Research Article

Shock Response Targeting Mechanism for the Poor and Vulnerable Urban Households in Nigeria

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Abstract

The COVID-19 pandemic has brought unprecedented hardship to the global community, with Nigeria being no exception. According to the World Bank's Poverty and Equity Brief for West Africa Nigeria (2021), more than 80 million Nigerians faced vulnerability and poverty due to the pandemic's socioeconomic impacts. In response, the Federal Government of Nigeria, through the National Social Safety-Nets Coordinating Office (NASSCO) in collaboration with the World Bank, implemented a Shock Responsive Mechanism (SRM) to provide targeted assistance to those most severely affected. This paper evaluates this mechanism's effectiveness, focusing on three innovative aspects: 1) the use of satellite remote sensing and machine learning algorithms for geographical targeting, 2) the performance of SMS/USSD remote registration platforms, and 3) the accuracy of beneficiary selection in identifying the urban poor. Our analysis of programme data covering over 2.7 million validated beneficiaries across Nigeria indicates that the satellite-based targeting approach successfully identified areas with population characteristics consistent with established urban poverty indicators. The mobile-based registration system achieved a 99% location accuracy rate when verified against field validation, though challenges related to timing and population mobility were noted. The socioeconomic profiles of beneficiaries align closely with established characteristics of urban poverty in Nigeria, suggesting effective targeting. This case study offers valuable insights for other countries with limited data infrastructure seeking to implement rapid, technology-driven social protection responses during crises.

Keywords

Rapid Targeting, Technology Innovation, Social Register, Economic Shocks, Geographical Targeting, Urban Poor.

1. Introduction

The COVID-19 pandemic created immediate and severe socioeconomic effects worldwide. In Nigeria, containment measures such as lockdowns and movement restrictions particularly affected urban informal sector workers who rely on daily income activities. Traditional social protection systems proved inadequate for rapidly identifying and supporting newly vulnerable populations in urban areas, necessitating innovative approaches to reach those most affected.

As of June 2022, Nigeria had recorded over 256,124 COVID-19 cases and 3,143 deaths (NCDC, 2022). However, the pandemic's indirect socioeconomic impacts are likely more extensive and enduring than the direct health impacts. World Bank estimates suggest that an additional 10-15 million Nigerians may have slipped into poverty within two years due to the pandemic (World Bank, 2021).

This paper examines Nigeria's innovative approach to addressing urban poverty during the COVID-19 pandemic through a technology-driven Shock Responsive Mechanism (SRM), which resulted in the creation of the Rapid Response Register (RRR) as its operational database. We assess three central questions:

1. How effective was satellite remote sensing technology in targeting urban poor communities?
2. To what extent did the SMS/USSD platform facilitate efficient and accurate registration of potential beneficiaries?
3. Did the targeting mechanism accurately identify households with characteristics consistent with urban poverty in Nigeria?

This study contributes to the growing literature on technology-enabled social protection systems in developing countries. While research on social protection targeting methods is extensive (Bastagli et al., 2016; Verme, 2016), studies examining the use of satellite imagery and mobile technology for poverty targeting in Sub-Saharan Africa remain limited (Smythe & Blumenstock, 2022; Jean et al., 2016). This paper presents one of the first comprehensive assessments of Nigeria's innovative targeting approach, offering insights relevant to other countries with similar data challenges.

2. Literature Review

2.1. Urban Poverty in Nigeria: Characteristics and Challenges

Understanding the characteristics of urban poverty is crucial for effective targeting of social protection interventions. In Nigeria, urban poverty manifests in distinct patterns compared to rural poverty, with specific settlement and livelihood characteristics.

Studies by Onibokun et al. (1995) identified several key features of urban poor settlements in Nigeria, including inadequate housing, lack of basic social facilities, overcrowding, and high population density. While this research is older, more recent work has confirmed its continued relevance. Olaoluwa (2018) characterized urban slums in Nigeria as areas with poor structural quality of housing, limited access to clean water, inadequate liquid and solid waste management, poor healthcare access, and insecure residential status.

Contemporary research by Unanam et al. (2021) highlighted additional dimensions of urban poverty, including social exclusion, unemployment, poor transport systems, lack of access to housing mortgage schemes, criminalization of informal small businesses, and high vulnerability to environmental risks and disasters. These findings align with the World Bank's Nigeria Poverty Assessment (2022), which noted that urban poverty in Nigeria is characterized by significant vulnerability to economic shocks. (Baker & McClain, 2008) noted that urban poor populations often reside in environmentally unsafe areas, such as polluted sites near solid waste dumps, open drains, sewers, and industrial zones.

The multidimensional nature of urban poverty presents significant challenges for targeting social protection interventions, particularly in the absence of comprehensive household survey data at the local level. Ajakaiye et al. (2016) in their analysis of poverty dynamics in Nigeria found that urban poverty often exhibits different characteristics from rural poverty, requiring distinct targeting approaches.

2.2. Technology-Enabled Targeting for Social Protection

Traditional targeting methods for social protection programmes include means testing, proxy means testing, geographic targeting, categorical targeting, community-based targeting, and self-selection (Bastagli et al., 2016). Each has strengths and limitations regarding accuracy, cost, and implementation feasibility.

Recent technological advances have enabled new approaches to identifying and reaching vulnerable populations. Satellite imagery and machine learning have emerged as promising tools for poverty mapping at a granular level. Smythe and Blumenstock (2022) demonstrated how high-resolution satellite imagery, combined with machine learning algorithms, can create detailed poverty maps that outperform traditional survey-based methods in terms of granularity and cost-effectiveness. This builds on earlier work by Jean et al. (2016), who showed that convolutional neural networks applied to satellite imagery could predict poverty with reasonable accuracy.

Similarly, Simoonga et al. (2009) validated the use of remote sensing and geographical information systems for identifying patterns relevant to social and health interventions in Africa. The use of satellite data for poverty targeting has gained momentum in recent years, particularly in contexts where traditional survey data is limited or outdated (Engstrom et al., 2022; Yeh et al., 2020).

