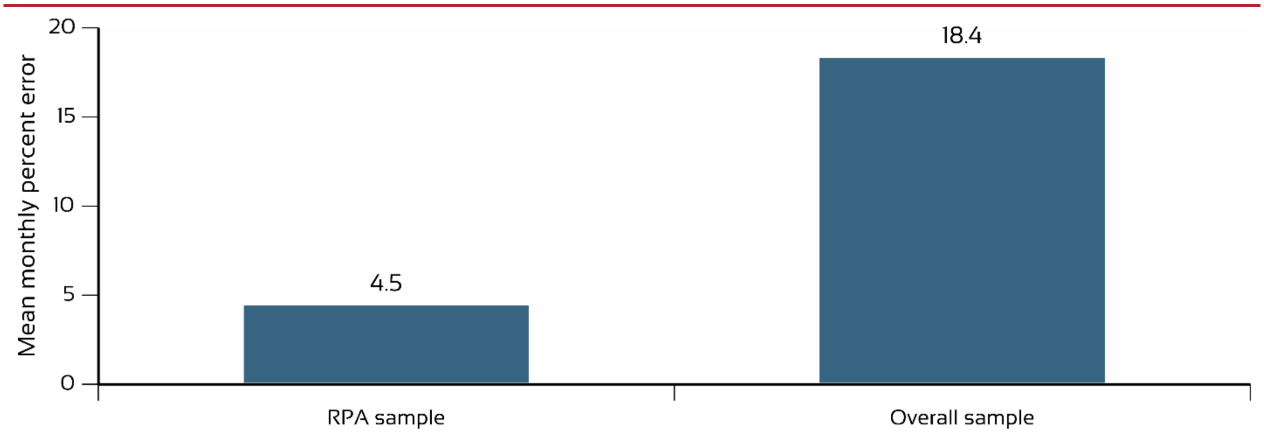
> [The RPA case notes] tell you that you have to address the income. So even if you don't hit all the pages that support the income, and it might be an oversight that you have not seen, but [RPA has] caught it.
>
> *—Frontline staff*

Another worker also noted the RPA always correctly updates a client's address in the system, which ensures notices are sent to the right address. In the past, typos and other data entry errors were more common.

Quantitative assessment

The study team examined trends in QC data patterns to assess the association between RenewalBOT implementation and Georgia's payment error rate. The team hypothesized that the overall payment error rate may decrease as a result of RPA implementation because the RPA can reduce data entry errors and more consistently follow SNAP policy. State staff noted they worked with the policy unit to ensure the RPA was not misapplying any SNAP policy, and frontline staff noted they felt the red flags were helpful to address case discrepancies. The study team calculated an error rate based on positive cases processed by the RPA and compared it with the overall QC sample error rate.[22] The mean monthly error rate observed for the RPA sample was 4.5 percent, statistically significantly lower than the 18.4 percent observed for the overall QC sample ($p < 0.001$; figure 4.6).

Figure 4.6. Mean Monthly Error Rate for RPA and Overall QC Samples, Georgia



Note: Difference is significant at $p < 0.001$.
QC = quality control; RPA = robotic process automation
Source: Insight tabulations of Georgia administrative QC reports

[22] The QC sample includes recertifications, new applications, and interim change reports. The study team estimated slightly different values for the QC sample error rate than the values provided by the State. The study team used the rates calculated internally to ensure consistency when comparing the error rates.

D. Challenges to RPA Use

Perceptions of the challenges related to RPA use varied between State and frontline staff. While State staff noted the RPA is unable to process about 1 percent of recertifications because of a business exception, they did not highlight any other ongoing challenges related to RPA use. Frontline staff who interact with the RPA daily raised two primary challenges with RPA use:

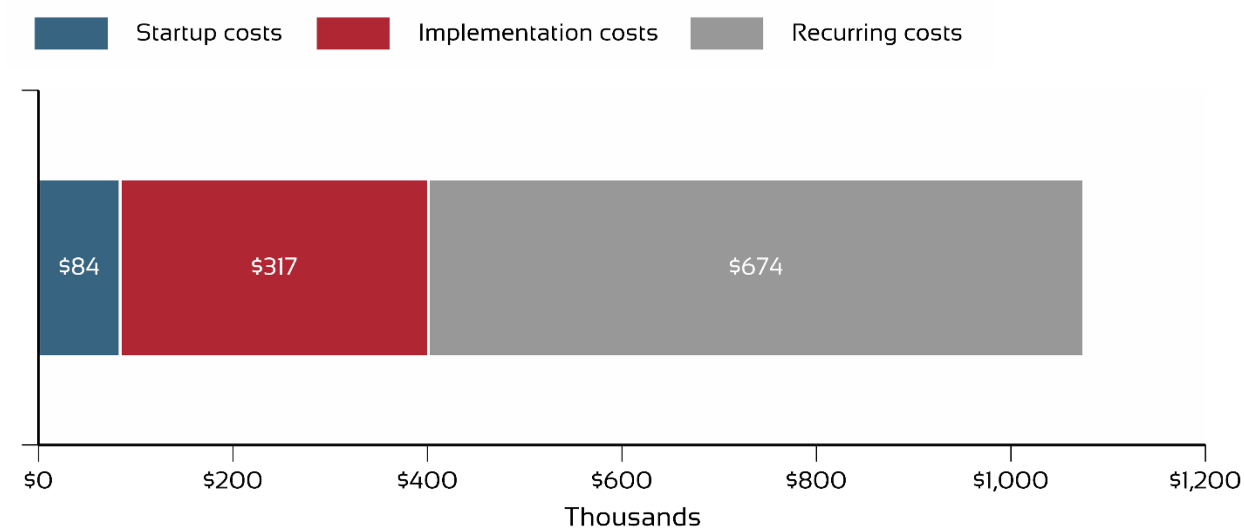
- Two of the three staff interviewed noted issues with the RPA overwriting updates a worker has made. At times, the RPA overwrites the changes made by the worker and updates the case with the different information from the renewal form. State staff noted this situation occurs when the RPA, for example, updates the name of the client's employer based on the information the client reported on their renewal form, but the employer's name differs from information in The Work Number (e.g., the interface uses the name of the parent company). In these instances, the information entered by the RPA is not incorrect—just different. The third interviewed worker did not recall this challenge.
- Two staff also noted that infrequently, about 1 in 10 times, an RPA works a case, but then the case does not get reassigned to a worker's queue. If this occurs, the worker is not aware that the case needs to be processed, and benefits may be delayed.

