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NOVISSI TOGO

Harnessing Artificial Intelligence to Deliver Shock-Responsive Social Protection

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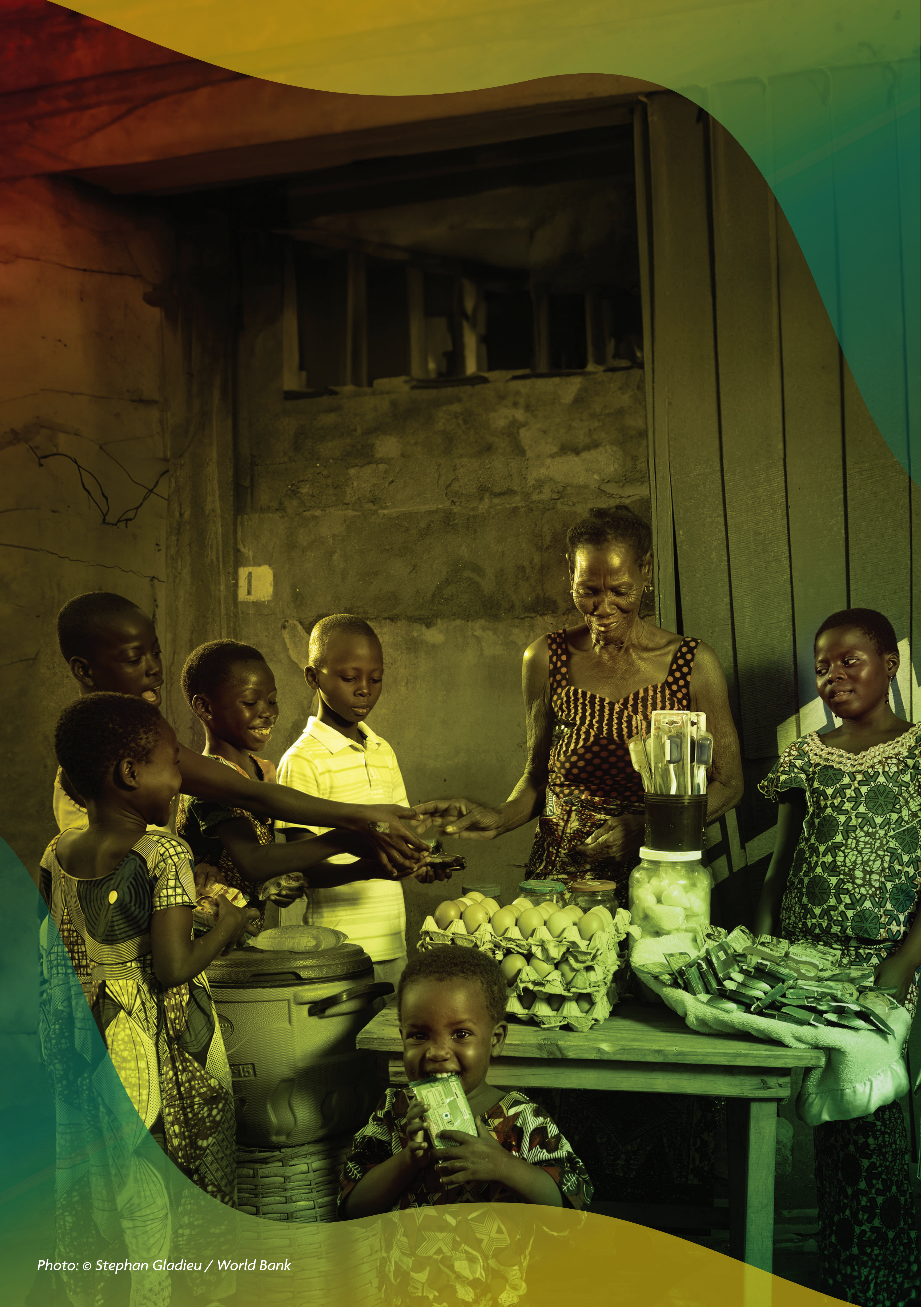

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I. Introduction

The COVID-19 crisis drove reversals in global poverty reduction in 2020, with an estimated 40 million new poor in Sub-Saharan Africa alone[1] (World Bank, 2020). With people at the heart of the COVID-19 recovery, more than 200 countries around the world launched over 3,000 social assistance measures in record time to tackle the economic and social impacts of the crisis (Gentilini et al., 2021). Togo was no exception. Located in West Africa, Togo is home to 8.3 million people with a GDP per capita of US$888 and poverty incidence standing at 45 percent using the national poverty line[2] (World Bank, 2021e). On April 8, 2020, just one month after the country's first reported case of COVID-19,[3] the Government of Togo launched NOVISSI, which means solidarity in the local *Éwé* language. NOVISSI is a large-scale unconditional emergency cash transfer program that initially supported informal workers whose incomes were disrupted or negatively affected by containment measures and was later extended to rural areas with higher poverty incidence. This initiative was a milestone for the social protection sector in Togo and, indeed, internationally, having been designed from scratch in ten days and delivered digitally from end to end. The program and the digital platform underpinning it were developed and implemented by the Government of Togo under the Ministry of Digital Economy and Transformation (Ministère de l'Économie Numérique et de la Transformation Digitale, MENTD in French) with oversight from an interministerial steering committee. NOVISSI's transfers in urban and peri-urban areas were financed through Togo's National Solidarity and Economic Recovery Fund and a grant from the French Development Agency (Agence Française de Développement, AFD in French). The expansion of the transfers to rural areas was financed by the American not-for-profit organization GiveDirectly. NOVISSI's delivery systems were funded with government spending and partly through International Development Association (IDA) from the World Bank. With a spend of US$34 million, NOVISSI benefited over 920,000 of the poor and vulnerable (around 25 percent of the adult population of Togo), 63 percent of whom were women.

Prior to the pandemic, steady economic growth contributed to moderate declines in poverty, yet some of those gains slowed due to COVID-19. Between 2008 and 2019, Togo grew at a 5.7 percent per annum pace and benefited from a stable macroeconomic framework. Togo's growth momentum was driven by the agriculture and service sectors, contributing to a decrease in headcount poverty rates, from 61.7 percent in 2006 to 45.5 percent in 2018–2019[4] (INSEED, 2020). While health impacts have been limited, the effects of the COVID-19 pandemic are estimated to have severely impacted welfare, leading to an increase in food insecurity and extreme poverty,[5] particularly in rural areas (World Bank, 2021e). Poverty continues to be widespread, especially in rural areas, where 58.8 percent of people live in poverty compared to 26.5 percent in urban areas.[6] Limited economic opportunities in productive activities have perpetuated low levels of income, and informality levels are striking, with more than 85 percent of the labor force

1. Measured using the international poverty line of US$1.90/day.
2. Corresponding to 4.3 million people under the national poverty line, which is estimated at CFA 273,619 per capita per year (about US$475).
3. The first COVID-19 case in the country was reported on March 6, 2020.
4. Based on the national survey, Questionnaires Unifiés des Indicateurs de Base du Bien-être (QUIB) which is not directly comparable to the Enquête Harmonisée des Conditions de Vie des Ménages (EHCVM) 2018–2019.
5. *Food poverty* is defined as the share of the population whose food consumption is below the food poverty line; *extreme poverty* is defined as the proportion of the population whose total consumption (including food, rent, clothing, energy, health expenditures, and education) is below the food poverty line (World Bank 2020e).
6. INSEED, 2020.

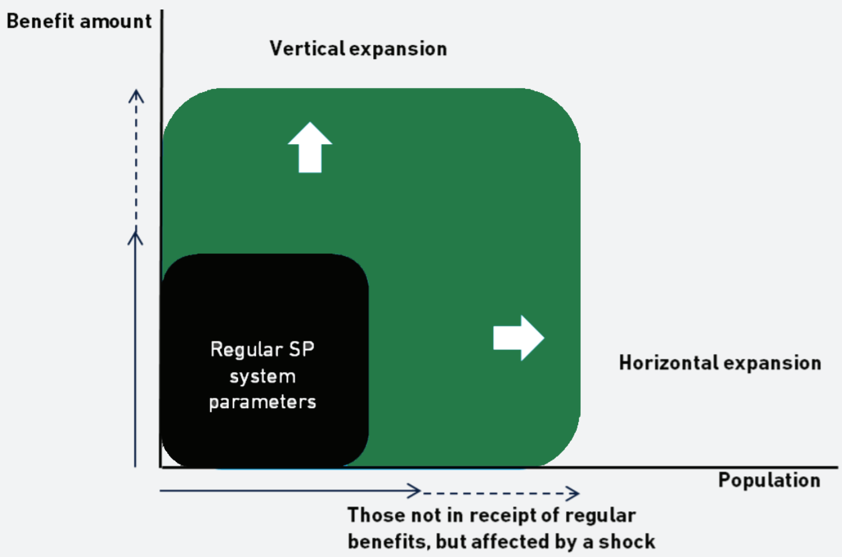
working in the informal sector. With the unfolding COVID-19 crisis, poverty conditions are expected to worsen, particularly among persons working in economic sectors such as tourism, transport and logistics, manufacturing, agriculture, and agribusiness, which were severely affected by internal and external shocks (World Bank, 2020a).

While the Government of Togo has made significant efforts to lay down the foundations of a robust social protection system over the past decade, its weaknesses were exposed by the crisis. Government spending on social protection and jobs programs has moderately increased over the last decade from 1.85 percent of GDP in 2009 to 2.06 percent in 2018 but remains below the levels of regional peers such as Mali and Senegal. Several programs were in place before the COVID-19 shock and continue to operate. However, these programs are limited in geographic scope and coverage. Recent evidence indicates low coverage of social protection, with only 38 percent of the poor receiving some kind of social safety nets transfer or subsidy in 2019 (World Bank Group, 2021d). Existing social protection programs include a national school feeding program, social safety nets transfers for the rural poor, public works, and entrepreneurship programs for rural youth, social protection insurance for civil servants and formal workers, and price subsidies on fuel, electricity, transport, and agriculture.

Indeed, the existing social protection paradigm left informal economy workers out of the picture, emerging as the "new poor" in the aftermath of the COVID-19 pandemic. The informal sector forms the backbone of most developing economies and employs a wide range of individuals, including smallholder farmers, street vendors, small traders, porters, casual laborers, artisans, hairdressers, fabric resellers, tailors, among others. In Sub-Saharan Africa, 89 percent of employed women and girls are in the informal economy workforce, accounting for 80 percent of total employment. They fall through the cracks of existing social protection programs as they are often not eligible for social safety net benefits, and being outside of the formal economy, they are ineligible for social insurance programs mandated for the formal sector. They are difficult to reach and tend to be mobile. Furthermore, the irregular and low earnings of informal workers leave them particularly vulnerable to economic shocks. In Togo, 84 percent of women and 74 percent of men work in the informal sector, with a higher incidence in rural areas. The containment measures to curb the spread of the virus impacted domestic economic activity, dispropor-

FIGURE 1

Existing social protection programs needed to be shock-responsive to expand horizontally



Source: Adapted from Bowen et al. (2020).

tionately affecting workers in the informal economy, particularly women who work in the hardest hit sectors, implying severe consequences for the well-being of children's health, nutrition, and education (World Bank 2020e). Existing social protection programs and delivery systems in Togo were not designed to reach the informal sector, limited to those already beneficiaries of programs (Figure 1).

The response to shock caused by the COVID-19 pandemic stress-tested the capabilities of social protection delivery systems worldwide. Countries with universal coverage of unique identification systems and social registries covering a large part of the population with frequently updated data on households and individuals were better prepared to deliver social assistance to those in most need.[7] In the absence of both a robust shock-responsive social protection policy framework and recent comprehensive data on household income and wealth, Togo's ability to implement shock-responsive social assistance using existing methods was put to the test. Moreover, traditional in-person data intake, registration, and cash payment delivery methods proved impractical for crisis response, requiring minimal physical contact to avoid the spread of the virus and agility to identify and register vulnerable people.