Mobile technology has also transformed social protection delivery. Togo's NOVISSI programme, implemented during the COVID-19 pandemic, used mobile phone records and machine learning to identify and deliver cash transfers to vulnerable individuals (Gentilini et al., 2021). This approach demonstrated how digital infrastructure could support rapid response during crises. Similar innovations have been deployed in Kenya through the give directly programme and in Pakistan through the Ehsaas Emergency Cash programme (Bourgault & O'Donnell, 2020).

2.3. Shock-Responsive Social Protection

Shock-responsive social protection refers to systems designed to expand coverage or increase benefits in response to shocks such as natural disasters, economic crises, or pandemics (O'Brien et al., 2018). These systems require flexible administrative systems, financing mechanisms, and targeting approaches to rapidly scale assistance during emergencies.

The COVID-19 pandemic highlighted both the importance and challenges of shock-responsive systems globally. Countries with pre-existing social registries and digital payment infrastructure generally mounted faster responses (Gentilini et al., 2021). However, many countries struggled to reach newly vulnerable populations not previously included in social protection databases, particularly in urban areas where poverty dynamics changed rapidly during the pandemic.

Within the African context, several countries implemented various forms of shock-responsive social protection during COVID-19. Kenya expanded its existing Inua Jamii programme, South Africa implemented a special COVID-19 Social Relief of Distress grant, and Rwanda utilized its community-based Ubudehe classification system for emergency support (Bodewig et al., 2020).

Nigeria's approach to shock-responsive social protection during COVID-19 represents an innovative case study of using technology to overcome data limitations and reach urban populations not covered by existing programmes. While Nigeria's National Social Registry (NSR) primarily covered rural areas, the COVID-19 response required rapid expansion to urban and peri-urban areas (Apera et al, 2021).

3. Methodology

3.1. Research Design

This study employs a mixed-methods approach to evaluate the effectiveness of Nigeria's COVID-19 Shock Responsive Mechanism (SRM) and its resulting Rapid Response Register (RRR). We analyze programme implementation data to assess targeting accuracy, registration efficiency, and beneficiary characteristics. Our evaluation framework considers three key components:

1. Geographic targeting using satellite imagery and machine learning
2. Beneficiary registration through SMS/USSD platforms
3. Field validation and verification of potential beneficiaries

We assess effectiveness by comparing targeting outcomes with established characteristics of urban poverty from the literature and by analyzing the socioeconomic profiles of selected beneficiaries.

3.2. Data Sources

This analysis draws on several data sources:

1. ***Programme Implementation Data:*** Records from the National Social Safety-Nets Coordinating Office (NASSCO) on the RRR targeting and registration process, including targeting criteria, implementation protocols, and validation procedures.
2. ***Satellite-Based Poverty Maps:*** Outputs from machine learning algorithms applied to satellite imagery, used for geographic targeting of urban wards.
3. ***USSD Registration Data:*** Records of applicants who registered through the SMS/USSD platform, including demographic information, self-reported household characteristics, and location data.
4. ***Field Validation Data:*** Information on beneficiaries validated through on-site verification, including verification of identity, residency, and household characteristics.
5. ***Beneficiary Socio-Economic Data:*** Collected during field validation, including education levels, employment status, housing conditions, and household composition.

6. ***Secondary Sources:*** Existing studies on urban poverty characteristics in Nigeria, including work by Onibokun et al. (1995), Olaoluwa (2018), Unanam et al. (2021), and Baker & McClain (2008), and comparative analyses of social protection programmes in other countries.
7. ***National Living Standards Survey (NLSS) Data:*** Used as a reference point for validating satellite-based poverty estimates.

3.3. Analytical Approach

Our analysis proceeds in three stages:

1. ***Assessment of Satellite-Based Targeting:*** We evaluate how effectively the machine learning approach identified urban poor areas by comparing targeting outcomes with established settlement patterns of urban poverty. We examine the correlation between satellite-based poverty estimates and poverty measures from the NLSS.
2. ***Evaluation of SMS/USSD Registration:*** We analyze the performance of the mobile registration platform by examining registration rates across states and regions, and by assessing the accuracy of registration data when verified through field validation.
3. ***Analysis of Beneficiary Characteristics:*** We examine the socioeconomic profiles of validated beneficiaries to determine whether they exhibit characteristics consistent with urban poverty as established in the literature. Key indicators include housing materials, employment status, education levels, household size, and access to basic services.

3.4. Limitations

This study has several limitations that should be acknowledged:

1. ***Lack of Counterfactual:*** Without a control group, we cannot definitively determine whether alternative targeting methods would have produced better or worse outcomes. This is a common challenge in evaluating emergency response programmes implemented rapidly during crises.
2. ***Limited Pre-Intervention Data:*** The rapid implementation of the programme precluded extensive baseline data collection on potential beneficiaries. Our analysis relies on post-registration validation rather than pre-targeting assessments.
3. ***Potential Selection Bias:*** Our analysis of beneficiary characteristics is based on those who successfully registered and were validated, potentially missing those who lacked mobile access or faced other barriers to participation. The digital divide may have led to systematic exclusion of the most vulnerable households.
4. ***Timing of Data Collection:*** Field validation occurred after initial registration, creating challenges due to population mobility. Some registered households could not be located during validation visits, which may bias our findings toward less mobile households.
5. ***Scope of Analysis:*** Our assessment focuses primarily on targeting effectiveness rather than impact on beneficiaries' welfare, which would require additional longitudinal data. We cannot determine whether the assistance provided improved household outcomes.
6. ***Self-Reported Data:*** Much of the registration data was self-reported through the USSD platform, potentially introducing reporting biases. While field validation helped mitigate this, we cannot eliminate the possibility of strategic reporting by applicants.

4. Results

4.1 Satellite Remote Sensing and Machine Learning for Geographical Targeting

The satellite-based targeting approach used machine learning algorithms to analyses patterns visible in satellite imagery, including roof materials, night lighting, population density, and infrastructure quality. These algorithms identified poverty patterns at a granular level, allowing for ward-level targeting that would not be possible with traditional survey data alone.