Two of the workers found the RPA relatively easy to work with because (1) the case notes are informative and easy to read; (2) the red flags the RPA generates help reduce errors; and (3) the repetitive data entry the RPA completes enables workers to focus on verifying income and expenses. The third worker noted the RPA was neither easy nor difficult to use. While this worker noted the case notes were easy to read, they were frustrated by the tendency of the RPA to overwrite information on a case.

E. Comparing RPA Costs and Benefits

Georgia's RPA cost approximately $1.1 million (see figure 4.7). Startup and implementation costs were 37 percent of total costs. Georgia's recurring costs, which include ongoing maintenance, monitoring and evaluation, and two annual contract costs, represent almost two-thirds of the total RPA cost.

Figure 4.7. Total Cost of Georgia RPA, in Thousands of Dollars

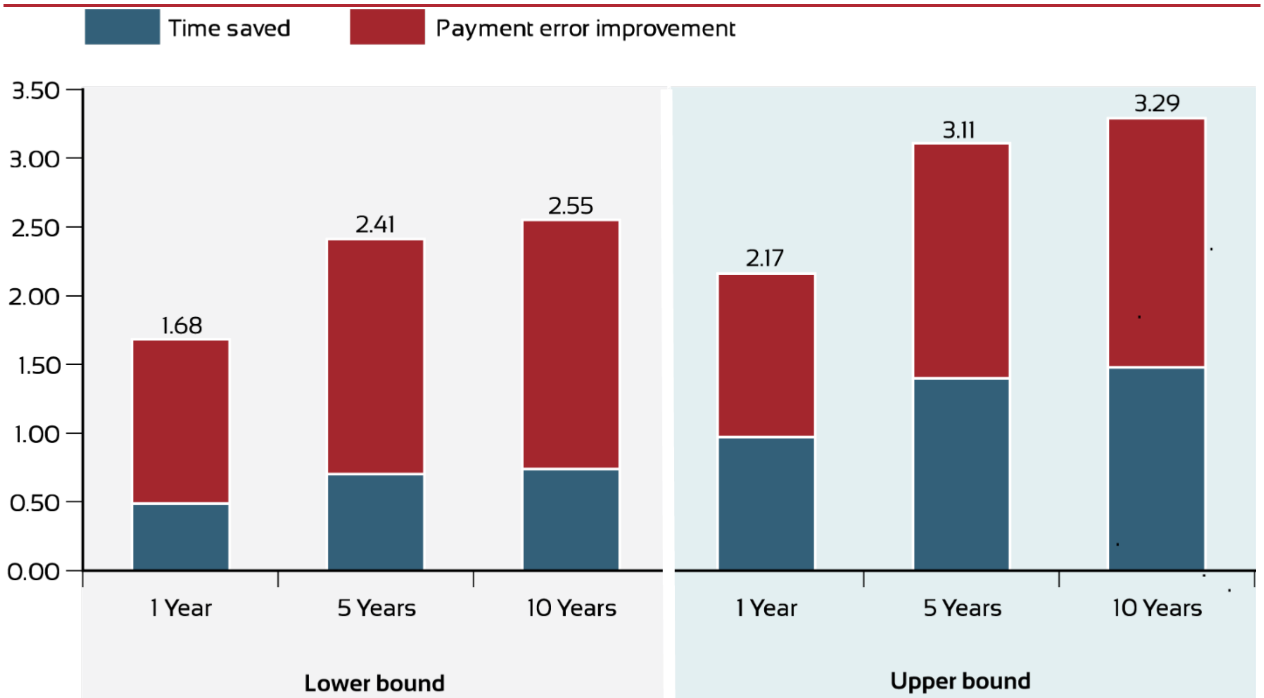


Note: Startup activities included proposal writing; the negotiation of the contract, license, and RPA purchase; policy and program planning efforts around the RPA; the development of the RPA specifications; and the planning and integration of the State AWS cloud infrastructure. Implementation included the UiPath Professional Services contract, which covered the development of the RPA, coordination efforts with contracted staff, and other systems and AWS cloud infrastructure updates. Georgia's recurring RPA activities include RPA maintenance, monitoring and evaluation, and ongoing reporting for 1 year. Georgia also pays for two annual contracts: the UiPath license and services contract, and an infrastructure and server contract. See appendix table C.8 for the cost sensitivity analysis.
AWS = Amazon Web Services; RPA = robotic process automation
Source: Insight tabulations of Georgia cost workbook

Since the RenewalBOT was implemented, Georgia has added several other RPAs. State staff reported that each subsequent RPA is less costly to implement because much of the backend IT work has already been completed (e.g., establishing connectivity between systems, cloud server migration). A senior State staff member also noted the importance of developing in-house RPA competency to keep recurring costs as low as possible. Because the RPA needs modifications whenever the Gateway system undergoes any changes, it is less costly and more efficient to complete these modifications in-house rather than relying on an outside contractor.

The study team conducted a cost-benefit analysis to assess whether the benefits of the RPA outweighed the costs. The team projected the annual recurring RPA costs and monetized two benefits: eligibility worker time saved and improvements in the payment error rate. Findings indicate the benefits of Georgia's RPA exceeded the costs within 1 year of implementation (see figure 4.8). The study team assumed an eligibility worker saves an average of 5 minutes per case in the lower bound scenario and 10 minutes per case in the upper bound scenario. In the upper bound scenario, Georgia almost breaks even from the benefit of eligibility worker time saved alone. The benefit from the lower payment error rate among RPA cases, compared with the overall QC sample (see figure 4.6), is higher than the benefit of time saved in both scenarios. The study team conservatively monetized the payment error rate using the current QC threshold ($39), so actual benefits realized may be higher than the estimates.