The Government of Togo took swift decisions to innovate, breaking with traditional paradigms and offering a mobile phone-enabled delivery of a social protection program to affected people. In record time, NOVISSI introduced a 100 percent "mobile phone-enabled" approach for on-demand self-registration, determination of eligibility, and payment of benefits. The program leveraged available sources of government administrative data sources, combined with satellite imagery, data science, and machine learning methods, to prioritize those most affected by the crisis. When NOVISSI was launched on April 8, 2020, it initially prioritized informal workers in areas under a declared state of emergency—mainly located in urban areas—that involved strict social distancing measures (henceforth referred to as model 1). Subsequently, the program was extended on November 2, 2020, to rural areas with a high prevalence of poverty (henceforth referred to as model 2). By August 2021, over 920,000 individuals had benefited from the program, of which 63 percent were women.

This case study, jointly authored by the Government of Togo and the World Bank, documents the innovative features of the NOVISSI program and posits some directions for the way forward. The study examines how Togo leveraged artificial intelligence and machine learning methods to prioritize the rural poor in the absence of a shock-responsive social protection delivery system and a dynamic social registry.[8] It also discusses the main challenges of the model and the risks and implications of implementing such a program. The study builds on consultations with program staff, partners, and academic researchers who provided technical support to the program's design. The study is organized as follows. Section II provides an overview of the NOVISSI program and the context in which it was deployed. Section III describes the delivery processes of NOVISSI's model 2 (high-tech approach) and dives deeper into the implementation of advanced spatial analysis techniques and mobile call detail records to assess needs and conditions to determine eligibility. Section IV presents a preliminary assessment of the results of the program and discusses the main challenges and limitations of the model. Finally, Section V concludes with a discussion of the lessons learned and what NOVISSI's innovations can implicate for the future of social protection delivery.

7. For instance, Egypt, Turkey, Peru, and Argentina proved agile with interoperable systems, pulling administrative data from different databases that tend to be updated more frequently (Gentilini et al., 2021)

8. Social registries are information systems that provide a gateway for potential inclusion into social protection programs. They support the "Assess" stage of the delivery process—from outreach to intake and registration to the assessment of needs and conditions—to help social systems determine potential eligibility for one or more programs. When Social Registries are dynamic, registration to social protection programs is open and continuous for all households, families, and individuals, allowing them to register when needed and update their information as it changes (Playbook on Dynamic Social Registries and Interoperable Social Protection Information Systems, forthcoming).

II. Enabling environment and program overview

At the onset of the COVID-19 crisis, the Government of Togo swiftly enacted strict policies[9] to manage the spread of the disease, accompanied by interventions to limit socioeconomic impacts. Containment measures to curb the spread of the virus disproportionately affected the informal economy. The majority of the labor force comprises workers who earn their livelihoods in the informal economy, with little to no access to social protection (World Bank 2021d). On the external side, global trade disruptions combined with the country's response to the pandemic affected export value chains. Critical economic sectors were affected by internal and external shocks, which translated into price increases in goods and services, including food staples and imports. The resulting income losses and consumption shocks likely forced an additional 0.3 million people into extreme poverty (World Bank Group, 2021e). With limited government spending on safety nets, low-income families are typically forced to rely on detrimental coping strategies that disrupt long-term human capital formation. To counter these effects, the Government laid down an emergency response plan to protect the lives, livelihoods, and future growth prospects to mitigate the negative impacts of the pandemic. Among others, the plan sought to prevent an increase in poverty by introducing an unconditional emergency cash transfer and electricity and water utility waivers.

Togo implemented a fully digital process supported by mobile devices without requiring in-person contact to register, enroll, and transfer financial aid to thousands of vulnerable people. This approach allowed the NOVISSI program to scale up faster than traditional cash transfer programs, which rely heavily on face-to-face interactions and prevalent statistical methods to infer well-being (Table 1). NOVISSI was facilitated by high mobile phone penetration rates and near-universal mobile phone coverage. Recent estimates from the *Enquête Harmonisée des Conditions de Vie des Ménages (EHCVM) 2018–2019* indicate that 65 percent of individuals in Togo own a mobile phone (54 percent in rural areas), and 85 percent belong to a household with one or more phones. At the end of 2020, SIM card penetration was 83.6 percent in Togo (ARCEP, 2021). While some people still do not possess a mobile phone, owning a SIM card and using it on a family member or friend's mobile device is not uncommon. Recent estimates using NOVISSI's administrative data show that 22 percent of SIM cards and 7 percent of SIM slots are shared in Togo (Aiken, Takhur, and Blumenstock, 2021).

NOVISSI's assistance unit were individual informal sector workers. This was a policy choice made by the Government of Togo, given the context of the pandemic and data constraints. In the absence of a dynamic social registry with up-to-date data on households and individuals, and without unique identifiers with universal coverage, some households may have received multiple transfers, provided that the assistance unit was determined to be individuals. It follows therefore that NOVISSI did not set out to ensure just one beneficiary within a household.

From the potential beneficiary's perspective, NOVISSI operated in three simple steps (Figure 2):

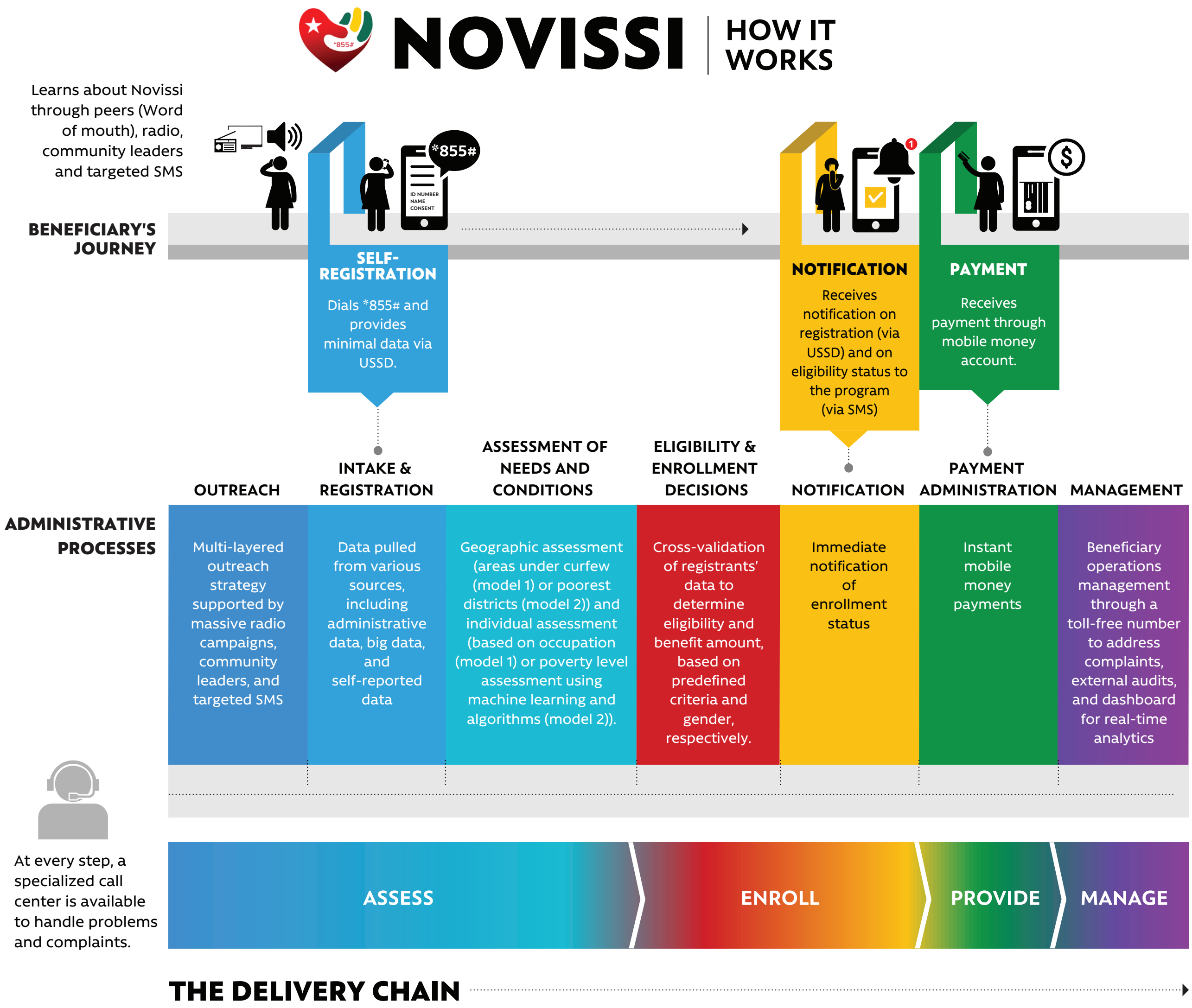
9. Togo's containment measures included, among others, cordoning off villages under a declared state of emergency, curfews, and border closures.

TABLE 1 NOVISSI (model 1 and model 2) compared to targeted cash transfer programs

Characteristic	NOVISSI model 1 *Low-tech approach*	NOVISSI model 2 *High-tech approach*	Social safety nets[1]
Geographic coverage	Urban and peri-urban	Rural	Rural
Geographic assessment	Areas under declared state of emergency	200 poorest cantons based on satellite imagery, population census data and machine learning	Poverty maps based on 2011 household surveys conducted by INSEED
Individual assessment	Categorical filter based on occupation and location as recorded in voter list	Welfare assessment based on machine learning and anonymized call detail records	Proxy means testing and community validation
Benefit amount	Women: 12,250 monthly	Women: 8,170 per installment	5,000 monthly
(CFA)	Men: 10,500 monthly	Men: 7,000 per installment	
Frequency of payments	Bi-weekly (half of the benefit amount was disbursed bi-weekly)	Monthly (100 poorest cantons in phase 1) and then bi-weekly (following 100 poorest cantons phase 2)	Quarterly
Duration of benefits	0.5 to 2 months, depending on the length of the state of emergency by area	5 months for the 1st phase (100 poorest cantons) and then 2.5 months (following 100 poorest cantons) for the 2nd phase	24 months
Number of installments	1 to 4, depending on the length of the state of emergency by area	5	8
Registration	On-demand self-registration via USSD	On-demand self-registration via USSD	In-person survey
Payment	Mobile money	Mobile money	Initially cash based. At the onset of COVID-19, mobile money
Period	April 2020 – March 2021	November 2020 – August 2021	February 2018 – December 2021
Number of beneficiaries	819,972	138,531	40,309
Share of female beneficiaries	63%	52%	60%
Number of registrants	1,632,942	519,972	N.A.[2]
Source of Funds	Government and AFD grant as refinancing of the initial transfer	GiveDirectly	IDA grant
Spending (USD)	23.9 million	10 million	N.A.

Source: Authors' elaboration using administrative data from NOVISSI and World Bank Group (2021c).
Note: 1. The Togo Safety Nets and Basic Services Project (*Filets Sociaux de Base*, FSB in French) seeks to provide poor communities and households with greater access to basic socioeconomic infrastructure and social safety nets, including cash transfers and school feeding. Data are reported for the cash transfer component under the existing arrangements when NOVISSI was deployed. Note that additional financing has been recently approved, entailing some improvements in the project design.
2. N.A. Not available

FIGURE 2 How NOVISSI Works: Journey mapping the perspectives of beneficiaries and administrators



Source: Original figure for this publication.

1. **Self-registration.** Interested individuals would self-register by dialing *855# from a mobile phone and inputting basic information in an Unstructured Supplementary Service Data (USSD) form for intake and registration. This information included identification number (from the voter list),[10] name, and consent to utilize their personally identifiable information (PII) to be further assessed by the NOVISSI program.