Figure 1a: Machine Learning Urban-Rural Wards Map (Source: Smythe, et al 2022)

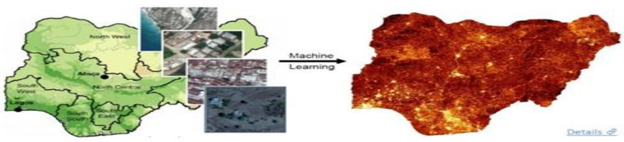


Figure 1b: Correlation Analysis Between Satellite and NLSS Data (Source: Smythe, et al 2022)

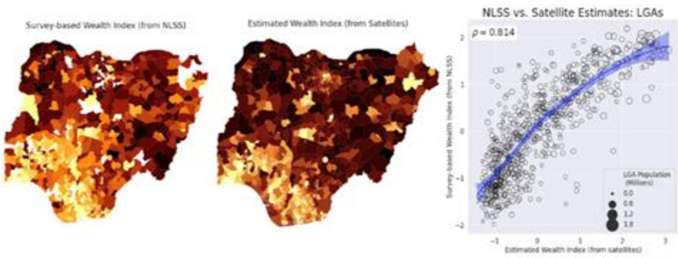


Figure 1a illustrates the machine learning-generated map of urban-rural divisions across Nigeria's wards. The varying shades represent different poverty levels, with darker areas indicating higher poverty rates. The targeting approach focused on the poorest urban wards, as rural poverty was already addressed through existing programmes. Validation against the National Living Standard Survey (NLSS) data showed strong correlation between satellite-based poverty estimates and survey-based measures (Figure 1b). This correlation suggests that the machine learning approach successfully captured meaningful patterns of urban poverty.

Based on this targeting approach, all 2,650 urban wards in Nigeria (out of 8,799 total wards) were ranked according to poverty levels. These urban wards, with an estimated population of 68 million people, were prioritized for the COVID-19 Shock Responsive Mechanism (SRM). Figure 2 shows the distribution of targeted communities across states, with over 15,000 communities included in the programme.

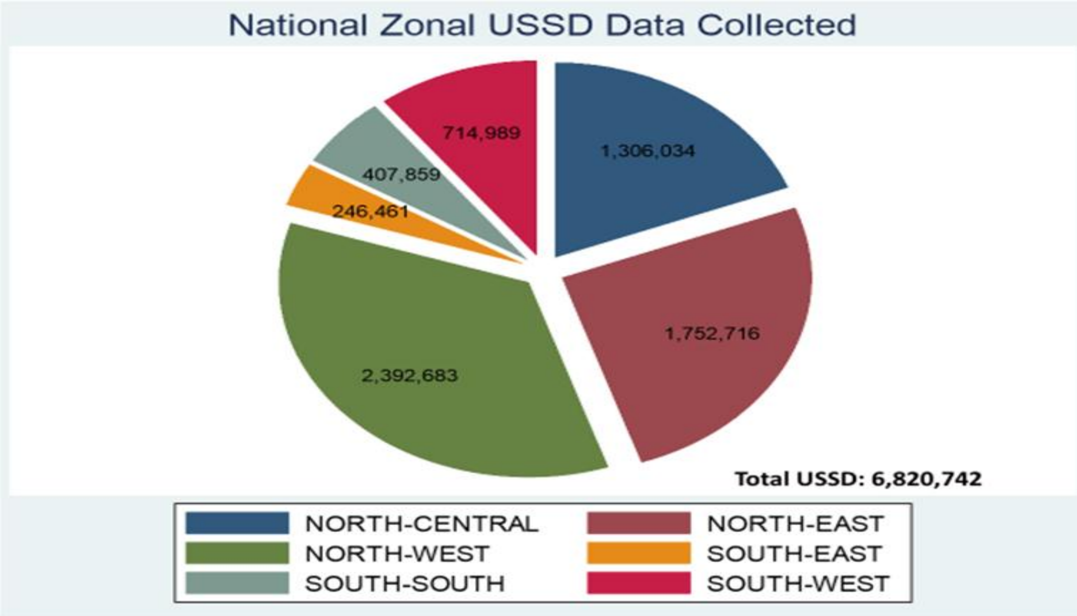
Figure 2: Number of Communities Targeted Per State (Source: Authors' Work)

When comparing the satellite-based targeting approach with previous community-based targeting methods used in Nigeria, the satellite approach demonstrated two key advantages: (1) it achieved greater geographic coverage, encompassing all urban wards rather than a subset of communities, and (2) it required significantly less time, with ward identification completed in weeks rather than months.

4.2. SMS/USSD Platform Registration Analysis

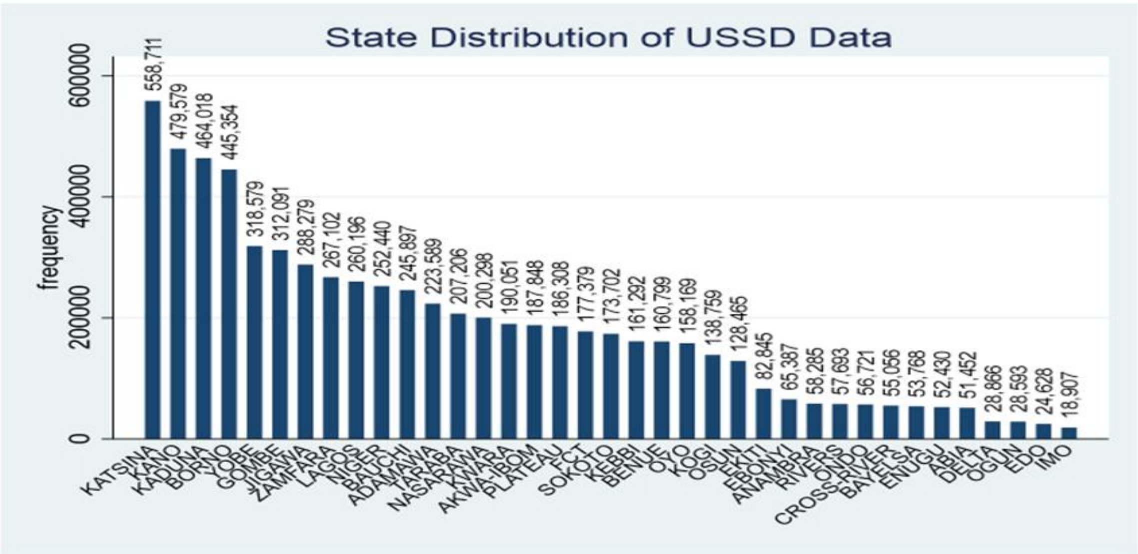
The SMS/USSD registration process began with community sensitization through various channels, followed by targeted text messages to residents in selected areas. Figure 3 shows the zonal distribution of USSD registrations, with the Northwest zone accounting for the largest share (35%), followed by the Northeast (26%) and North Central (19%) zones. The Southeast recorded the lowest participation (3%).