Figure 4.8. Results of Georgia Cost Benefit Analysis



Note: A ratio greater than 1 indicates the RPA's benefit outweighs the cost. The study team assumes an eligibility worker saves an average of 5 minutes per RPA case in the lower bound estimate and 10 minutes per case in the upper bound estimate. See appendix table C.9 for the cost and benefit inputs used to construct the ratio.
QC = quality control; RPA = robotic process automation
Source: Insight's estimation using data from Georgia's cost workbook, staff interviews, and administrative QC reports

> The [RPA] have been helpful for me personally. I can't really speak for anyone else, but for me it does increase my task numbers.
>
> *—Frontline staff*

Anecdotally, State and frontline staff agreed the benefits of the RPA outweighed the costs. In particular, one senior State staff member noted it would have been extremely difficult, if not impossible, for the State to process their SNAP recertifications without the assistance of the RPA. One frontline staff member noted that although the RPA's abilities are not limitless (e.g., it is unable to update income on the case), the benefits outweighed the challenges because the RPA saved them time and helped them complete more recertifications.

F. Conclusions

Overall, the implementation of the RenewalBOT in Georgia proceeded smoothly. Anecdotal evidence from frontline staff indicates the RPA helps save time, enables workers to complete more tasks, and improves case accuracy. Interviews with State and frontline staff revealed three facilitators to RPA implementation and continued operations in Georgia:

- **Buy-in from senior leadership.** Both high-level staff at the Governor's Office and the Office of Budget and Planning were on board with RPA implementation. This buy-in meant the SNAP agency had the necessary funds and approvals to quickly acquire and implement the technology. The total cost of Georgia's RPA was about $1.1 million, so this support was crucial for Georgia's successful procurement.
- **In-house RPA competency.** The SNAP State agency decided to develop in-house competency to ensure State staff, rather than outside contractors, could maintain the RPA software. In-house competency enables the State to be nimble in its operations and, according to State staff, saves costs compared with working with an outside party. Because RPAs require ongoing maintenance, having the infrastructure (e.g., staff, hardware) to support the technology is important to their continued success.
- **Staff training.** Interviewed frontline staff spoke of the importance of the training they received. Allowing workers to observe RPA operations helped establish trust between the new technology and staff. One caseworker was worried the RPA would be used as a surveillance tool and was gratified to learn the RPA was implemented to help workers with their tasks. States should be aware that they may encounter initial mistrust of the RPA technology among workers, especially veteran employees. Comprehensive training is an important tool to help minimize this hesitancy.

The study team used administrative data to assess two key outcomes: days to decision and payment accuracy. Results indicate that implementation of the RPA was not associated with a statistically significant change in the number of days it takes a worker to process a case. This analysis had several limitations. The RPA was implemented during the height of the COVID-19 PHE; waivers, staffing shortages, and other policy changes may have influenced the length of time needed to process a recertification. The study team was only able to assess outcomes 6 months postimplementation; additional months of data could be valuable. Lastly, because of data limitations, the study team was unable to assess worker time saved on an individual renewal task; this assessment could be a fruitful avenue for future research.

However, findings from an analysis of QC administrative reports suggest using an RPA to help process recertifications may be associated with lower payment error rates. Staff noted the RPA cannot make typos or other data entry errors, and the red flags it leaves help provide insight to workers on the most error-prone aspects of a case. States considering implementing an RPA may wish to ensure their RPA can complete similar "checks."

Results of a cost-benefit analysis suggest the benefits of the RPA outweigh the costs. The study team monetized two benefits: eligibility worker time saved and improvements in the payment error rate. The lower payment error rates associated with RPA cases, compared with the overall caseload, produce a higher benefit than eligibility worker time saved.

Chapter 5. Use of RPA in New Mexico

As of October 2022, New Mexico's Human Services Department (HSD) reported using six RPAs. HSD implemented the RPAs over a 12-month period (see figure 5.1) with the goal of improving customer service quality and consistency. Many of the RPAs were implemented following the launch of New Mexico's Consolidated Customer Service Center (CCSC), which was designed to provide a "one-stop shop" to meet customers' needs. The RPAs assist with administrative tasks across SNAP and other safety net programs. The remainder of this chapter focuses on the UpdateBOT, which can help update the address or authorized representative listed on a case. Appendix C provides further details about the other RPAs.

Figure 5.1. New Mexico RPA Implementation Timeline

Note: CCSC = Consolidated Customer Service Center; PHE = public health emergency

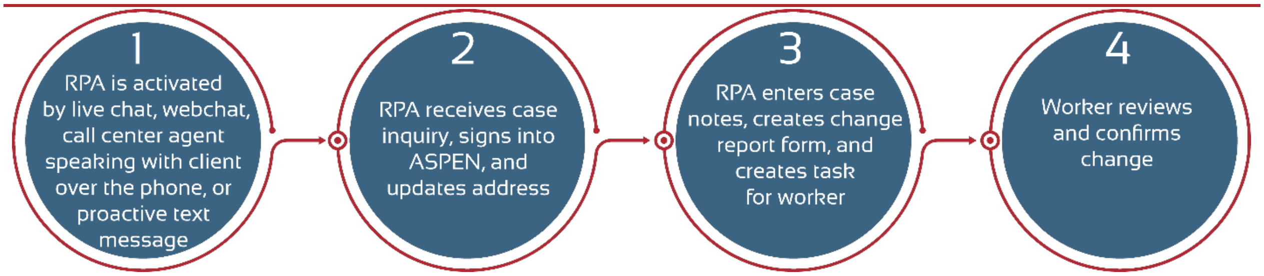
A. RPA Features

In New Mexico, the UpdateBOT is used primarily to help process changes to a client's mailing or physical address.[23] The UpdateBOT can be activated in one of four ways: (1) live chat with a call center agent; (2) client-facing webchat (i.e., client chats with an AI on the New Mexico website); (3) call center agents when on the phone with a client; and (4) proactive text messages.

The RPA works similarly regardless of how the client provides their updated address. For call inquiries and live chats, the agent first updates the address in Salesforce, the State's customer relationship management software. When a client uses the webchat, the AI chatbot walks the client through a series of prompts to collect all required information for the address change. The call center agent and the AI chatbot then submit a case update inquiry to the RPA. The RPA pulls the inquiry; signs in to the Automated System Program and Eligibility Network (ASPEN), New Mexico's integrated eligibility system; and navigates to the case. The RPA updates all address fields within ASPEN and enters a case note. The RPA then creates a change report form and establishes a task for an eligibility worker to certify the change based on ASPEN's workflow routing rules. As the final step, an eligibility worker reviews and confirms the change. Figure 5.2 presents an overview of the process.

[23] The UpdateBOT can also help process changes to an authorized representative listed on a case. However, interview respondents focused on address updates since they are more commonly used.