2. **Notification.** Applicants would be notified by USSD about their registration in the program and will then get an SMS to inform them about their eligibility status and enrollment decision.[11] The eligibility requirements

10. An administrative dataset produced by the national independent electoral commission. The voter list was used as a means to identify beneficiaries as it was the most widespread, up-to-date, and structured database available to the program. About 86 percent of the adult population owns a voter's ID credential, compared to about 30 percent of people who own a national ID card.

11. Eligibility decisions consist of determining which applicants qualify for a program based on pre-defined eligibility criteria. Enrollment decisions, that is to say, whether an eligible applicant is enrolled in the program (becomes beneficiary) or not (waitlisted) are typically made based on budget and operational capacity criteria (Lindert et al., 2020). In NOVISSI, all eligible applicants were enrolled in the program.

included being a Togolese citizen and resident, aged 18 years or older, possessing a valid voter ID credential, living in one of the eligible areas[12,13] and meeting the individual vulnerability assessment criteria based on occupation[14] (model 1) or welfare status (model 2).

3. **Payment.** Immediately after eligibility notification, beneficiaries would receive their first payment on the mobile money account linked to the phone number they registered with. For beneficiaries who did not have a mobile money account before enrollment into the program, one was automatically created by their corresponding mobile network operator (MNO). The know-your-customer (KYC) processes were conducted by MNOs using their own procedures at the time of account opening. The amount disbursed ranged from CFA 10,500 for men to CFA 12,250 for women, per month, in model 1 (with half of the amount being disbursed every 2 weeks), and CFA 7,000 for men to CFA 8,170 for women, per installment, in model 2 (Table 1).

A toll-free number was set up to accompany the process so that registrants and beneficiaries could reach out to a specialized call center to handle problems and complaints.

From an administrative perspective, the beneficiary's journey was facilitated at the backend by four key steps consistent with the Social Protection Delivery Systems Framework[15] (Figure 2):

1. **Assess.** Individuals' characteristics, needs, and conditions were assessed through several sources, including the voter list, big data, and self-reported data via USSD, in order to prioritize people for social assistance. All applicants received an SMS acknowledging registration and informing them that they would be considered for financial aid if they became eligible for the program.

2. **Enroll.** Registrants' profiles were cross-referenced against eligibility criteria. Subsequently, eligible applicants received a second notification informing them about the enrollment decision. Non-eligible individuals were still considered for automatic future enrollment into the program if the eligibility criteria changed (for example, if a new geographic location became eligible). All eligible applicants were enrolled in NOVISSI.

3. **Provide.** Enrolled beneficiaries received the emergency cash transfer in their mobile money account. This involved, among other key partnerships, strong collaboration with MNOs to ensure interoperability between the NOVISSI platform and their mobile payment systems.

4. **Manage.** Accompanying measures such as a solid grievance redress mechanism (GRM), external audits, and real-time analytics enabled the program to operate in a transparent and traceable way and adapt to the beneficiary's needs.

In the context of limited administrative[16] and survey data[17] combined with restrictions on in-person program delivery, NOVISSI had to innovate to reach individuals who needed assistance the most. Administrative data collected by governments and service providers during their day-to-day business is an increasingly important source for evidence-informed policy-making. Survey data can be combined with administrative data to increase the preci-

12. Model 1's eligible geographic areas were those placed under a declared state of emergency where containment measures were stricter. These areas are predominantly urban or peri-urban and include: Agoè-Nyivé, Golfe, Tchaoudjo, Soudou, Cinkassé, Kpendjal, Kpendjal-Ouest, Oti, Oti-Sud, Tandjouaré and Tône.
13. The 200 poorest cantons were eligible for NOVISSI's Model 2.
14. 2,328 unique occupations were considered informal and eligible in the scope of NOVISSI model 1. The most common eligible professions included retailers, seamstresses, hairdressers, housekeepers, and drivers.
15. Developed by Lindert et al. (2020).
16. Government agencies do not incur additional costs for administrative data collection, so they also do not impose an additional burden on respondents. They typically contain the full population of participants in the program, so the sizes of the datasets are often much larger than those of a statistical survey. Administrative data are often longitudinal, which enables tracking individuals or businesses over time.
17. Household surveys are an important source of socio-economic data.

sion of survey estimates with little additional cost. In other cases, different administrative datasets can be combined to replace existing surveys or to reduce reliance on survey data (Harris-Koetjin et al., 2017). However, Togo lacks a unique identifier covering all persons in the territory and a dynamic social registry, allowing to prioritize those most affected by the shock. In terms of survey data, the first round of the EHCVM was carried out in Togo in 2018–2019 and data processing was completed in 2020. The most recent population census was completed in 2011 without collecting welfare or income information. Collecting new survey data through traditional methods was not possible due to the health crisis: the country required quick and decisive action while being subject to limited fiscal resources and social distancing constraints.

NOVISSI's deployment consisted of two complementary delivery models (Table 1). In delivery model 1, a low-tech approach, the program leveraged the voter list to determine applicants' uniqueness, location, and occupation. This was a pragmatic choice based on the readily available administrative data on registered voters to allow for the verification of unique individuals. The voter list was compiled based on a mass registration campaign for Togolese citizens aged 18 years or older, conducted over a three-day period at the end of 2019.[18] Registered voters received a biometric voter identity credential for the February 2020 presidential elections. A total of 3,633,898 individuals were registered, representing an estimated coverage of 86.6 percent of the adult population (Aiken et al., 2021).[19] The voter list includes a unique number for each voter, which, in the absence of a foundational unique identification system with universal coverage of the population, was helpful to reliably verify registrants to the NOVISSI program, thereby limiting the duplication of benefits delivery. Additionally, the voter's registration exercise collected occupation and residence data. After intense data scrubbing work to categorize occupations, NOVISSI model 1 used the voter list not only to guarantee the unicity of the beneficiaries but also to verify whether registrants met geographical and occupation criteria. Individuals were deemed eligible if their occupation and home residence, as reported in the voters' list, matched the predefined eligible geographic areas and occupations.

Expanding NOVISSI to rural areas required a more innovative approach to prioritize the poorest. Hence, delivery model 2, a high-tech approach, was developed to leverage administrative, survey, and big data. NOVISSI continued relying on the voter list to verify a person's uniqueness and home residence for rural expansion. However, given insufficient variation in rural occupations and limited budget to cover entire districts (or cantons), NOVISSI utilized new technologies and leveraged big data from satellites and mobile phone call detail records (CDR)[20] to prioritize the delivery of benefits to the most vulnerable individuals. The Government of Togo established two guidelines for this endeavor, first to focus on the poorest districts and second to prioritize the poorest individuals within those districts. Togo's Government partnered with a group of academics from Innovations for Poverty Action (IPA), the Center for Effective Global Actions (CEGA), and the University of California, Berkeley, to build a poverty map of Togo using satellite imagery. Based on this exercise, Togo's 397 cantons were ranked from poorest to richest.[21] The 100 poorest cantons were selected by the Government and GiveDirectly (the funding partner for NOVISSI model 2) to provide them with financial aid. This number was subsequently extended to the following 100 poorest cantons. Within each selected canton, the poorest individuals were prioritized by leveraging big data and machine learning to estimate individual consumption using CDR, as described in further detail in Section III.

18. Voter's registration took place nationwide and in selected countries between November 29 and December 1, 2020.

19. Alternative functional identification systems had lower coverage and did not include information on key eligibility criteria. According to Government administrative data, over 1.3 million individuals possess a national identity card and almost 0.5 million possess a passport.

20. A call detail record (CDR) is a data record produced by a telephone exchange or other telecommunications equipment that documents the details of a telephone call or other telecommunications transactions (e.g., text message) that passes through that facility or device. The record contains various attributes of the call, such as time, duration, completion status, source number, and destination number (Wikipedia).

21. Togo has a total of 397 cantons. Cantons are Togo's smallest administrative divisions (Admin-3).

Geospatial data[22] sourced from private data producers[23] was employed to create fine-grained poverty maps to locate the least wealthy cantons. Using machine learning algorithms, geospatial satellite, connectivity, demographic, and geographic data were analyzed to find patterns that predict wealth and poverty. Images such as roofing materials, road surfaces, size plots of land, proximity to bodies of water, among others, were interpreted to produce high-resolution estimates of consumption.[24] These estimates were then combined with population density estimates to generate a weighted average of wealth per canton. The calculations were calibrated using the EHCVM 2018–2019 household survey containing the exact geo-coordinates of each surveyed household. This survey data provided a "ground truth" against which the model was trained. Finally, cantons were ranked to identify those with a higher concentration of people living under US$1.25 per day.

Afterward, individual-level mobile phone usage data was analyzed to prioritize the poorest individuals in selected cantons. Researchers analyzed mobile phone metadata containing information on calls, SMS, mobile data usage frequencies, and mobile money transactions to predict consumption at the individual level. Specifically, a phone-based survey was administered among a large and representative sample of mobile phone subscribers from the poorest cantons. These data were then matched to each subscriber's history of phone usage in order to train a supervised machine learning algorithm to predict average daily consumption at the individual level.[25] Based on this information, roughly 750,000 individuals across the country were shortlisted as potentially eligible, given their likelihood of living under US$1.25 per day.

Deploying NOVISSI required the engagement of multiple partners. The Government of Togo collaborated with various stakeholders, each of whom played a specific role in the delivery chain and across delivery models (Annex 1). Implementation was overseen by the Government of Togo. An inter-ministerial steering committee provided oversight of the program's implementation and supported strategic decision-making. MENTD operated the program, including setting up the information system to assess (register with available data), enroll (determine eligibility, enroll, and notify), and provide (deliver the payments). This also involved outreach to the population, putting in place a toll-free number managed by a call center to address grievances, and program monitoring and evaluation. GiveDirectly provided funding and implementation support for NOVISSI's expansion to rural areas (model 2). Academics developed the prioritization[26] methodology for the deployment of NOVISSI in rural areas (model 2), which resulted in a potential eligibility list containing minimal data (phone numbers) that was transferred to MENTD for eligibility check purposes. The World Bank, through IDA, provided financing for data collection for research and feasibility testing of machine learning and data-driven methods to prioritize the poorest, as well as for equipment and audit. Togo's two leading mobile phone operators provided anonymized mobile phone metadata (also referred to as CDR) to the team of academics for selected periods to support the deployment of an emergency cash transfer in the midst of a historic crisis.

Transparent institutional arrangements were put in place to mitigate data privacy concerns. To protect the confidentiality of CDR data, researchers hash-encoded each phone number into a unique identifier prior to analysis and stored all data on secure servers. Call-detail records were never transmitted to anyone else, not even the Government

22. As with administrative records, data on weather conditions, water quality, traffic, geospatial data, among others, are not created with the primary intention of being used for statistical or social protection purposes, yet they may provide valuable information for official statistics (Harris et al. 2017).
23. NASA Harvest, University of Berkeley School of Informatics.
24. Using this methodology, a total of 10,119 wealth estimates for 2.4 km^2 tiles were produced for Togo.
25. Participants' consent was requested to match mobile phone metadata to survey responses.
26. Throughout this report, we use the terminology of prioritizing people for social assistance in place of the term "targeting." See Lindert et al. (2020) for a detailed discussion.

of Togo. Only specified researchers accessed them under a non-disclosure agreement and a data use agreement signed by the University of Berkeley with each of the two MNOs.

Relatively speaking, NOVISSI operated in a policy environment with limited choices for shock-responsiveness, prompting the Government to make strategic design decisions to proactively respond to the emergency. With the lack of a shock-responsive social protection policy framework and a dynamic social registry in place to prioritize those most affected by the COVID-19 pandemic, combined with restrictions on in-person social protection delivery, NOVISSI was the only feasible alternative at the time for a lightning response. Digital approaches, such as the one introduced by NOVISSI, have the potential to introduce significant gains in terms of efficiencies for governments and financial inclusion. However, as such, they can also exclude some groups and raise important data privacy concerns, as explained in greater detail in the final sections of the report.