Figure 3: Zonal Distribution of USSD Platform (Source: Authors' work)



At the state level (Figure 4), Katsina had the highest number of registrations (over 500,000), while Imo had the lowest (approximately 18,000). These variations appear to be influenced by differences in sensitization efforts, with states conducting more extensive outreach activities showing higher registration rates.

Figure 4: State Distribution of USSD Data (Source: Authors' Work)



The total number of people registered through the USSD platform across Nigeria demonstrates the potential of mobile technology to facilitate rapid registration at scale, even in areas with limited digital infrastructure. Figure 5 showed the USSD/SMS registration coverage across the country totaling over 54,000 communities, 2,652 wards and 735 LGAs in the 37 states including the Federal Capital Territory (FCT).

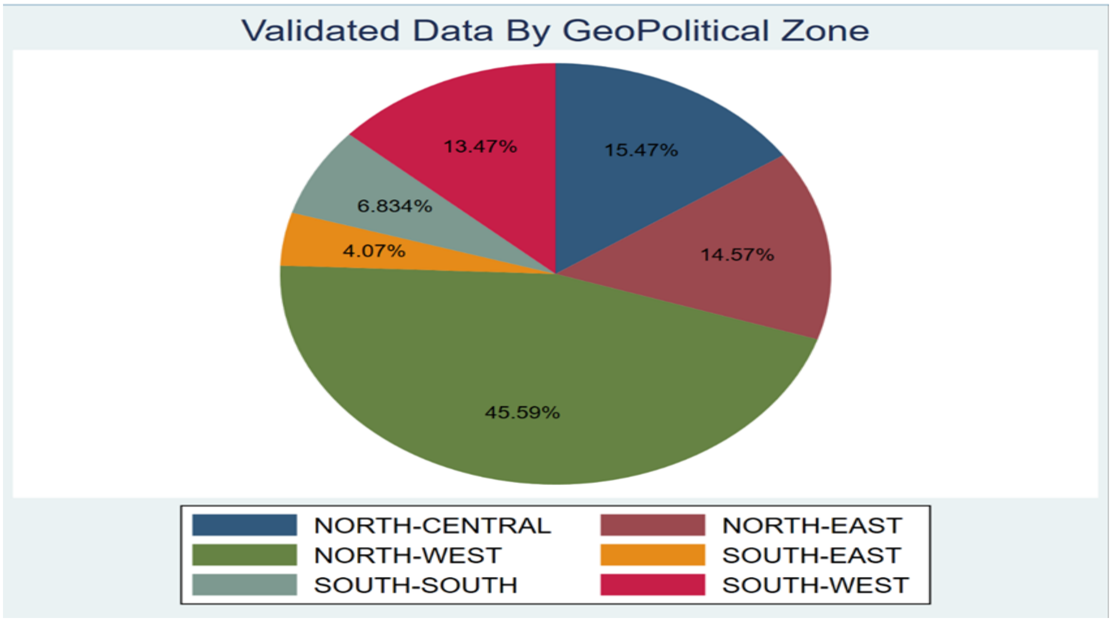
Figure 5: USSD Preliminary Registration Data (Source: Authors' work)

The SMS/USSD platform demonstrated advantages over traditional paper-based registration approaches in terms of speed and resource efficiency. However, the digital approach also presented challenges. Data quality checks identified incomplete registrations and potential duplicate submissions. Furthermore, the system could not fully address the digital divide, as households without mobile phones or in areas with poor network coverage faced barriers to participation.

4.3. Field Validation and Beneficiary Selection

Following initial registration, field teams validated potential beneficiaries to verify their information and eligibility. Figure 6 shows the distribution of validated beneficiaries across Nigeria's geopolitical zones. The Northwest zone accounts for the largest share of validated beneficiaries (45.59%), followed by North Central (15.47%), Northeast (14.57%), and Southwest (13.47%). The Southeast had the lowest representation (4.07%).

Figure 6: National and Zonal Validated USSD Data (Source: Authors' Work)



The validation process showed a 99% location accuracy rate, indicating that the vast majority of registrants resided in the targeted poor urban areas. This accuracy rate was calculated based on the proportion of registrants who were found to be residing in the targeted geographic areas (wards) during the validation process.

The main challenge encountered during validation was population mobility between registration and validation, highlighting the dynamic nature of urban poverty. Some registered households could not be located during validation visits, likely due to relocation or provision of incorrect contact information.