Figure 5.2. New Mexico UpdateBOT Process



Note: ASPEN = Automated System Program and Eligibility Network; RPA = robotic process automation

At the time of the study, New Mexico had 30 RPA licenses or "digital workers." Each RPA can run 24 hours a day, 7 days a week, and perform all RPA tasks. That is, each license can run the UpdateBOT, BabyBOT, or any of New Mexico's other RPAs. State staff update the priority of each RPA task in accordance with current policies or timelines. High-priority tasks include tasks where a customer needs an immediate response, such as an account unlock or password reset. Lower priority tasks, such as address changes, can be processed at the end of the day or after hours.

State staff noted their interest in pursuing further RPA use cases but noted additional guidance from FNS was necessary before they could proceed. State staff shared it would be beneficial for FNS to provide guidance on allowable RPA use case scenarios within SNAP. State staff indicated this process could help streamline future RPA implementation and help scale RPA across States because each State would not need to individually request permission from FNS to implement the technology.

Interviewed nonmerit CCSC call center agents also suggested future opportunities for improvement to UpdateBOT. Staff noted the RPA could also be used to help process updates to other client contact information, such as phone numbers. At the time of the study, call center staff could only provide updated phone numbers as case comments.[24] Because eligibility workers may not always reference the full case comments, they may miss a note about an updated phone number and call the client at their old number.

B. Development and Implementation

New Mexico HSD decided to implement RPA to provide higher quality customer service by decreasing customer wait times and minimizing errors (e.g., typos). In particular, the UpdateBOT was implemented as part of the greater CCSC effort to create more efficient customer service processes. The COVID-19 PHE accelerated the need for more RPA as caseloads increased.

[24] Call center staff are nonmerit workers and do not have access to ASPEN, the State's integrated eligibility system. As a result, all updated phone numbers could only be shared via case comments.

New Mexico used client feedback surveys, focus groups, and user data to make decisions regarding RPA development and improvements. For example, State staff held client focus groups during the webchat development process to help understand whether the interface was intuitive and whether the webchat was replying to clients promptly. State staff emphasized the importance of client feedback to help ensure the utility and user acceptance of new technology.

> "[We] are very data driven, and so we use [data] as a source for identifying what we need to move the needle.... It is also customer driven."
>
> *—State staff*

1. Development

Each of New Mexico's RPAs automates small, straightforward administrative tasks. State staff noted the importance of starting small and emphasized that an RPA is most useful for repetitive, rules-based tasks that often fall to the bottom of a worker's to-do list, such as address changes. State staff shared that they initially tried to develop a more complex RPA that verified income, but it proved too difficult to program. State staff also noted the importance of working with FNS early to ensure all necessary approvals are received and the RPA does not have to be retrofitted later.

New Mexico partnered with its CCSC contractor, Accenture, to implement the RPA. The RPA code was developed by Blue Prism, an RPA software development company. State staff shared, however, that they are interested and looking to nurture in-house RPA development competency for future projects. Programming the RPA was challenging because the RPA contractor does not maintain New Mexico's integrated eligibility system, ASPEN, and was not familiar with all the screens in ASPEN and the intricacies of the system. State staff also had to act as intermediaries between the two contractors, which led to further inefficiencies. Developing in-house competency could mitigate the challenges related to the multiple IT vendors New Mexico currently uses.

Respondents noted that all necessary entities were invited to attend RPA design sessions, including the business team, CCSC governance group, testers, and policy experts. The CCSC governance group included divisional representatives from Child Support, the Behavioral Health Division, Office of the Inspector General, Income Support Division, Medical Assistance Division, IT Division, and the Fair Hearings Bureau. Including representatives from a large swath of HSD helped ensure any potential unintended consequences of the RPA were not overlooked. Policy experts were included in the design session to guarantee the RPA was programmed in accordance with SNAP policy.

2. Testing

Before launch, New Mexico's RPA went through two rounds of testing: quality assurance (QA) testing and user assurance (UA) testing. The QA testing was conducted by the contractor, while UA testing was conducted by State agency staff. To complete the UA testing, the tester first logged in to the testing environment and simulated an address update in Salesforce. The tester waited to be notified by the RPA that the update was successful and then checked ASPEN to confirm the address change was made correctly. If the UA testers found any technical errors, they sent a report to the contractor to make the necessary corrections.

State staff reported challenges with the testing process because the RPA contractor was unfamiliar with the State's eligibility system. They noted it may have been beneficial to conduct all testing internally because State staff are more knowledgeable about SNAP policy and can create better testing scenarios. For example, State UA testers made sure the RPA could differentiate between SNAP and Medicaid cases. While the RPA can certify Medicaid changes, the tester ensured the RPA stopped and created a task for an eligibility worker to certify any changes on a SNAP case.

New Mexico also conducts continuous monitoring of the RPA. The State developed an accuracy improvement team to monitor and review cases assigned to the RPA. State staff also test the RPA whenever ASPEN, Salesforce, or the RPA code are updated.

3. Training

> I learn hands on, so once [the trainers] actually had [us] start taking calls and listening … that's what help[ed] me … once you're … in the calls, [that's] when you do finally get a handle of how to use the program.
>
> *—CCSC staff*

RPA training in New Mexico varied by worker category. For some workers, the RPA was implemented behind user interfaces and appeared seamless. The State felt training for these workers was not necessary because the RPA operated in the background, unbeknownst to staff. For example, merit eligibility workers certify all address changes using the same process, regardless of whether the update was initiated by an UpdateBOT or submitted by a client via a mailed change report.[25]

The State determined training was necessary for CCSC staff who interacted directly with the UpdateBOT via live chat or calls with clients. For these workers, UpdateBOT training was packaged within a broader training on CCSC technologies. These CCSC staff, who are nonmerit staff, were trained by the RPA contractor. Staff reported appreciating the hands-on learning opportunities the training provided. Staff are also able to ask questions or troubleshoot challenges via a Teams group chat or weekly meetings with team leads.

C. Outcomes

New Mexico State and frontline staff discussed three primary goals of the RPA: save time for staff by standardizing processes, improve accuracy (e.g., eliminate typos), and provide higher quality service to customers.

[25] As one step of the process, the RPA created a change report form to append to a client's case with their new address.