III. A deep dive into NOVISSI's high-tech delivery model (model 2)

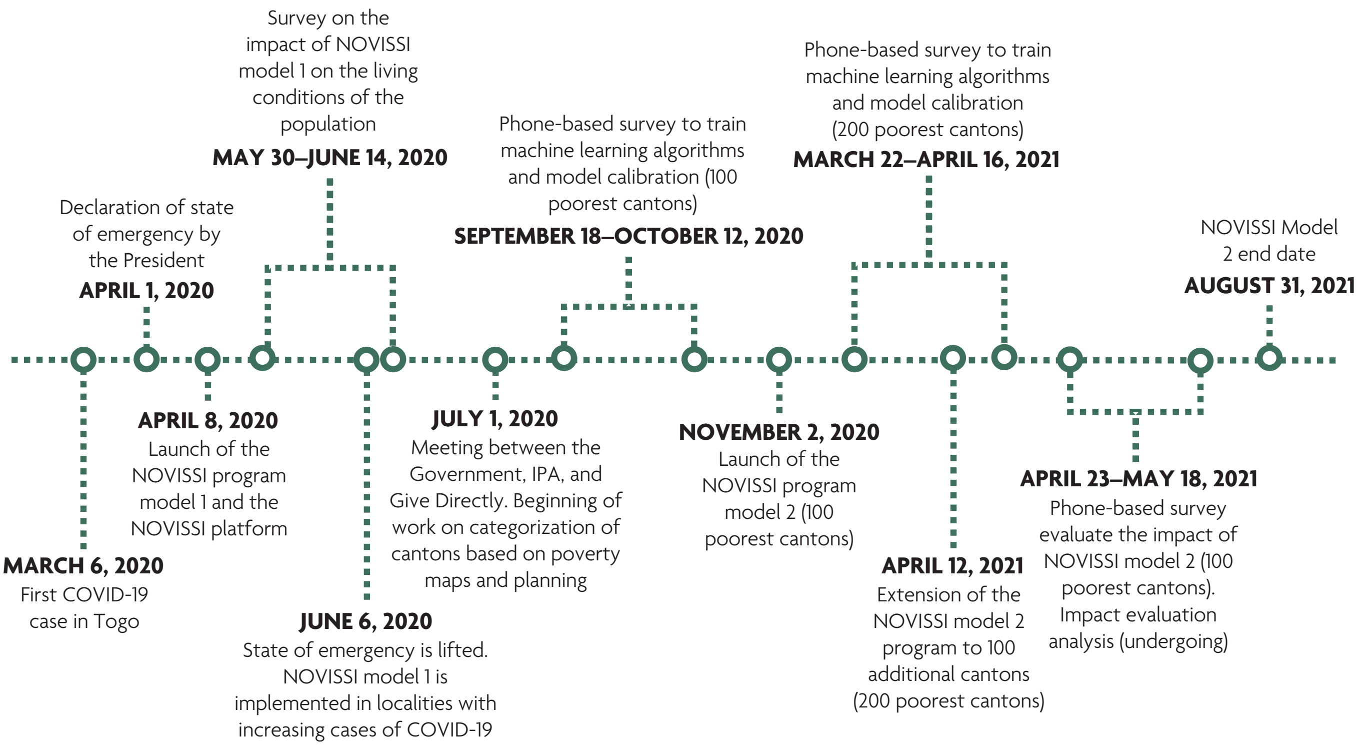
In expanding NOVISSI to rural areas, the delivery model covered the entire gamut of end-to-end delivery processes. Using the Social Protection Delivery Systems Framework from Lindert et al. (2020) as a guiding framework, this section illustrates NOVISSI's implementation phases and key actors, focusing on the program's expansion to rural areas. The section also highlights the role of technology as an enabler in automating processes and manage information.

1. Outreach

Immediately after launch, the program quickly attained high take-up rates.[27] Part of the success was probably due to a multi-layered outreach strategy. Outreach for NOVISSI was supported by proactive and extensive radio campaigns in approximately 30 stations in seven languages (French, Ewé, Mina, Kotokoli, Losso, Kabyè, and Moba). In addition to announcing the program objective and the steps

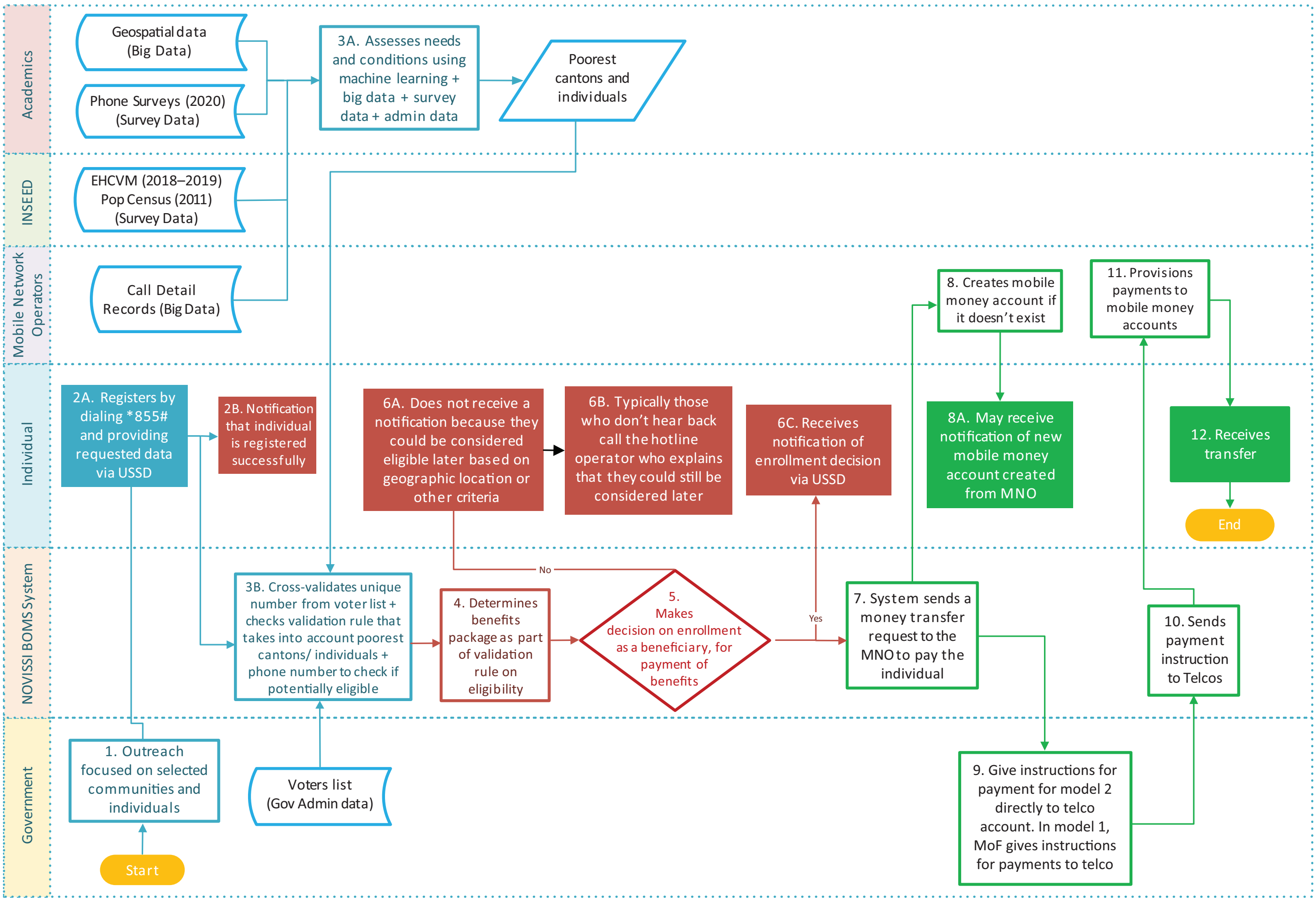
27. Although the systems were designed to take over 700 registration requests per second, the program's high demand in the first three days of implementation resulted in systems saturation.

FIGURE 3 NOVISSI's implementation timeline



Source: Original figure for this publication.

FIGURE 4 NOVISSI's Model 2 delivery chain process mapping



Source: Original figure for this publication.

necessary to register and receive the benefit, frequently asked questions were answered through radio ads and statements from Government officials. They were also shared with the call center so teleoperators could understand the program and have the relevant information to respond to people's questions. A user-friendly website containing program information was created. Social media handles also provided daily registration and beneficiary metrics to the population. At the local level, NOVISSI was promoted actively through local radio networks. Community leaders were onboarded to inform communities about the program. While these features of the outreach strategy were standard across both models, model 2 introduced an innovation by sending targeted outreach messages. Individuals identified as potential beneficiaries received text messages inviting them to apply for NOVISSI. The ads asked people to dial *855#, a special number that would prompt them to respond to a brief questionnaire over USSD to register for NOVISSI.

2. Intake and registration

NOVISSI's data intake to allow for the assessment of needs and conditions and eligibility determination used four primary sources:

- **Government administrative sources.** Data were pulled from the voters' list to verify the uniqueness of individuals and obtain demographic information for eligibility verification and determination of benefits package. These variables included the voter's unique identification number, a second validation number (*Numéro de Suivi du Formulaire d'Inscription*, NSF in French) available only in printed credentials, name, sex, home location, and occupation. Data-sharing protocols to access the voters' list were facilitated by the declaration of emergency measures to combat the crisis.

- **Non-traditional data sources.** Big data were gathered and analyzed offline to prioritize areas and individuals. Independently, the team of academics leveraged geospatial data and mobile phone metadata to assess needs and conditions at the canton and individual levels, respectively. In many cases, datasets were publicly available, while others required specific licenses from international entities. Due to the nature and sensitivity of data, access to CDR data required non-disclosure and data use agreements between academics and MNOs. All of these datasets were accessed and processed exclusively by academics. Ultimately, the ranking of the poorest cantons, along with the list of phone numbers of potentially eligible individuals meeting the criteria of predicted wealth below a predetermined threshold (US$1.25/per day), were transmitted to the Government for eligibility determination.

- **Survey data.** Survey data collected by the National Institute of Statistics in Togo (*Institut National de la Statistique et des Études Économiques et Démographiques*, INSEED in French) and researchers were used to calibrate the machine learning algorithms. These included the EHCVM 2018–2019 survey and phone-based surveys.

- **Self-reported data.** NOVISSI introduced an on-demand registration system to apply for the program using a simple USSD[28] form. Interested individuals could register for NOVISSI's benefits by dialing *855#. This would prompt a USSD menu where applicants were asked to provide minimal data to verify their eligibility. Registrants would need to grant their consent to share information for the purposes of the NOVISSI program, including their voter's unique identification number, a second validation number (NSF) only available in printed voter credentials, and their last name. The NSF helped the program ensure that the beneficiary was actually in possession of the voter's card.[29] These data were automatically processed and triggered the eligibility determination process.