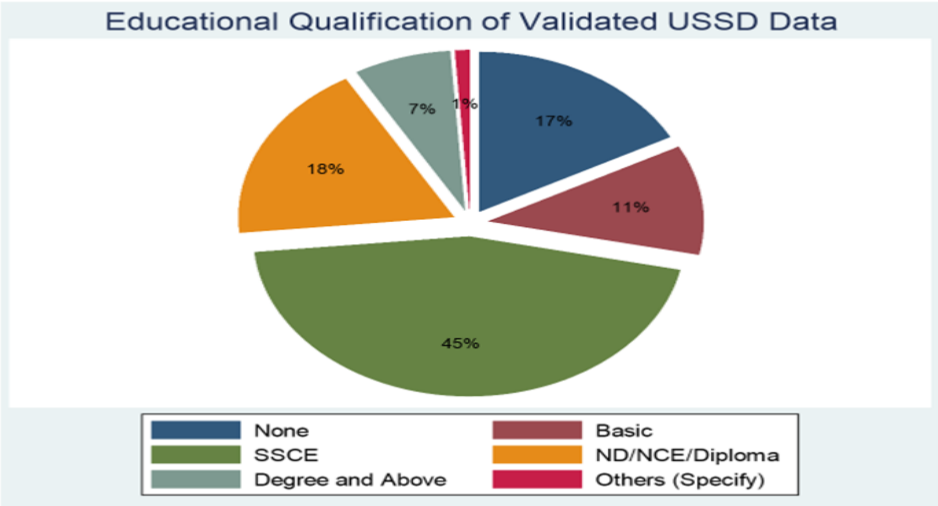
The validation process also revealed that a significant portion of registrants did not meet the programme's eligibility criteria upon closer inspection. This suggests that while geographic targeting successfully identified poor areas, individual targeting mechanisms were still necessary to identify the most vulnerable households within these areas.

4.4. Socio-economic Characteristics of Validated Beneficiaries

The socioeconomic profiles of validated beneficiaries reveal patterns consistent with established characteristics of urban poverty in Nigeria:

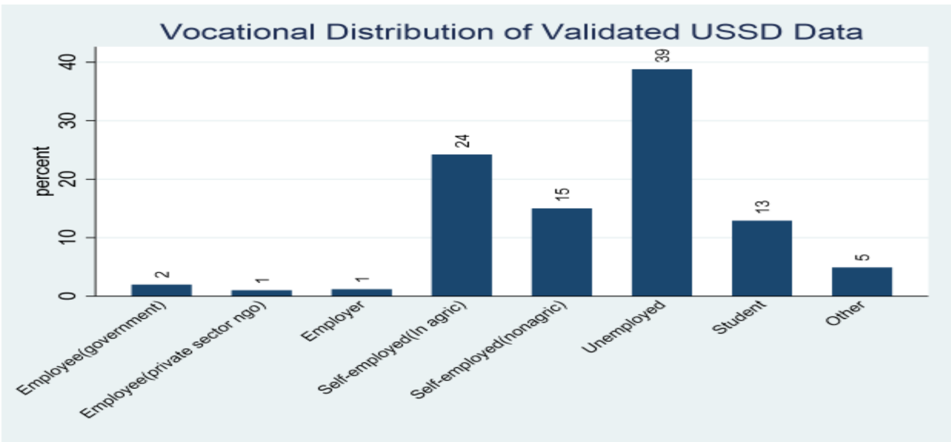
1. **Education Levels (Figure 7):** 45% of beneficiaries had secondary education, 18% had National Diploma or NCE, 17% had basic education, 11% had no formal education, and only 7% had university degrees. The high proportion of beneficiaries with some education reflects the "new poor" affected by COVID-19 economic disruptions.

Figure 7: Educational Qualifications by Validated USSD Data (Source: Authors' Work)



2. **Employment status (Figure 8):** 39% were unemployed, 24% were self-employed in agriculture, 15% were employed in non-agricultural sectors, and 13% were students. The high unemployment rate aligns with Unanam,'s (2021) observation that unemployment is a key characteristic of urban poverty.

Figure 8: Vocational Distribution by Validated USSD Data (Source: Authors' Work)



3. **Housing Quality:** Figure 9 shows that 45% of beneficiaries lived in homes with earth/mud floors, 42% with concrete floors, and only 8% with tile floors. Figure 10 indicates that 57% had corrugated iron sheet roofing, 24% wooden roofs, and 11% palm leaf roofs—all consistent with the poor structural quality of housing identified by Olaoluwa (2018).

Figure 9: Floor Type by Validated Data (Source: Authors' Work)