1. Time Savings

> The goal of an RPA is to say staff are now able to allocate their time to complex areas, improve professional development, provide better customer service. We aren't replacing staff but supporting staff so they can have better outcomes.
>
> *—State staff*

State and frontline staff felt the UpdateBOT (and all of New Mexico's RPAs more generally) saved time for both clients and eligibility workers. State staff reported the UpdateBOT can process address changes within hours; previously, it may have taken days to reflect the change in the system after the client submitted the change request. Administrative data the State provided suggest the UpdateBOT can process an address change in about 4 minutes (range: 7 seconds to 119 minutes).[26] A productivity study conducted by New Mexico prior to RPA implementation indicated that eligibility workers spent, on average, an hour processing a change (median: 8 minutes). While this average time accounts for any change (i.e., is not specific to an address change) and reflects circumstances prior to RPA implementation, the magnitude of the difference suggests time savings may be associated with the UpdateBOT.

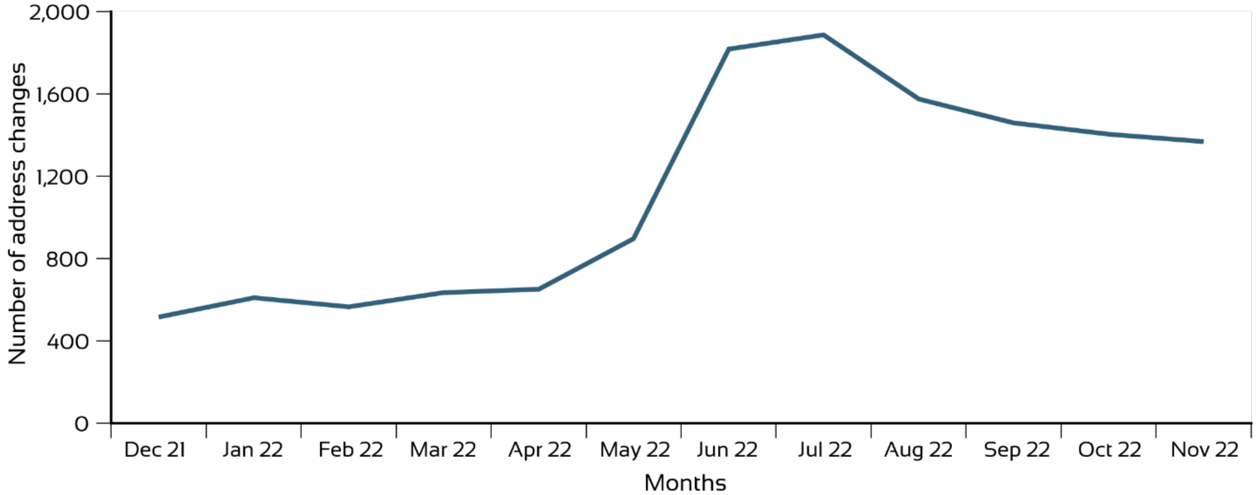
State staff also expected the RPA to enable eligibility workers to shift their time from repetitive to more complex tasks. However, State staff noted this shift in tasks has not yet been observed, largely because of the high volume of work attributed to pandemic-related caseloads. While the RPA may reduce time spent on specific tasks (e.g., address changes), State staff felt this work has been replaced with other data entry tasks the RPA cannot handle.

Increased use of UpdateBOT

Increased use of the UpdateBOT can lead to further time savings. Administrative data New Mexico provided show a continued increase in the number of address changes processed by the RPA (see figure 5.3). In December 2021, a year after implementation, New Mexico processed 516 address changes with the UpdateBOT; by November 2022, the UpdateBOT has processed more than 2.5 times the number of address changes. UpdateBOT processed the most address changes in July 2022 (n = 1,887). The data may reflect increased RPA capacity, increased number of address changes received by the State, or both.

[26] Only 6 of the 14,000 address changes took longer than 30 minutes; the UpdateBOT did not complete these cases. Removing these cases reduced the average processing time by 3 seconds. On average, changes completed by the UpdateBOT (n = 6,750) took significantly longer for the UpdateBOT to process (p < 0.001) than incomplete cases (n = 7,425).

Figure 5.3. Trends in UpdateBOT Address Changes, December 2021–November 2022



Note: RPA = robotic process automation
Source: Insight tabulations of New Mexico RPA data

2. Improved Accuracy

New Mexico expected the RPA to reduce data entry errors. Specifically, State staff believed the UpdateBOT would lead to fewer address typos and, in the longer term, a reduction in returned mail. Upon review of RPA cases, New Mexico's accuracy improvement team noted the RPA was not associated with any errors or inaccuracies. This is to be expected because the RPA follows the same code every time and cannot make a typo or miss a screen.

> Seeing the accuracy identified through the bot has opened our eyes to the possibilities of automation and motivates us to do more and think of where else we can use it.
>
> *—State staff*

3. Higher Quality Service

New Mexico emphasized the primary reason the State implemented RPA was to improve the client experience. State staff noted the RPA could lead to reduced wait times and improved client satisfaction. The State provided data on the length of time a client spent in a live chat between December 2021 and December 2022. An average live chat lasted just under 10 minutes and ranged from 1 minute to over an hour. Although the State could not provide average wait times prior to implementing the live chat, call center staff reported that before implementing the UpdateBOT, some callers would need to wait up to 2 hours to speak with an eligibility worker to process their address change.