3. Assessment of needs and conditions

The assessment of needs and conditions for expanding NOVISSI to rural areas utilized machine learning to analyze non-traditional data in two steps. When NOVISSI was rolled out in urban areas (model 1), the Government used a categorical approach based on individuals' geographic location and occupation to identify the program's potentially eligible population. Prioritizing informal workers in places with a declared state of emergency, implying harsher mobility restrictions, helped target benefits to vulnerable individuals affected by the COVID-19 pandemic. This initial approach focused deliberately on the hardest-hit urban areas. However, that approach would not have been conducive to reaching the poorest households in the rest of the country, primarily in rural areas. For NOVISSI's expansion to rural areas, the task of locating the poorest geographic regions in the country and the poorest mobile subscribers in those regions was performed by a team of academics[30] with a two-step approach that used geospatial and mobile phone data as inputs. The outputs were (i) a poverty map of Togo ranking the cantons (districts) from

28. USSD is communication protocol used to send text messages by opening a real-time session between a mobile phone and a network or server that enables a two-way exchange of information. Users interact directly from their mobile phones and select different options among predefined menus.
29. Debenedetti (2021) documents that "[...] voter rolls (used to verify that voters are correctly registered ahead of casting their votes) were still posted at some of the country's polling stations from the February elections, which left open the possibility of attempting to register for the program through other people's voter ID numbers on the posted registers. The government was able to detect and prevent fraudulent registration attempts by requiring applicants to furnish their NSF number as part of the registration process. The NSF is a security code included on each person's voter identification card which, critically, is not published on voter rolls."
30. See Annex 1.

TABLE 2 Data sources used for assessing needs and conditions

Data	Source
1. Road density	Open Street Map
2. Urban (or built up)	NASA (MODIS)
3. Elevation	USGS
4. Slope	USGS
5. Precipitation	NASA/Japan Aerospace Exploration Agency
6. Population	Humanitarian Data Exchange
7. Number of cell towers	Facebook
8. Number of WiFi access points	Facebook
9. Number of mobile devices	Facebook
10. Number of Android devices	Facebook
11. Number of iOS devices	Facebook
12. Nightlights / Radiance (VIIRS)	National Center for Environmental Information Earth Observation Group
13. Satellite imagery	Digital Globe
14. EHCVM 2018–2019	INSEED
15. CDR	Togocel and Moov
16. Phone survey	Academics

Sources: Aiken et al. (2021) and Chi et al. (2021).
Note: Data sources 1–14 were used for the prioritization of cantons' algorithm (step 1), while data sources 14–16 were used for the prioritization of individuals' algorithm (step 2).

the poorest to the richest and (ii) a potential eligibility list with minimal information on individuals living under the poverty line (US$1.25/day) located in the poorest cantons prioritized by the program (200 cantons in total). The potential eligibility list was transferred to the Government of Togo to determine eligibility and enroll beneficiaries. A summary of the data sources used for this process is provided in Table 2.

Model 2—Step 1. Selecting the poorest areas in Togo

The first step of model 2 was to find the poorest areas in Togo. Before partnering up with academics, Togo did not possess recent poverty estimates at the levels of prefecture (Admin-2)[31] or canton (Admin-3).[32] The only available, most updated, representative estimates were aggregated at the

31. The most recent estimates of poverty representative at the prefecture level were from 2015.
32. Latest available data from the Demographic and Health Survey (DHS) 2013-2014 surveyed 185 (47 percent) of cantons, while the EHCVM 2018–2019 surveyed 260 (65 percent) cantons. This implies that one or more households per canton provided socioeconomic information; however, poverty estimates are not representative of the canton.

BOX 1

Supervised machine learning algorithms in a nutshell

Supervised machine learning algorithms model a function to predict an ***outcome variable*** that cannot be easily obtained (e.g., wealth, consumption, population, etc.) based on a set of ***predictors*** readily available (e.g., non-traditional data). In order to train the model to predict the outcome, a statistical learning method is applied to extract features and find patterns in ***ground truth data*** (also referred to as input data). The model is then extrapolated to obtain outcome variable predictions beyond existing data points. Essentially, the algorithm learns to identify patterns in input data indicative of an outcome variable.

national and regional levels.[33] However, prioritizing support to the poorest cantons in Togo required more granularity. NOVISSI's geographic prioritization strategy followed Chi et al.'s (2021) methodology to produce high-resolution estimates of wealth and poverty, with some tweaks specific to the country. Chi et al. (2021) estimations for over 135 low- and middle-income countries (LMICs) are available for free public use.[34] NOVISSI's expansion to rural areas was initially planned for the 100 poorest cantons and extended in April 2021 to an additional 100 cantons.

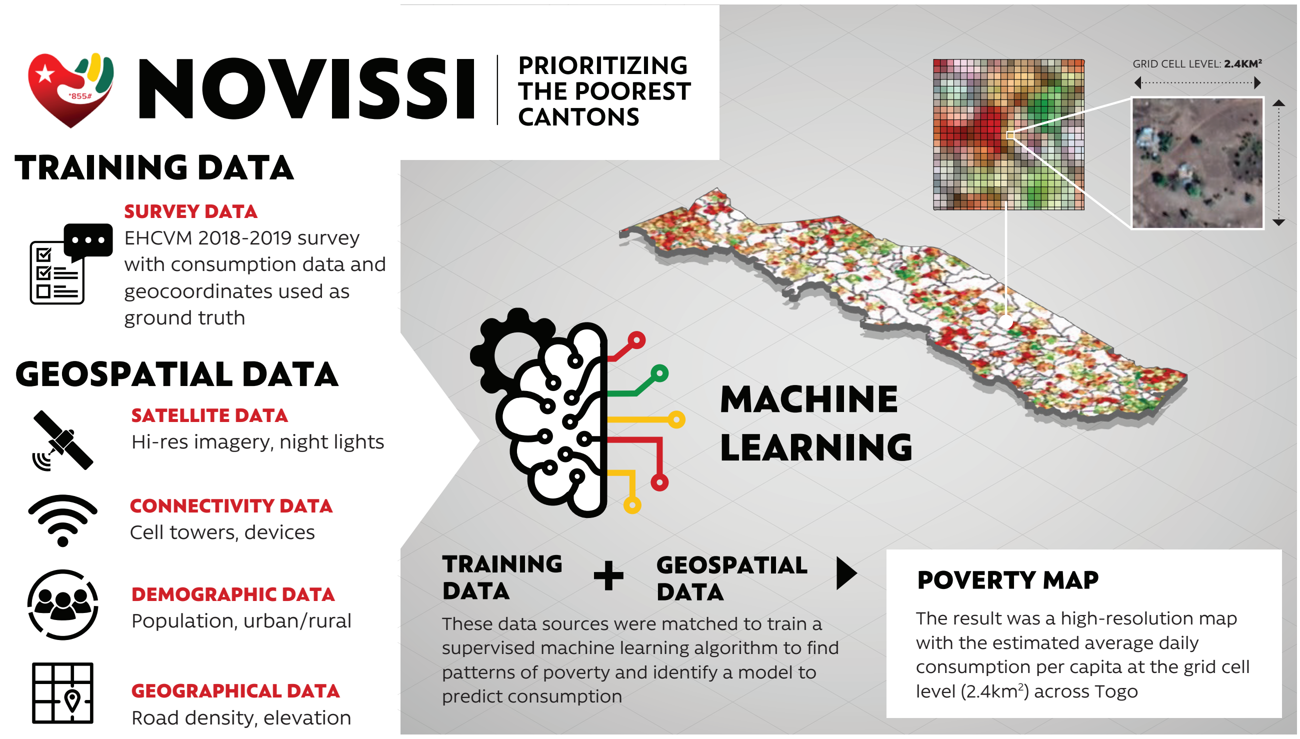
NOVISSI's selection of the poorest cantons was based on a model producing micro-estimates of consumption (Figure 5). In Togo, the approach predicted average consumption (outcome variable) for each 2.4 km^2 grid cell or tile.[35] The size of the tile was determined based on the resolution of input data, but also considering that smaller grid cells could compromise the privacy of individual households (Chi et al., 2021). While wealth estimates were also produced for the various cantons in Togo, the NOVISSI program employed consumption estimates to prioritize benefits, given the direct connection of this indicator to poverty lines measurement and a more intuitive interpretation of the index.

The ground truth data used to train the predictive model of consumption was derived from the EHCVM 2018–2019 survey. The EHCVM 2018–2019 is a nationally and regionally representative household survey administered by INSEED. A total of 6,172 households were surveyed, covering 265 cantons (65 percent) and 922 unique tiles (9.1 percent) (Chi et al., 2021). Data collected include questions on education, health, labor, household characteristics, assets, and expenditures, among other topics, along with the exact geo-coordinates of household location. Using the EHCVM 2018–2019, the researchers constructed a measure of daily per capita consumption. This indicator was used as a ground truth measure of consumption, while the tile-level average of consumption was the target variable for the machine learning model.

Survey data were linked to a vast range of non-traditional big data records to predict average consumption. Geospatial satellite, connectivity, demographic, and geographic data were integrated into the model as predictors of consumption (Chi et al., 2021). Specifically, satellite data included hi-resolution imagery and nightlights. Connectivity data contained characteristics of telecommunications infrastructure, like cell towers and WiFi access points,

33. Togo has only five Admin-1 level regions.
34. https://data.humdata.org/dataset/relative-wealth-index
35. The statistical learning method applied by Chi et al. (2021) was a gradient boosted regression tree. The standard reference for gradient boosting is Friedman (2001), while the standard reference for random forests is Breiman (2001). Natekin and Knoll's (2013) provide an introduction.

FIGURE 5 Prioritizing the poorest cantons in Togo (Model 2)



Source: Original figure for this publication based on Chi et al. (2021) with inputs from Josh Blumenstock.

and mobile device features, such as quantity and operating systems. Demographic features included high-resolution population density maps and urban-rural domain markers. Geographic properties such as road density, elevation, and precipitation were also considered. All geospatial features were aggregated for each grid cell to mitigate privacy concerns. Previous preparation to compress satellite imagery was required since these data are usually unstructured and multi-dimensional.[36] 112 features of non-traditional big data were then matched to the ground truth data to find patterns of poverty in geospatial data and identify a model to predict consumption in tiles without ground truth data. The result was a high-resolution map with the expected average daily consumption per capita at the grid cell level.

Micro-estimates of consumption were combined with population density estimates to identify the poorest cantons. Using high-resolution population density estimates from the Humanitarian Data Exchange,[37] the team of academics calculated a weighted average of consumption for all 2.4 km^2 grid cells within each canton. This allowed cantons to be ranked by their predicted degree of consumption as well as their population density, giving more prominence to cantons where a larger share of the total population was expected to live under US$1.25 per day. The result of this exercise located and ranked the 397 districts in Togo from the poorest to the richest. The 200 poorest cantons were selected to receive benefits during the program's extension to rural areas. The first phase of the program's extension to rural areas focused on the 100 poor-

36. Compressing satellite data required using unsupervised machine learning techniques, specifically, convolutional neural network methods, to produce a vector of 2,048 features from 256x256 pixel images. Then, principal component analysis (PCA) helped reduce the number of features to only 100 (Chi et al., 2021).
37. Available at https://data.humdata.org/dataset/highresolutionpopulationdensitymaps