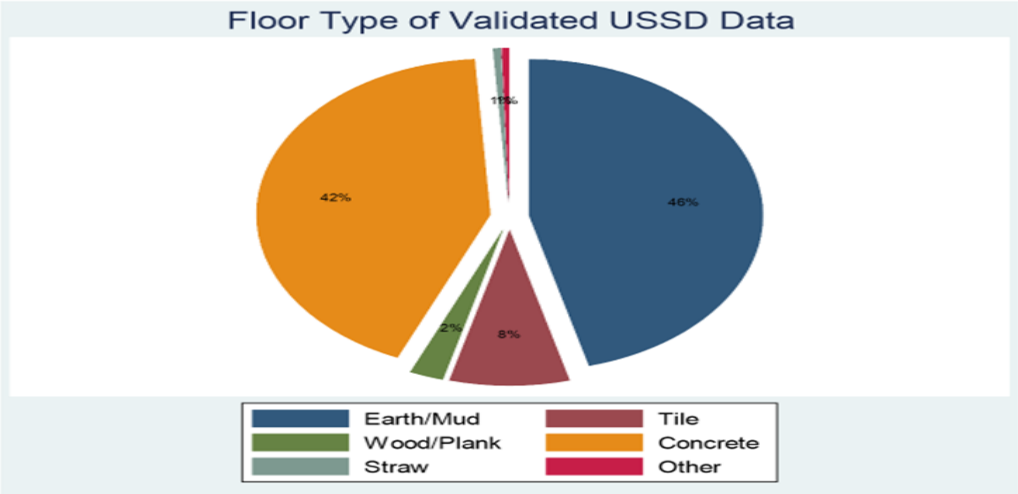
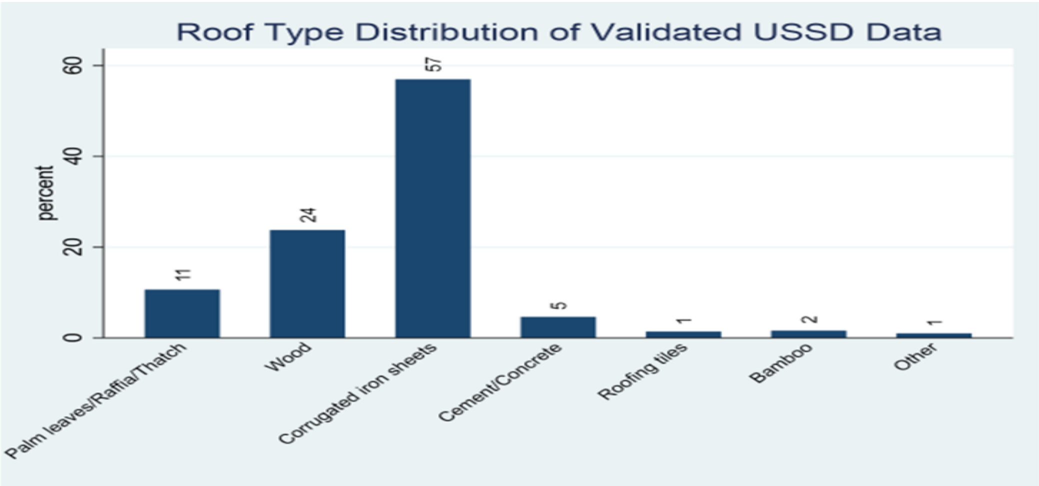
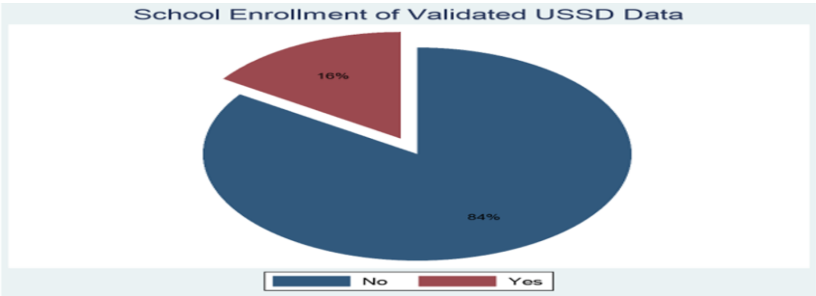


Figure 10: Roof Type Distribution by Validated USSD Data (Source: Authors' Work)



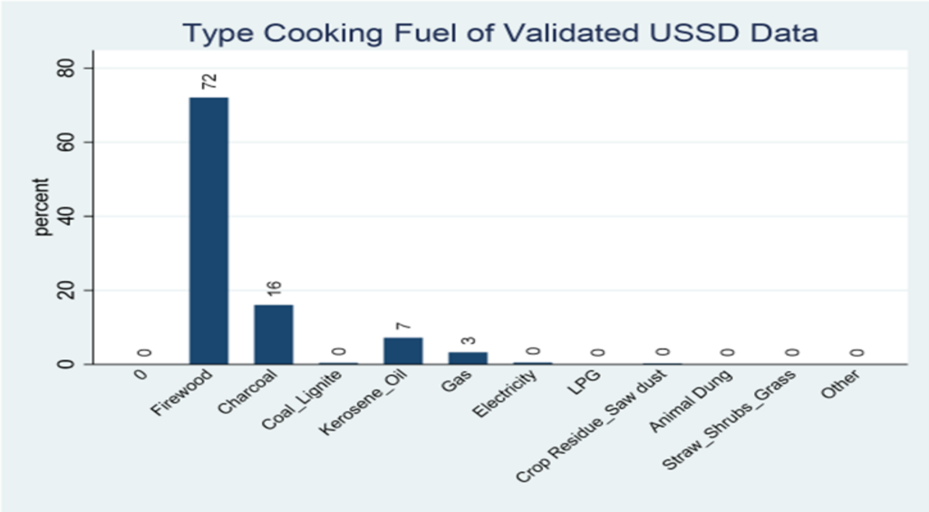
4. **Education enrollment (Figure 11):** 84% of beneficiaries were not enrolled in educational institutions, highlighting limited access to educational opportunities among the urban poor.

Figure 11: School Enrolment by Validated USSD Data (Source: Authors' Work)



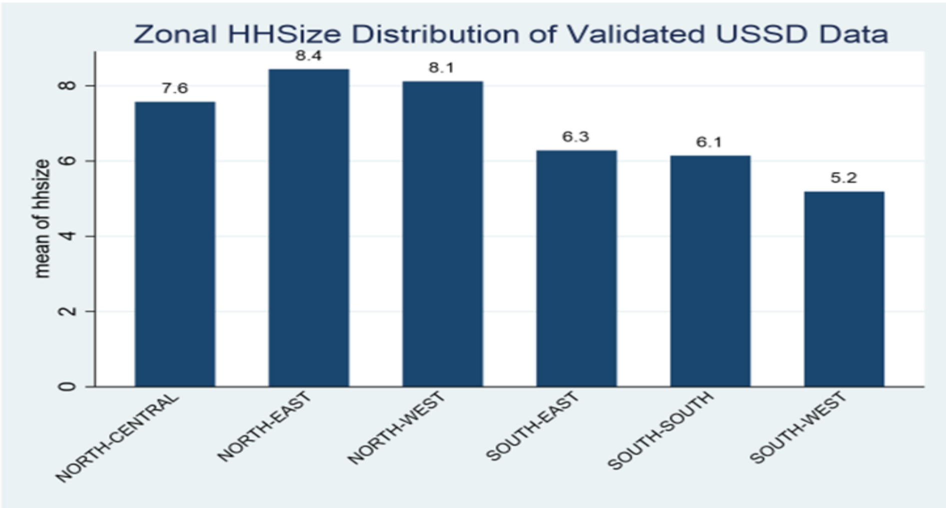
5. **Energy Use (Figure 12):** 72% of beneficiaries relied on firewood for cooking and 16% on charcoal, indicating limited access to clean energy sources.