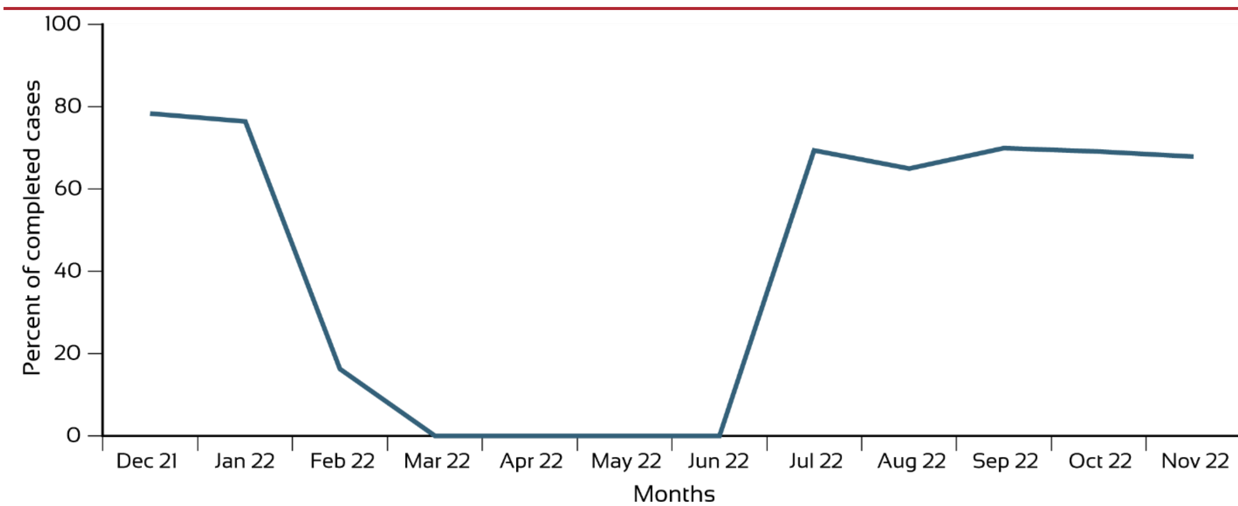
D. Challenges to RPA Use

Frontline staff noted three key challenges associated with the UpdateBOT:

- Though call center staff reported the UpdateBOT has become more consistent over time, occasional lapses in task completion still occur. Usually, staff try to check the status of their inquiries to confirm the RPA has made the change. If needed, staff escalate the issue to an eligibility worker who can resolve the issue manually in ASPEN. However, at times, address changes may slip through the cracks if call center staff are unable to check on the status of the inquiry.
- Call center staff mentioned the UpdateBOT is unable to process changes to both physical and mailing addresses simultaneously. Staff prioritize updating the mailing address and instruct the client to report changes to their physical address on YesNM, the State's client-facing web portal.
- Call center staff expressed concern about duplicating efforts. If a client calls back and speaks to a different agent, the agent might duplicate an existing case update inquiry because they cannot see if another agent already submitted an inquiry. Call center staff believed duplicate requests may affect the efficacy of the RPA, though State staff noted the RPA is able to complete all its daily tasks.

Because RPAs are programmed to replace human inputs into an eligibility system, any change to the screens or layout of the system can affect RPA performance. In 2022, New Mexico transitioned ASPEN, a web-based system, from Microsoft Internet Explorer to Microsoft Edge. State staff noted this transition affected RPA success rates. The change in the web browser may have also affected UpdateBOT performance. UpdateBOT was unable to complete its assigned cases between March and June 2022 (see figure 5.4)—a sharp contrast to other months, when the RPA completed most of its assigned tasks.

Figure 5.4. Percent of Completed Cases Among All Cases Assigned to the UpdateBOT

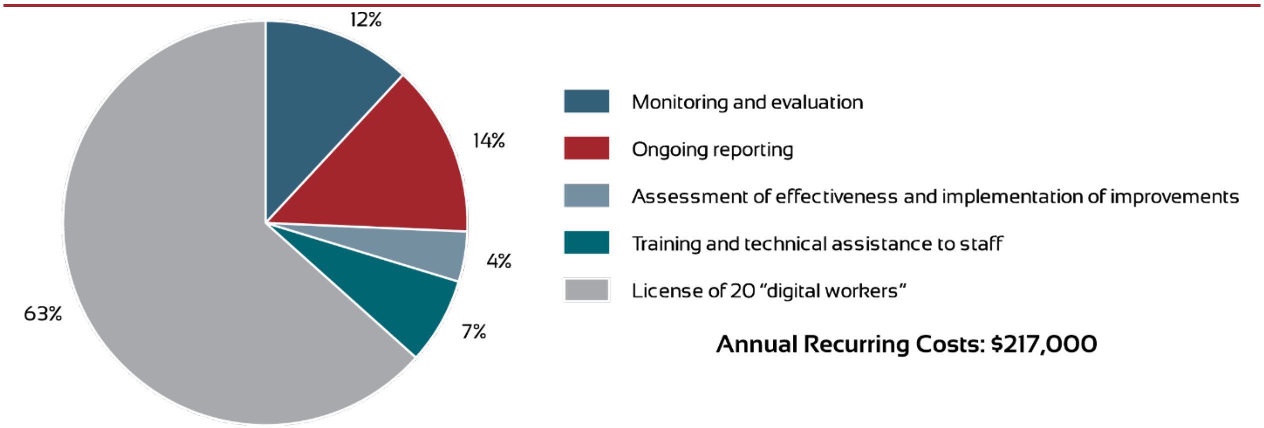


Note: RPA = robotic process automation
Source: Insight tabulations of New Mexico RPA data

E. Comparing of Costs and Benefits

As part of the study, New Mexico provided information on ongoing maintenance costs for all RPAs and chatbots. These costs total approximately $217,000 (see figure 5.5).[27] The digital worker licenses account for the largest proportion of the ongoing costs (63 percent). Other ongoing costs include monitoring and evaluation, reporting, presentations, assessing and improving effectiveness, and providing ongoing training to staff.

Figure 5.5. Share of Annual Recurring Costs in New Mexico, by Activity



Note: These annual costs support New Mexico's five RPAs and two chatbots. The figure displays the cost share of each recurring activity supporting New Mexico's RPAs and chatbots. It excludes recurring activities with missing cost information, such as recurring activities involving contract staff.
RPA = robotic process automation
Source: Insight tabulations of New Mexico cost workbook

Because New Mexico was unable to provide salaries for contractor staff or all direct costs (e.g., RPA software), the presented costs underestimate the true cost of the RPA in New Mexico. However, State staff believed RPA benefits outweigh the costs because the relative cost of a license is low compared with the amount of work each RPA can complete. Staff noted the RPA enables the State to better support workers and improve outcomes.

F. Conclusions

New Mexico implemented its UpdateBOT to improve customer service, enable eligibility workers to spend time on more complex tasks, and improve accuracy. Although the study team was unable to quantitatively assess many of these outcomes as a result of data limitations, discussions with State and frontline staff showcased the benefits of the RPA. In the past, clients had to submit paper change report forms or speak directly with an eligibility worker to update an address. With the RPA, clients can submit an address change via webchat on their own time or through a quick conversation with call center staff. While in the past a client may have waited over 2 hours to speak with an eligibility worker, data shared by the State indicate clients

[27] New Mexico was unable to provide preimplementation and implementation costs. The recurring cost also excludes recurring activities involving contract staff. A larger technology contract supports efforts by contract staff, and New Mexico was unable to disentangle this cost.

spend an average of about 10 minutes in a live chat. It takes the RPA, on average, only 4 additional minutes to update the address within the eligibility system.