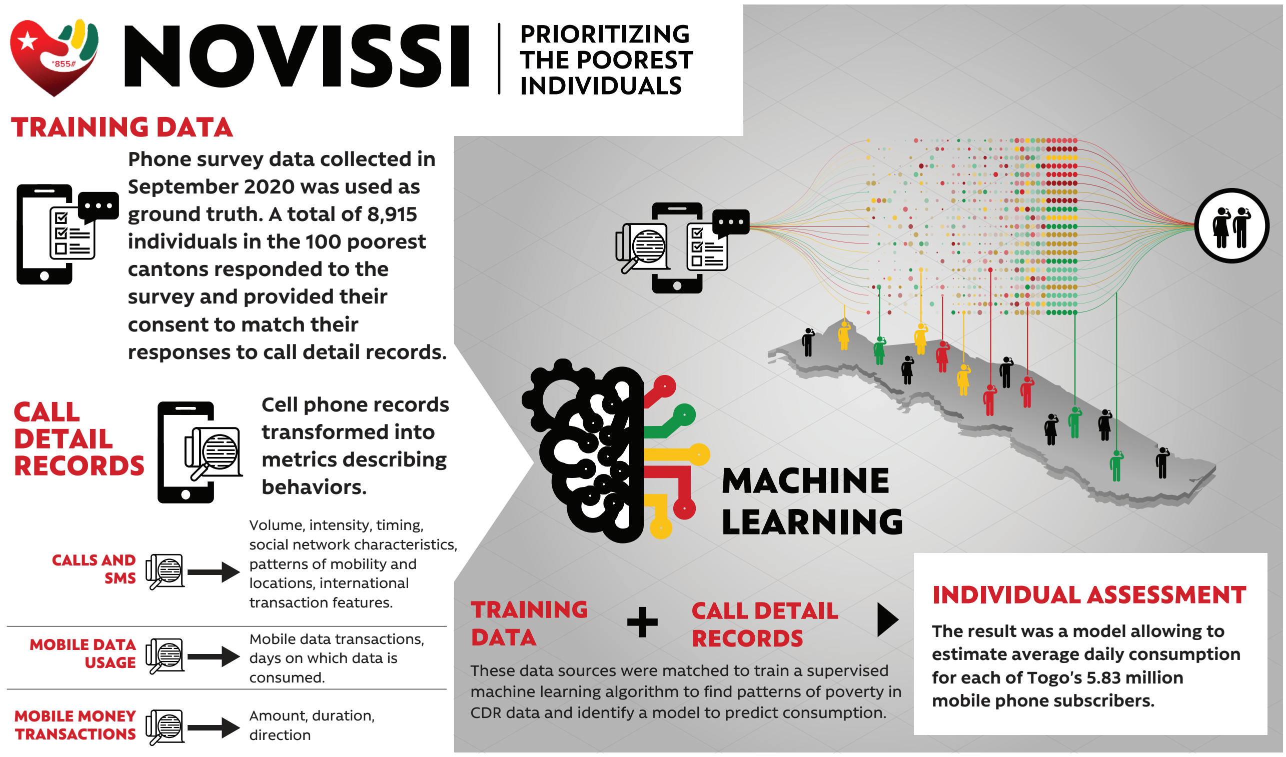
est cantons, then on the following 100 poorest cantons in the second phase. Although the canton selection process responded to technical criteria, the team of academics validated the model calibrations through various exchanges with government officials to take into account their deep knowledge of practical realities.

Model 2—Step 2. Prioritizing the poorest individuals

The second step of model 2 consisted of prioritizing the poorest individuals living in the poorest cantons. Without an up-to-date and dynamic social registry to assess needs and conditions of households and/or individuals, combined with constrained resources to collect new survey data amidst the pandemic, the Government of Togo explored groundbreaking opportunities to prioritize the poor. In this context, the team of academics proposed a methodology that had only previously been theoretically tested[38] in which poverty was proxied using mobile phone metadata and machine learning algorithms. The approach was replicated for the first time in a real cash transfer delivery context in Togo.

The approach builds a predictive model to estimate daily consumption for each of the country's 5.83 million mobile phone subscribers (Figure 6). The intuition behind the method is similar to the one employed to estimate poverty maps in the previous step. A supervised machine learning algorithm was trained on survey-based measures of individual-level consumption to recognize patterns of poverty in CDR input data.[39] Mobile phone usage is likely

FIGURE 6 Prioritizing the poorest individuals within the poorest cantons (Model 2)



Source: Original figure for this publication based on Aiken et al. (2021) and inputs from Josh Blumenstock.

38. See Blumenstock, Cadamuro and On (2015) and Blumenstock (2018) and Aiken et al. (2020).
39. The machine learning method used to train models that predict poverty from CDR features was a gradient boosted regressor tree (Aiken et al., 2021).

to be different between poor and non-poor people. For instance, individuals with a larger volume of international phone calls, a higher mobile money balance, or more extensive networks are likely better off than their counterparts.

Data collected through a phone survey of active mobile phone subscribers were used as ground truth to train the model. In September 2020, before the expansion of NOVISSI to rural areas, the team of academics administered a phone-based survey financed by the World Bank to provide ground truth information representative of mobile network subscribers inferred to be living in the 100 poorest cantons eligible for NOVISSI. When the Government decided to extend the program to the following 100 poorest cantons (200 in total), further data were collected to retrain the models. The sampling frame included all mobile phone subscribers active on one of the two mobile networks in Togo between March 1 and September 30, 2020, equivalent to 5.83 million subscribers.[40]

The phone surveys solicited consent from respondents to match their information to mobile phone transaction data. The phone surveys were conducted over two weeks with an average duration of 40 minutes. They gathered data on demographics, asset ownership, and well-being. A survey was considered complete if participants consented to merge their data with mobile phone records and responded to the entire set of questions. 28 percent of the phone numbers sampled met these conditions, amounting to 8,915 individual observations available for training data in the first survey wave (100 poorest cantons).

Since phone surveys did not collect consumption data, academics developed a consumption proxy. Phone surveys did not collect data on consumption because these are usually more complicated and time-consuming to enumerate. Considering that the Government was interested in *predicting* consumption given its more straightforward interpretability, academics developed a consumption proxy to be used as ground truth for training the machine learning model. Using the EHCVM 2018–2019 survey, a Ridge regression (similar to a proxy means test) was used to identify a small subset of the most predictive features of consumption and the weight associated with each of them. These features can be roughly grouped into household assets, location, education, and the number of children. The fitted model was then used to produce consumption estimates for each phone survey observation, interpreted as per capita daily US dollars consumption per day.

Mobile phone metadata obtained from mobile network operators were used as inputs to do out-of-sample consumption predictions. CDR captures rich information beyond phone usage. They also embed information on an individual's social network, travel patterns and location, and histories of consumption and expenditure (Blumenstock, 2015). Raw input data from mobile phones used for NOVISSI contained records of calls, SMS messages, mobile data usage, and mobile money transactions (Aiken et al., 2021). Specifically, data logs like the call or SMS recipient's number, date, time, and duration of each operation, identification number of the associated cell tower or antenna, among others, were obtained for each mobile phone subscriber. These transaction logs were transformed or "featurized" into a large set of metrics or variables describing behaviors like the volume, intensity, timing, and directionality of communication; social network characteristics; patterns of mobility and locations; international transaction features; and characteristics of mobile money transactions like amount, duration, direction, and other descriptive statistics. An anonymized version of these CDR features was matched to all 8,915 observations in the training data to do out-of-sample predictions of individual-level consumption for all mobile-phone subscribers in Togo.

40. The sample was stratified based on four criteria: (i) inferred probability of living in one of the 100 poorest cantons; (ii) predicted probability of having registered before to the NOVISSI program; (iii) expected wealth; and (iv) total mobile phone expenditure. A more detailed description of the sampling methodology and weighting is provided in Aiken et al. (2021), including a description on the methods used to predict each metric employing machine learning algorithms.

This process resulted in a potential eligibility list transmitted to the Government for eligibility and enrollment decisions. Roughly 750,000 individuals from all over the country were shortlisted to be potentially eligible for NOVISSI, given their predicted daily consumption of US$1.25 or less per day. The threshold corresponds to the 29th percentile of the predicted poverty distribution obtained from the training data survey. The total number of shortlisted individuals was constrained by budget and assumed an 85 percent registration rate among eligible individuals. The resulting potential eligibility list containing only the phone number of shortlisted individuals was conveyed to the Government under strict data protection protocols. The Government did not access CDR, nor did it directly observe individuals' consumption; instead, they received the processed list of eligible individuals. This list was uploaded into NOVISSI's system to support eligibility and enrollment decisions. Importantly, access to CDR data was exceptionally granted by Togo's MNOs to the team of academics under non-disclosure and data use agreements.

4. Eligibility determination, enrollment, and notification

Once registration was completed, it automatically triggered a cross-validation process within NOVISSI's beneficiary operations management system to determine eligibility. Through an eligibility and enrollment decisions module within NOVISSI's system, self-reported data through the USSD self-registration platform were validated against the voter's list and the potential eligibility list produced by the team of academics (in the case of NOVISSI model 2). Three specific validations were simultaneously performed: authentication, location, and individual eligibility:

1. **Authentication.** The first check verified the voter's unique identification number and the NSF security number reported by the registrant against the voter list to verify uniqueness.

2. **Location.** The individual's home location, as reported in the voter list, was verified against the list of selected poorest cantons.

3. **Individual eligibility.** The individual's phone number, retrieved automatically from the USSD system, was cross-checked against the individual-level potential eligibility list.

An additional validation step conducted concomitantly was the verification of sex which determined the amount of benefit each person would receive. NOVISSI's potential eligibility list factored in information on sex and the corresponding amount of benefit that each beneficiary was entitled to. Since its conception, NOVISSI has sought to actively include and empower women and reduce the existing gender gaps by offering them more incentives to register and benefit from the program. Women tend to be poorer, more informally employed, and more excluded from digital and financial services than men.[41] At the same time, an extensive body of research has documented how women are more likely than men to take care of basic household needs (for example, Rubalcava, Teruel and Duncan, 2009; Attanasio and Lechene, 2010; De Brauw et al., 2014). In NOVISSI's delivery model 2, women received US$15 per installment, almost 17 percent more than men, receiving US$12 per installment. Once registrants were deemed eligible, NOVISSI's systems verified the sex of the individual using the voter's list to determine the benefit amount to be disbursed.

All eligible registrants were enrolled in the program and notified about the enrollment decision. After completing the USSD-based application form, all registrants were systematically notified of their successful registration by SMS, letting them know that they would receive a subsequent notification in the event of being eligible. If the registrant's self-reported data met the eligibility criteria, they were enrolled in NOVISSI and received a second

41. For instance, according to the Global Findex 2017 survey, in Togo, mobile money account ownership is 27 percent among men and 16 percent among women.

SMS with information on the decision. Beneficiaries were also informed that their benefits would soon be reflected in their mobile money account. Non-eligible applicants remained under consideration for future enrollment into the program in case of changes in their eligibility status if, for instance, their canton was selected for assistance. The list of beneficiaries with information on their identity and benefits level was systematically produced and fed into the payroll for the administration of benefits.

5. Payments administration, provision, and reconciliation

Instant mobile cash payments were made to NOVISSI's beneficiaries. Following enrollment confirmation, the payment of benefits was issued automatically facilitated by the interoperability of NOVISSI's system with mobile money platforms which enabled the direct transfer of payments from GiveDirectly to beneficiaries. Funds were preemptively deposited into the MNOs operating account in order to ensure timely payments. The consecutive disbursements were automatically set up following a payroll schedule defined by the program. Note that in NOVISSI's model 1, payments ran similarly, with differences in the amount, frequency, and duration of benefits and with direct payment from the Ministry of Finance to beneficiaries. Payments were deposited into the beneficiaries' mobile money account, managed by the corresponding MNO.

Payments administration involved the following subprocesses:

- **Payment provision contract.** A contract between the Government of Togo and each of the two MNOs (Togocom and Moov Africa Togo) was signed for the provision of payments to program beneficiaries. The contracts established the terms and conditions of the service, including creating a mobile money account for their subscribers (if they did not already have one), the disbursement of benefits, and ensuring the availability of mobile money agents within a 5 km radius of the beneficiary's residence. The contracts also laid down the terms so that each company's payment system was interoperable with NOVISSI's system to ensure the speed of payments.

- **Establishing the payroll and issuing payment instructions.** Once a person was deemed eligible, NOVISSI's system automatically produced an individual payroll schedule based on enrollment data. This was verified and certified through automatic cross-checks within NOVISSI's systems and facilitated through an application programming interface (API). Payroll included information on beneficiaries such as name, voter's unique identification number, phone number, benefit amount, and payment date. The payroll schedule was transferred to the corresponding telecom operator, triggering an instruction to issue the first payment.