Figure 12: Cooking Fuel Type by Validated USSD Data (Source: Authors' Work)



6. **Household Size (Figure 13):** The average household size among beneficiaries was 6.3 persons, with the highest average in the Northwest zone (8 members) and the lowest in the South-South zone (5 members). This aligns with Pat-Mbano and Nwadiaro's (2012) findings on population density in urban poor settlements.

Figure 13: Zonal HH size Distribution of Validated USSD Data (Source: Authors' Work)



The characteristics of RRR beneficiaries can be compared with data from the 2018/2019 NLSS for urban households in the lowest two wealth quintiles. This comparison suggests that the targeting approach successfully identified households with socioeconomic characteristics similar to the urban poor as measured in national surveys.

5. Discussion

5.1. Effectiveness of Satellite-Based Targeting

Our analysis suggests that satellite-based targeting using machine learning algorithms can effectively identify urban poor areas in contexts with limited granular data. The correlation between satellite-based poverty estimates and NLSS data indicates that visible features in satellite imagery—such as roof materials, settlement patterns, and road infrastructure—can serve as reliable proxies for poverty.

The targeting approach successfully identified communities where residents exhibited characteristics consistent with established urban poverty indicators. This validates the potential of satellite remote sensing as a cost-effective method for geographic targeting when conventional household survey data is unavailable or outdated.

However, geographic targeting alone cannot account for the heterogeneity of poverty within communities. Even in predominantly poor areas, some residents may be better off than others. This limitation is evident in the finding that a substantial proportion of registrants were deemed ineligible during field validation. This Suggest that satellite-based targeting is best used as an initial screening tool that requires complementary individual or household-level assessment.

5.2. Performance of SMS/USSD Registration

The SMS/USSD platform demonstrated effectiveness in rapidly registering a large number of potential beneficiaries across Nigeria. The registration of millions of people within a short timeframe represents significant reach, particularly given the challenging circumstances during the pandemic.

The high location accuracy rate (99%) when verified through field validation suggests that the platform successfully reached residents in the targeted poor urban areas. The mobile-based approach also likely reduced physical contact during the pandemic, enhancing safety for both programme staff and beneficiaries.

However, regional disparities in registration rates highlight potential challenges. The lower participation in the Southern regions, particularly the Southeast (3% of registrations), warrants further investigation. Possible explanations include differences in:

1. Mobile phone ownership and digital literacy
2. Effectiveness of community sensitization efforts
3. Trust in government programmes
4. Severity of COVID-19 impacts across regions
5. Cultural and ethical diversity

Mobile ownership and digital literacy and severity of COVID-19 cannot be ruled out of the causes of low participation. According to Vanguard report (2024) consistently ranks last in active voice and internet subscriptions per zone, indicating lower penetration rates compared to other zones. However, COVID-19 severity has one of the lowest confirmed cases of 6.7% in the southeast according to Muhammad D.G & Gbonjubola Y.T. (2021). Among the above factors for low participation, apathy to Government programs, sensitization and cultural and ethical diversity are likely and obvious cause for the low turnout owing to the project review meeting reports based on field validation and enumeration exercise.

Further to mobile registration, when compared to similar mobile-based registration systems in other countries, Nigeria's approach achieved substantial participation. However, the significant proportion of registrants who did not meet final eligibility criteria suggests potential for improving the screening process in future implementations.

These findings underscore the importance of complementing digital registration with appropriate community engagement and outreach to ensure equitable access. Future implementations should consider multi-channel registration options to mitigate digital exclusion risks.

5.3. Accuracy in Identifying the Urban Poor

The socioeconomic profiles of validated beneficiaries align closely with the characteristics of urban poverty described in the literature. Key indicators such as housing quality, employment status, education levels, and energy use all suggest that the targeting mechanism successfully identified households experiencing urban poverty.

Particularly notable is the high proportion of beneficiaries with secondary education (45%) and the significant unemployment rate (39%). These figures reflect the "new poor" phenomenon during COVID-19, where previously employed urban residents with some education fell into poverty due to economic disruptions.

The predominance of poor-quality housing materials (earth/mud floors, corrugated iron roofs) and reliance on biomass fuels (firewood, charcoal) further confirms effective targeting of the urban poor. Similarly, the relatively large household sizes align with known patterns of overcrowding in urban poor settlements.

This similarity suggests that the combined approach of satellite-based geographic targeting, mobile registration, and field validation successfully identified households with characteristics consistent with urban poverty in Nigeria.

Regarding inclusion and exclusion errors, our results provide some insights. The field validation process revealed that a substantial proportion of initial registrants did not meet eligibility criteria, suggesting significant pre-validation inclusion error. However, after validation, the remaining beneficiaries closely matched the profile of the urban poor, indicating reduced inclusion error in the final beneficiary list.

Exclusion error is more difficult to quantify without comprehensive data on all eligible households in targeted areas. The digital divide likely contributed to some exclusion, with the poorest households potentially unable to access the SMS/USSD platform. Future research should prioritize estimating exclusion errors through representative household surveys in targeted areas. Moreover, other means of inclusion in the program such as third-party registration in call-in centres, community intermediaries and radio registration for those that may not have access to USSD and SMS platform will address toa large extent the error of exclusion in the registration.