State staff noted the RPA is best suited for small and repetitive tasks. Staff shared they initially tried to use the RPA for a more complex task involving verifying income but quickly realized the programming would be too challenging. They believe starting small enabled the team to become more familiar with the RPA, gain trust, and develop in-house competencies that would one day enable the State to consider more complex projects. Thinking ahead, staff suggested the UpdateBOT could be used to help update other case contact information (e.g., phone numbers). State staff also emphasized the importance of additional guidance from FNS to support further RPA implementation.

Chapter 6. Considerations for Future Use of RPA in SNAP

As of the time of this study, RPA remains a nascent technology in SNAP operations. The three study States—Connecticut, Georgia, and New Mexico—each approached RPA differently and, as a result, experienced unique challenges and facilitators to implementing the technology. These States and FNS Regional Office staff shared their thoughts on the scalability of this technology and recommended actions to be taken by FNS to encourage further RPA use.

A. Key Findings

While RPA implementation was not without its challenges, staff in each of the three States believe the RPAs were beneficial. Staff in Connecticut and Georgia felt the RPA helped save worker time and increased accuracy in recording case information. Data limitations prevented the study team from conducting a comprehensive analysis of worker time saved. Instead, the team used the number of days it took to process a case as a proxy and found the RPA did not decrease the days to decision. However, this approach may not be sensitive enough to capture real changes. Confounding factors, including lack of staff trust in the RPA, pandemic-related staffing shortages, and increased caseloads, also likely influenced the analysis. Findings from an analysis of Georgia QC data suggest the RPA helps prevent errors by flagging error-prone elements for staff. In New Mexico, staff felt the UpdateBOT helped improve customer service by making it easier for clients to update their address. Findings suggest the use of the UpdateBOT in New Mexico has increased postimplementation, and the RPA is able to complete most of the requests it receives.

The study team also conducted a cost-benefit analysis in Connecticut and Georgia. Ultimately, the benefits of Connecticut's RPA did not exceed the costs, even projecting 10 years postimplementation. To break even, Connecticut's RPA would need to process 10 times as many cases each year (about 127,000), or eligibility workers would need to save 1.6 hours per case, more than the average time spent on a case. However, the analysis likely underestimates the potential benefits of the RPA because the study team was able to monetize only eligibility worker time saved. Anecdotal evidence from interviews with State and frontline staff suggests Connecticut's RPA may have other benefits, such as enabling workers to focus on more complex tasks or improving accuracy in recording case information, which the study team was unable to measure. In Georgia, the study team was able to monetize eligibility worker time saved and an improvement in the payment error rate. Georgia's RPA benefits exceeded the costs within 1 year of implementation. Although the improved error rate yields a larger benefit, the time saved by eligibility workers nearly exceeds the costs when assuming an average savings of 10 minutes.

In general, States with larger SNAP caseloads will see a greater dollar benefit when conducting a cost-benefit analysis. While RPA costs were relatively similar in Connecticut and Georgia, Georgia's caseload was over 2.5 times larger than Connecticut's. As a result, any per case benefit would be higher in aggregate (e.g., time saved per case would sum to larger savings in a State with a larger caseload). RPA capacity also influences the magnitude of the benefit; States with more RPA licenses can process more cases simultaneously and in total. During the study period, Georgia had over 100 RPA licenses, and Connecticut had 3.

B. Recommendations and Strategies to Mitigate Potential Challenges

Though every RPA project is unique, States may wish to consider the following recommended practices before moving forward with implementation. The study team also observed two key challenges to RPA use; potential mitigation strategies follow.

1. Recommendations for States

- **Develop clear RPA documentation.** Connecticut worked iteratively with its IT contractor to develop an RPA requirements document. The document outlines all RPA actions, identifies issues the team encountered during testing, and lists the defined business exceptions. This documentation enabled collaboration between the State and its contractor and ensured the project team considered every possible scenario before launching the RPA; the document more than quadrupled in length during the testing process.

  The States also developed user guides for frontline staff describing RPA actions and listing the possible RPA business exceptions. Georgia's user guide includes a description of every possible RPA red flag and instructions for how to proceed should a worker encounter one. All three States also developed videos of the RPA to help workers and other interested parties better understand the technology.

- **Build in sufficient time for comprehensive testing.** Two States—Connecticut and New Mexico—provided the study team with detailed descriptions of their comprehensive RPA testing approaches. Connecticut's QM team leveraged manual and dry run tests to see how the renewal RPA performed in specific scenarios and when working with actual client cases. New Mexico implemented two rounds of testing: QA testing and UA testing. In both States, staff emphasized the importance of building in sufficient time to conduct testing, especially when working with an outside RPA contractor. Connecting internal QC staff with developers at the RPA contractor early could also help identify errors or business exceptions earlier in the development process because internal staff have greater familiarity with SNAP policies and the intricacies of integrated eligibility systems.

- **Consider agency bandwidth and needs before deciding on a specific RPA.** Both Georgia and Connecticut implemented a relatively complex RPA to help process recertifications. New Mexico followed a different approach and started with a smaller RPA. New Mexico State staff believed starting small enabled the team to become more familiar with RPA, gain trust, and develop in-house competencies that would one day enable the State to consider more complex projects. Before States begin their RPA projects, leadership should consider agency bandwidth, staffing, and other resources. More complex RPAs, like Georgia's RenewalBOT, may have a larger impact on relevant outcomes (e.g., time savings for staff) but also require more dedicated resources and in-house expertise.

Depending on a State's circumstances, starting with a smaller project could be more successful.