- **Mobile-money account opening for those without an active one and disbursement.** Once MNOs received the payroll, they automatically created a mobile money account for beneficiaries without one using the associated mobile phone number and issued the payment. Know-Your-Costumer (KYC) processes for mobile money account opening occurred at the MNO level and followed their own internal procedures. Once the deposit was issued, MNOs notified beneficiaries via SMS, per its pre-established procedures.

- **Payment reconciliation.** The Government of Togo retained an external auditor to conduct daily reconciliation of payments and determine whether the transfers were successfully credited on time. The external auditor would receive the payment logs from NOVISSI and MNOs to ensure that all payment instructions matched the eligibility criteria and were indeed processed. Payment logs contained information such as payment reference number, MNO, date of payment issuance, payment date, region and prefecture of the beneficiary, beneficiary's unique identifier, beneficiary's phone number, transfer amount, sex, and occupation.

- **Sensitization and nudges.** Although NOVISSI is an unconditional cash transfer program, beneficiaries were encouraged to use their benefits to cover basic expenditures, including food and water, water and electricity bills, or airtime. They were also spurred to transact electronically instead of cashing out the benefits to avoid overcrowding at payment points and to maintain social distancing.

6. Beneficiary operations management

Accompanying measures such as a solid grievance redress mechanism (GRM), external audits, and real-time analytics enabled the program to operate in a transparent and traceable way and adapt to needs. From the beginning, a toll-free number dedicated to the program was set up to file complaints at any stage of the delivery process, from intake and registration to enrollment decisions to payment provision. A frequently asked questions guide was made available to the call center to support the operations of the GRM. A report of complaints received, processed, and resolved was prepared on a daily basis. The call center was instrumental in gathering and resolving problems. For instance, with NOVISSI's delivery model 1, the NSF security code available only on voters' physical credentials was requested at the time of intake and registration after multiple fraudulent registration attempts were reported to the call center (Debenedetti, 2021). Feedback could also be submitted through the USSD form. Moreover, an external auditor was hired to ensure proper program accountability through daily reconciliation of accounts. Real-time monitoring provided helpful information to improve the program's operations. For example, the USSD-based registration system integrates audit logs to inform program operators about difficulties encountered during registration. Moreover, when NOVISSI was extended in rural areas, GiveDirectly, which financed the cash transfers, continually conducted phone check-ins with program beneficiaries and community members to monitor program integrity.

IV. Preliminary assessment: achievements and challenges

Since its launch in April 2020, NOVISSI has supported the livelihoods of more than 920,000 individuals. Shock-responsive programs, which face constraints on available time and fiscal space, are much more binding than during regular times and call for greater cost-efficiency and speed of implementation. NOVISSI's approach—model 1 low-tech and model 2 high-tech—allowed the Government to rapidly disburse emergency cash transfers at scale amidst the COVID-19 shock while sidestepping risks of exclusion errors, out-of-date data, limited survey, and administrative data, and absence of a dynamic social registry, notwithstanding less feasible alternative scenarios at that time. Togo's digital infrastructure readiness was key to NOVISSI's apparent success. Good pre-existing conditions such as mobile network coverage, mobile phone penetration, and digital literacy were essential to deploying NOVISSI swiftly. Nevertheless, despite its perks, some caveats are worth considering when assessing NOVISSI's results.

Potential efficiency gains

NOVISSI's innovative technology and data-driven approach can potentially reduce the costs of social protection delivery, increase efficiency for administrators, and introduce convenience for beneficiaries. NOVISSI has likely had important fiscal efficiencies for Togo. Compared to traditional cash transfer payments, efficiency gains due to the digital delivery of payments have reduced the Government's transaction costs and increased the speed of disbursements to only a few minutes after registration. The use of big data and on-demand USSD intake and registration has resulted in a faster and more cost-efficient way to collect data than prevailing in-person collection. From the beneficiaries' perspective, streamlined processes could have improved their experience and increased the quality of the services by decreasing overcrowding, waiting times, transportation costs, and the number of visits needed to receive benefits.

Although not conclusively evaluated yet, it is also likely that NOVISSI's digital payments approach helped reduce leakages and errors, while the intake of unique identifiers via USSD forms may have minimized corruption and fraud at the registration stage. Nonetheless, further analysis will be required to quantify the efficiency gains introduced by NOVISSI and benchmark them to other approaches, as well as to identify whether these gains were concentrated in a specific population segment.

Financial inclusion

Mobile money payments introduced by the program may have accelerated financial inclusion in Togo. Ever since the introduction of mobile money in Togo in 2013, the number of users has shown an upward trend. The NOVISSI program has encouraged individuals without an account to open one and has expedited the process. Between April 2020 and January 2021, the program created a total of 170,278 new mobile money accounts, accounting for a 7 percentage point increase in mobile money penetration in the country (World Bank Group, 2021b). Mobile money payments have enabled users to make deposits, withdraw money, purchase airtime, pay for goods and services, and receive social protection payments. A frequent constraint to mobile payments is the limited liquidity of mobile money agents, especially in rural areas. However, in Togo, the availability of agents within a close range of program beneficiaries may have helped lessen this barrier, thus mitigating the risk of mobile money being less attractive to rural populations. Despite mobile money gaining ground through NOVISSI, merchants in Togo have been slow in accepting it,[42] leading to most beneficiaries transacting in cash within the first 48 hours of the transfer. Whether access to digital accounts, incentivized by NOVISSI, served as a gateway to access other financial services remains to be studied in order to inform future operations. Moreover, according to government officials, NOVISSI contributed to maximizing the compatibility of mobile money platforms with government payments administration systems and improving the overall quality of MNOs payments systems due to increased equipment investments.

Risks of exclusion

With an end-to-end digital approach for cash transfer delivery, specific design features could have led to the exclusion of some interest populations.

- **Mobile phone adoption and use.** The latest available estimates suggest that 85 percent of individuals in Togo are in a household with one or more phones,[43] and around 83.6 percent of individuals own a SIM card.[44] While this share is likely to have increased by the time NOVISSI was scaled to rural areas, part of the population still did not meet this requirement. Research shows that socioeconomic and demographic traits are drivers of digital technologies' adoption and use (Rodriguez-Castelán et al., 2021). Unequal access to mobile phones for some groups could have excluded those in most need; however, the extent to which the existing digital divide excluded some people from accessing the program is yet to be quantified and addressed in the future through an all-doors-open approach.

- **Digital literacy.** Similarly, some may have faced challenges completing the USSD-based registration due to a lack of reading skills and digital competencies. Literacy rates in Togo have improved but remain low: in 2019, only 67 percent of the population aged 15 years old or older could read or write.[45] For NOVISSI, 72 percent of mobile phone subscribers who initiated the registration process were able to complete it, while the average registration required four attempts (Aiken et al., 2021). While some beneficiaries were unfamiliar with mobile technologies, preliminary qualitative evidence indicates that in many cases, applicants relied on social, family, and peer learning networks to complete the registration procedures.

- **Limitations of the voters' registry.** Due to a lack of universal coverage of unique identifiers and a dynamic social registry, the only available source at the time to verify the uniqueness of potential beneficiaries, in addition to location and occupation data, was the voters' registry. An estimated 86.6 percent of the Togolese adult population possesses a voter's identification credential (Aiken et al., 2021). This card, however, is only available to Togolese citizens aged 18 years old or more, meaning that foreign residents, individuals who could not prove citizenship, or underaged individuals were excluded by design. Moreover, those having recently moved from ineligible cantons to eligible cantons may have also been excluded from the program due to the static nature of data contained in the registry.

- **Program awareness.** Although the Government of Togo implemented a multi-layered approach to outreach, a lack of awareness of the existence of the program could have negatively affected registration rates. Around 40 percent of mobile phone subscribers were aware of the NOVISSI program as they attempted to register for NOVISSI in delivery model 2 (Aiken et al., 2021).

42. World Bank Group (2020b).
43. EHCVM 2018–2019.
44. ARCEP (2021).
45. UNESCO Institute for Statistics (uis.unesco.org). Data as of September 2021.

While the Government recognized these potential risks of exclusion, they were outweighed by the risks of not being responsive to vulnerable people in a historic crisis. Due to the rapid transmissibility and the virulence of the COVID-19 virus, in-person registration could have exposed and put at risk the lives of many; accordingly, registration was to be done on-demand and via mobile devices. The Government of Togo needed to ensure that payments were made only to verified unique individuals. In the absence of a foundational unique identification system, Togo's most pragmatic option was to utilize unique identifiers generated by the voter's list to allow people to register. At the time the program was launched, the voter's registry was the most up-to-date and widespread means of identification. Furthermore, it provided information on the place of residence and occupation of the card owner, which were the main eligibility criteria for NOVISSI model 1. Without a dynamic social registry and universal coverage of unique identifiers, Togo leveraged available administrative data, survey data, and big data to swiftly expand social protection benefits horizontally to as many vulnerable individuals as possible in a short period of time.

Model limitations

Similar to other statistical methods traditionally used to prioritize benefits based on an estimation of welfare, machine learning algorithms are also prone to prediction errors. In the case of NOVISSI, some of the model limitations include the following:

- **Poverty maps produced with machine learning algorithms have proven to be highly accurate. However, validations have mainly focused on estimates of asset-based rather than consumption-based wealth.** Using census data for a sample of 15 countries on three continents and independently collected micro-data from three countries in Africa, Chi et al. (2021) found that their model explains more than 70 percent of household asset-based wealth.[46] While asset-based and consumption-based wealth are highly correlated, the latter is more challenging to measure. For instance, some features more directly related to consumption are not observable on geospatial data, unlike in the asset-based wealth index where roofing materials and plot characteristics, for example, are observed. Since no alternative consumption data are available for Togo, no further validations of the model's accuracy have been made to date. Therefore, the accuracy of asset-based poverty maps is likely to present an upper bound of the accuracy of consumption-based poverty maps.

- **The algorithm to prioritize amongst rural individuals was trained on a proxy of consumption calibrated with survey data collected before the shock hit.** The consumption index developed to train the machine learning algorithm for individual-level prioritization was computed using data collected before the crisis. Moreover, variables such as household assets, location, education, and the number of children—used in NOVISSI's model 2—while correlated, are less likely to fluctuate as much as consumption during crises. Although more data and analyses are needed, the ground truth data against which the model was trained may have introduced some bias by potentially excluding individuals who were directly hit by the shock but reduced consumption instead of, for example, household assets as a coping strategy. The Ridge regression, used to estimate consumption, as other estimation methods traditionally used, is also subject to prediction errors.

Importantly, while machine learning algorithms can encode bias, several tests confirm the fairness of the phone-based algorithm for different groups in Togo. Algorithmic decision-making can unwittingly discriminate against some groups. Aiken et al. (2021) audited the fairness of the phone-based prioritization model for a large number of groups. No evidence of systematic exclusion was found

46. Using data from Togo (not used to train the machine learning model), Chi et al. (2021) find that the model's predictions explain 76 percent of the variation in wealth at the 2.4 km^2 grid cell level, and 84 percent of the variation in wealth of cantons,

by gender, ethnicity, religion, age, or household characteristics. Compared to the alternative scenarios mentioned below, the authors find that none achieve perfect parity, but the most prominent differences occur in the purely geographic approach.