2. Challenges and Potential Mitigation Strategies

- **Coordination with an outside RPA contractor.** At the time of the study data collection, an outside contractor hosted Connecticut's RPA. State staff were required to coordinate routine RPA maintenance, testing, and operations with the vendor and were dependent on the availability of contractor staff. New Mexico used different vendors for the RPA implementation and the eligibility system. State staff served as intermediaries between the two vendors and relayed all communications. This process proved challenging when an update to the eligibility system (i.e., transition from Internet Explorer to Edge) resulted in errors in the RPA because the layout of individual screens in the system changed.
  - **Potential mitigation strategy:** Georgia decided to develop in-house competency to ensure State staff, rather than outside contractors, could maintain the RPA software. This capability enables the State to be nimble in its operations and, according to State staff, saves costs compared with working with an outside party. In February 2023, Connecticut moved the RPA to an in-house server which enabled the State to conduct routine activities internally.
- **Lack of staff trust in the RPA.** One of the primary challenges to implementing any new technology is ensuring trust among frontline staff. This proved to be a challenge in Connecticut and Georgia. One staff member in Georgia was unsure whether the RPA would be used as a surveillance tool, while staff in Connecticut shared that initially some workers thought the RPA was a fellow worker who was not doing their job. Lack of worker trust in the RPA can dampen the benefits of the technology. For example, if staff are redoing the work completed by the RPA, the time savings associated with the technology could be minimal.
  - **Potential mitigation strategy:** States should provide sufficient RPA training before launching the technology statewide. Training should be offered in several formats (e.g., webinar, written materials) to ensure frontline staff do not miss any announcements. Enabling workers to observe the actions the RPA performs can help establish trust between the new technology and staff. Creating videos of the RPA and sharing them with staff may also be beneficial.

3. Additional Considerations

States that implement a new RPA should ensure they can track RPA metrics to demonstrate the efficacy of the technology. All three States noted a key goal of the RPA was saving time for eligibility workers. However, because productivity data were unavailable, the study team was unable to assess this potential outcome. Working with an outside evaluator from the onset can help States determine key outcome measures ahead of implementation and ensure the correct data are captured before and after launch. An outside evaluator can also help determine a reasonable time horizon for the benefits to be realized and help develop an experimental design that truly tests the efficacy of the technology. However, States should consider data needs in advance of project launch even if they do not work with an evaluator.

C. Scalability

This study profiled two types of RPA. Connecticut and Georgia use an RPA that helps process online recertifications. New Mexico uses an RPA to help process case updates (i.e., address changes and changes to the authorized representative). Both types of RPA use information clients provide through an online renewal form, a webchat, or when speaking with a call center worker to update data within the State's integrated eligibility system. The benefits of using an RPA to update information are clear: The technology is not able to make any typos or skip a screen, and the information entered will always exactly match what the client provided. All three RPAs were also able to create new tasks for workers and leave case notes documenting their actions. In Georgia and Connecticut, the RPA was also able to perform interface checks.

Though many States could benefit from similar RPAs, scaling these projects across States is not simple. As one Regional Office staff member noted, even States using the same eligibility system vendor have different business processes, so an RPA could not easily be copied from one State to another. Because the RPA replaces human inputs into eligibility systems, it must be developed with specifics of that system in mind. Scaling the same RPA code across States would be challenging because the exact elements on each screen vary across eligibility systems.

All three study States were considering either increasing the capacity of their current RPA or implementing additional RPAs. Each had recently added RPA licenses to increase the number of tasks the RPA could complete daily. Connecticut was considering the feasibility of introducing another RPA to add newborns to a Medicaid case (i.e., BabyBOT) or help process periodic report forms. New Mexico was considering expanding the use of its internal policy chatbot to other programs (for further information, see description of BrainyBOT in appendix C.) Georgia was working to gain FNS approval for a new attended RPA that staff could deploy in real-time while working on a case (e.g., the RPA could perform interface checks while the worker was conducting an eligibility interview with a client). Any rules-based task could theoretically be completed by an RPA, and the study States all shared their enthusiasm for discovering new RPA use cases as they become more familiar with the technology.

Staff did share, however, that potential large-scale benefits of RPA in SNAP were limited by SNAP regulations. Unlike other benefit programs, such as Medicaid, SNAP regulations state that a merit worker must make the final decision on every case. Because a worker still needs to review any updates made to a SNAP case by the RPA, the sheer number of tasks assigned to a worker does not diminish, though they may not need to spend as much time on each task. As one State staff member noted, this can be difficult in an integrated eligibility system because clients may not understand why processing times vary by program. Staff also shared that different Federal agencies have different levels of acceptance and enthusiasm for the use of emerging technologies, which can lead to challenges for States that use integrated eligibility systems.

D. Recommendations for FNS

If carefully selected and consistent with SNAP regulations, RPAs may offer opportunities to expedite processes and reduce errors. States continue to face large caseloads and challenges with staffing. RPA may be one potential tool to help mitigate these challenges. However, across the board, respondents observed that little information is available to guide States in selecting and implementing an RPA. To better enable States to make decisions regarding RPA implementation, FNS may consider providing the following additional guidance to States:

- **Define RPA.** Several Regional Office staff noted they (and other States in their regions) had limited experience with RPA. Providing a clear definition of this technology and explaining how it differs from (and interacts with) other technologies (e.g., chatbots, batch processing, barcoding, other automated system processes) could help States and Regional Offices identify opportunities for RPA.
- **Provide clear guidelines on acceptable uses of RPA in SNAP.** Several respondents noted that standardized information from FNS could help guide RPA implementation efforts and improve compliance with complex policies. For example, a list of allowable RPA projects could simplify design and FNS approval processes. One respondent noted FNS could develop similar guidance as it did to clarify the acceptable uses of vendor staff in call centers. Respondents also noted that finding resources for RPA use in SNAP can be difficult because it is still a niche technology. Further guidance from FNS could help make the technology more mainstream and enable States to select from a larger number of vendors, which could lower costs and promote further use.
- **Establish consistent metrics to measure RPA efficacy.** States noted difficulties in providing FNS with requested data. Some respondents felt the requested elements were hard to quantify. Another State noted it was challenging to accommodate FNS reporting requirements because the scope was outside the data the State typically collects or not fully reflective of the benefits of the RPA. FNS may consider working with States to develop a consistent set of metrics for future RPA projects. One State noted that FNS could also consider removing reporting requirements[28] for RPAs that had been deemed acceptable use cases to promote further use among States. FNS may also consider further data collection to assess the time savings associated with RPA, such as by conducting modified random moment time studies. Under this approach, eligibility workers would receive a random email asking them to report how much time they think they saved on the last RPA case. Collecting enough data randomly from all workers in the State would provide information on time saved.

[28] As part of the waiver approval process, FNS has asked States implementing RPA to provide standalone reports. One State reported these reports were time-consuming and burdensome because the formats were not aligned with State systems and required data considered outside the scope of the RPA.

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