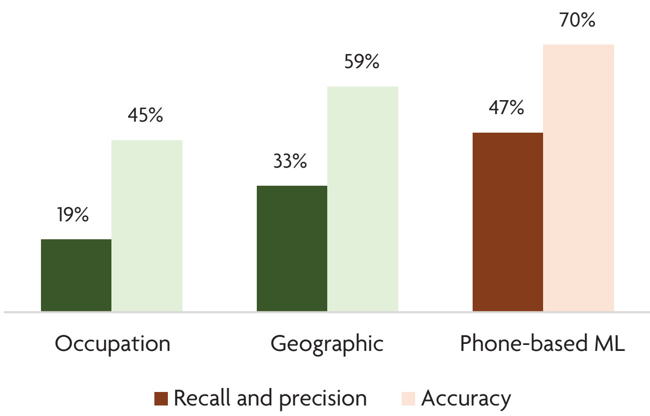
Performance of NOVISSI's model 2 approach against other methods

Compared to available and feasible alternatives to prioritize transfers, the phone-based machine learning approach reduced targeting errors. Aiken et al. (2021) tested the phone-based machine learning model's performance against alternative strategies to assess needs and conditions available to the Government of Togo at the time. The first scenario consisted of universal coverage in the poorest locations (geographic approach), while the second replicated NOVISSI's Phase 1 occupation-based prioritization strategy (occupation approach). Aiken et al. (2021) compute performance using indicators of accuracy (proportion of observations correctly identified as poor and non-poor) and precision and recall (interpreted as one minus the exclusion error). Using the phone survey data, their results show that the phone-based model significantly reduces exclusion and inclusion errors relative to the feasible alternatives (Figure 7).

However, when comparing the phone-based approach to traditional targeting methods, models requiring a comprehensive social registry (not available at the moment) outperformed the model. In the context a hypothetical cash transfer program, Aiken et al. (2021) compared the performance of the machine-learning phone-based approach against four alternative prioritization methods: (1) universal coverage of poorest prefectures, (2) universal coverage of poorest cantons, (3) prioritization based on an asset-based index, and (4) prioritization based on proxy means testing. The authors found that the phone-based machine learning algorithm performed best than the geographical targeting methods (1 and 2) to prioritize the poorest individuals (Figure 8). In contrast, the well-being assessment methods (3 and 4) outperformed the phone-based machine learning algorithm in terms as seen in Figure 9. Nevertheless, well-being assessment methods, which rely on a comprehensive social registry, were not feasible at the time of NOVISSI's deployment.

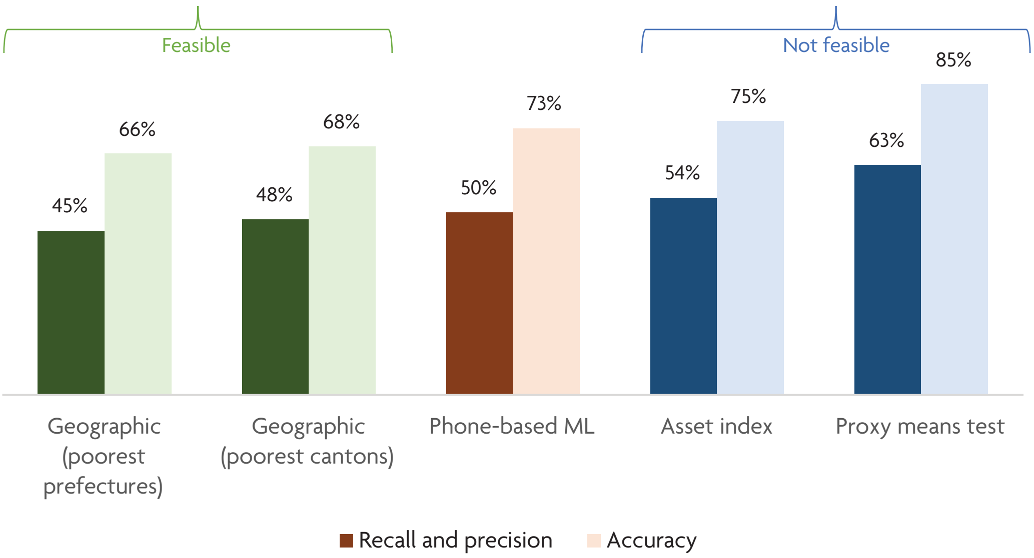
An impact evaluation of NOVISSI's welfare effects is ongoing. Data for the impact evaluation were collected in a phone survey between April and May 2021, with around 12,500 respondents. The results will make it possible to assess the program results on a variety of welfare outcomes and food security, detect unintended biases against vulnerable groups, and evaluate exclusion and inclusion errors more broadly. It can also set the ground for a cost-effectiveness analysis to inform future operations.

FIGURE 7 Performance of feasible targeting approaches



Source: Aiken et al. (2021).

FIGURE 8 Performance of different targeted approaches in the context of a hypothetical nationwide program



Source: Aiken et al. (2021).

V. Going forward

NOVISSI is a prime example of the potential of technological innovation and leapfrogging in building adaptive and shock-responsive social protection systems. Togo's experience has shifted the paradigm of how we think about social protection delivery and offers valuable lessons for the region and beyond. Under specific circumstances, NOVISSI was able to reach scale quickly by using novel approaches and building a new delivery model for social protection systems. In the absence of a reliable foundational unique identification system and a dynamic social registry, these innovative methods provided a way to support Togolese residents in the context of urgency. The NOVISSI approach constitutes a new tool within the social protection delivery toolkit, expanding the choices available to policymakers but also introducing new challenges, such as greater dependency on digital readiness.

NOVISSI's innovations inspire optimism by introducing significant efficiency gains in the delivery of social protection programs, yet these gains need to be balanced against new concerns. By heavily depending on digital technologies, this novel delivery model can potentially exacerbate exclusion risks that are yet to be quantified. Previous infrastructure investments in mobile network infrastructure, payment ecosystems, and digital literacy enabled NOVISSI's delivery model, yet these enabling factors are not necessarily distributed uniformly or progressively within Togo's socioeconomic landscape. Data privacy is another concern that is potentially heightened by NOVISSI's delivery approach since mobile subscribers do not necessarily intend for their phone usage to be a proxy of their socioeconomic status. New opt-in and opt-out mechanisms should be considered as these innovations mature and inform other initiatives.

Leveraging machine learning and big data, combined with administrative and survey data for social program targeting, shows promise; however, the accuracy, implications, and trade-offs of this novel approach are yet to be exhaustively studied. The literature on the use of machine learning for social protection prioritization is limited and inconclusive. When compared to a traditional proxy means testing, the performance of machine learning algorithms depends heavily on (i) the data sources used, (ii) the performance metric, and (iii) the program policy objectives (whether it is a welfare threshold or a quota). For example, exclusion errors were larger in the phone-based machine learning algorithm than in alternative but unfeasible scenarios depending on a comprehensive social registry (Figure 9) (Aiken et al., 2021). Moreover, all algorithms can encode bias. As training data becomes outdated or is not representative of the population, the model performance declines and can increase both types of targeting errors. Careful design, calibration, and audit of decision-making algorithms are crucial to examine if specific vulnerable groups are more likely to be excluded. Whether individuals or households change their behavior as they learn that transactional or satellite data are used to determine eligibility for benefits remains unanswered; however, ongoing efforts seek to make these approaches more robust to certain strategic behaviors.[47]

The risks of using private consumer data are profound and require robust institutional arrangements. Building institutional safeguards is imperative. This should include, at least, minimizing access to sensitive data, anonymization, encryption, and strict storage protocols. A registrant's consent to use their data for program administration

47. See for example, Hardt et al. (2015) and Björkegren, Blumenstock and Knight (2020).

purposes is not only necessary but can also be an opportunity to inform them about their data privacy rights. This requires capacity and a regulatory framework to manage and protect data appropriately. In Togo, MNOs provided access to CDR data to researchers for selected periods and areas on an exceptional basis due to the pandemic. It needs to be further determined how best to put in place a sustainable and feasible longer-term arrangement. However, data trusts[48] can be a viable option to look after and make decisions about data on behalf of communities.

Technology can be both an enabler and a source of exclusion for human capital services absent complementary investments in digital transformation. Countries have made significant strides in mobile phone coverage and penetration over the past decades. Nevertheless, more action is still needed as technology can support the post-COVID-19 economic recovery and alleviate poverty. Democratizing access to mobile phones through sustainable models such as pay-as-you-go schemes is an essential step toward digital transformation. Funding digital infrastructure, increasing access to electricity, and building digital skills will pave the way for inclusive digitalization. Accompanying measures to develop a digital economy ecosystem will also be critical. Increasing the density of mobile money agents, proliferating the acceptance of mobile payments among local traders, and multiplying acceptance technologies would further incentivize users to transact electronically and become a conduit for financial inclusion while driving costs down both for customers and governments.

Having robust foundational unique identification systems and dynamic social registries is instrumental to a truly adaptive social protection delivery system. Leveraging unique identification platforms can help countries quickly scale social registries and benefits payments platforms to deploy shock-responsive programs with potentially universal coverage. Under a 72 million IDA financing through the WURI program, the Government of Togo is building a foundational unique identification platform to register all individuals in the territory, which will be the basis of a dynamic social registry of individuals and households for on-demand, multi-channel intake and registration. Both projects are listed as priorities on the Government's 2020-2025 roadmap and will contribute to creating an innovative and shock-responsive social protection system that can serve as a model for other countries.

Going forward, countries can leverage the innovations introduced by NOVISSI and combine them with more conventional approaches to increase the reach of social protection systems. Local conditions such as digital readiness or urgency call for differentiated, complementary, and flexible policies to optimize program delivery. Hybrid models that combine traditional with new approaches can be a viable alternative. For example, in-person census sweeps can be used to build the foundations of a social registry that could rely on remotely collected and passively generated data for dynamic updating. Combining approaches requires forward-thinking design, including using modular data structures to integrate future data sources and ensure the interoperability of administrative, survey, and big data sources through unique identification systems.

48. Ruhaak (2021)

Annex

TABLE A.1 **Overview of NOVISSI's stakeholders**

Stakeholder	Role
The President of the Republic	The President's political leadership was key to the success of NOVISSI in Togo. He galvanized the different stakeholders and ensured access to government resources needed to successfully implement NOVISSI.
Inter-ministerial Steering Committee	Led by the President of Togo, the committee defined eligibility criteria for state-funded NOVISSI-powered social cash transfer programs.
Ministry of Digital Economy and Digital Transformation (MENTD)	Implemented and shaped state policies around the NOVISSI digital cash transfer system. Supervised relationships among government agencies, funding partners, and NOVISSI technical delivery unit to ensure successful execution.
Ministry of Economy and Finance	Managed the state accounts and made payments to the NOVISSI account with the MNOs to ensure the availability of funds for direct transfer to beneficiaries.
NOVISSI technical delivery unit	Developed the core NOVISSI technical platform and integrations with APIs while ensuring that NOVISSI responds to high performance and security standards.
Telecommunications regulator	Facilitated acquisition and uniformization of USSD codes to ensure cross-network functionality.
Mobile network operators (MNOs)	MNOs provided free access to their APIs, created mobile money accounts for beneficiaries, provided anonymized CDR needed to identify vulnerable persons (model 2), and ensured that USSD platforms could support the long sessions NOVISSI needed.
Academics/research team (Center for Effective Global Action at University of California Berkeley, Northwestern University, University of Mannheim)	Developed and coordinated training of machine learning algorithms using satellite imagery and CDR to build a poverty map of Togo and identify the poorest individuals. They also conducted an impact evaluation of the program through a mix of high-frequency phone surveys and analysis of state-provided data and mobile phone metadata.
Call Center	Ensured customer relations management and grievance redress through a toll-free hotline.
External auditor	Independent daily auditing and data reconciliation. This involved confirming that NOVISSI payment orders were in line with the program requirements and that these orders, as triggered by the platform, matched the actual payments made by the MNO.
National Statistics Office (INSEED)	INSEED carried out high-frequency mobile phone surveys to collect data needed for NOVISSI's impact evaluation.
Donors (GiveDirectly)	Provided funding for direct transfer to beneficiaries in a bespoke program designed by UC Berkeley and powered by the NOVISSI platform cf. GIVEDIRECT-NOVISSI.
Development partners (World Bank-IDA, AFD)	Provided funding for various aspects of the implementation NOVISSI program, including refinancing of cash transfers and funding for studies and IT equipment.

Source: Original for this publication.

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