5.4. Limitations and Challenges

Despite the overall positive assessment, several limitations and challenges should be acknowledged:

1. **Inclusion and Exclusion Errors**: Without comprehensive data on all urban poor households, we cannot fully assess the extent of inclusion errors (non-poor beneficiaries receiving assistance) or exclusion errors (poor households not receiving assistance). The field validation process helped reduce inclusion errors but may have introduced other biases.
2. **Digital Divide**: The reliance on mobile phones for registration potentially excluded extremely poor individuals lacking mobile access. While community sensitization efforts aimed to mitigate this, the risk of digital exclusion remains. The observation that only 11% of beneficiaries had no formal education—lower than would be expected among the poorest segments—may indicate that the most vulnerable were underrepresented.
3. **Time Lag Between Registration and Validation**: Population mobility between registration and field validation created challenges, potentially excluding eligible households who relocated during this period. The registrants who could not be located during validation may represent a particularly vulnerable group with unstable housing arrangements.
4. **Reliance on Self-Reported Information**: The initial USSD registration relied on self-reported data, which could be subject to misreporting. Field validation helped mitigate this risk but may not have eliminated it entirely.
5. **Limited Impact Assessment**: Our analysis focuses on targeting effectiveness rather than the impact of assistance on beneficiaries' welfare, which would require additional longitudinal data. Without impact data, we cannot determine whether the targeting approach translated into meaningful poverty reduction.
6. **Scalability and Sustainability Concerns**: While the approach proved effective for emergency response, questions remain about its applicability for long-term social protection programmes. The costs and technical requirements may limit replicability in other contexts with more severe resource constraints.

5.5. Comparison with Other Social Protection Approaches

Nigeria's SRM approach can be compared with other COVID-19 social protection responses in Africa. Several countries implemented different approaches to identifying and supporting vulnerable populations during the pandemic.

Nigeria's approach stands out for its innovative use of satellite-based targeting but required significant time for implementation compared to some other programmes. Some countries achieved greater population coverage, while others were able to leverage existing social registries for faster deployment.

These comparisons highlight the trade-offs between speed, coverage, targeting accuracy, and administrative capacity. Nigeria's approach emphasized targeting accuracy through multi-stage verification but at the cost of implementation speed.

6. Conclusion and Recommendations

6.1. Summary of Findings

This study evaluated Nigeria's innovative approach to targeting urban poor households during the COVID-19 pandemic, using satellite remote sensing, machine learning algorithms, and mobile technology. Our findings suggest that:

1. Satellite-based targeting effectively identified urban poor areas, with poverty estimates correlating strongly with traditional survey data, demonstrating the potential of this approach for geographic targeting.
2. The SMS/USSD registration platform facilitated rapid enrollment of millions of potential beneficiaries, demonstrating the potential of mobile technology for crisis response, though with regional disparities in participation rates.
3. Field validation confirmed a 99% location accuracy rate, indicating successful targeting of residents in poor urban areas, though a significant proportion of initial registrants did not meet final eligibility criteria upon verification.
4. The socioeconomic profiles of validated beneficiaries aligned closely with established characteristics of urban poverty in Nigeria, suggesting effective identification of vulnerable households.

These findings indicate that technology-enabled targeting can be effective in contexts with limited data infrastructure, particularly during crises requiring rapid response.

6.2. Policy Implications

Our analysis has several implications for social protection policy and practice:

1. **Technology Integration**: Social protection systems should integrate satellite imagery, machine learning, and mobile technology to enhance targeting capabilities, particularly in contexts with limited household survey data. The correlation between satellite-based estimates and traditional survey data suggests that these technologies can serve as cost-effective complements to conventional approaches.
2. **Preparedness for Shock Response**: Developing the technological infrastructure and targeting methodology before crises occur can enable more rapid and effective responses when shocks materialize. Pre-established systems could potentially shorten implementation timelines.
3. **Complementary Approaches**: While technology-enabled targeting shows promise, it should complement rather than replace other targeting methods. The finding that many registrants were deemed ineligible during field validation underscores the need for combining geographic targeting with individual or household assessment to enhance accuracy.
4. **Inclusivity Considerations**: Digital approaches should be accompanied by strategies to include those with limited digital access, such as community outreach and alternative registration options. The regional disparities in registration rates highlight the importance of addressing the digital divide in programme design.
5. **Data Protection**: As technology-enabled targeting expands, robust data protection frameworks are essential to safeguard beneficiaries' privacy and security. The collection of sensitive household information through digital platforms necessitates appropriate data governance protocols.

6.3. Recommendations for Future Research and Practice

Based on our findings, we recommend:

1. **Impact Evaluation**: Conduct longitudinal studies to assess the welfare impacts of assistance on beneficiaries targeted through this approach. Future research should investigate whether households identified through this targeting mechanism experienced meaningful poverty reduction from the interventions.
2. **Comparative Analysis**: Compare the accuracy and cost-effectiveness of satellite-based targeting with alternative methods to establish best practices. Rigorous evaluations with control groups would strengthen the evidence base for technology-enabled targeting approaches.
3. **Inclusion Error Assessment**: Develop methodologies to better estimate inclusion and exclusion errors in technology-enabled targeting. This could involve representative household surveys in targeted areas to identify eligible households missed by the system (exclusion errors) and non-eligible households incorrectly included (inclusion errors).
4. **Digital Divide Mitigation**: Investigate strategies to ensure that technology-enabled targeting does not exacerbate existing inequalities in digital access. Potential approaches include community focal points with shared mobile devices, hybrid registration methods, and targeted digital literacy campaigns.
5. **Cross-Country Learning**: Facilitate knowledge exchange between countries implementing technology-enabled targeting to accelerate learning and innovation. Nigeria's experience should be systematically compared with programmes in other countries to identify transferable lessons.

6. **Integration with Existing Systems**: Explore how technology-enabled targeting can complement and enhance traditional social registry approaches for long-term social protection systems. The RRR methodology could potentially enhance the urban coverage of Nigeria's National Social Registry, which has historically focused more on rural areas.
7. **Real Time Tracking and Monitoring Dashboard**: it is important to create a realtime data dashboard to monitor and track potential risk and disaster areas using the satellite remote sensing model. This will enable an early warning system to the geographical target areas regarding the impending natiral disaster and possible mitigation and intervention measures.

6.4. Conclusion

Nigeria's COVID-19 Shock Responsive Mechanism (SRM) and its resulting Rapid Response Register (RRR) represent an innovative case of using technology to overcome data limitations and rapidly identify vulnerable populations during a crisis. The combined use of satellite imagery, machine learning, and mobile technology offers promising potential for enhancing targeting in resource-constrained environments.
The approach demonstrated several strengths, including its ability to identify geographic areas with high poverty concentration, its capacity to rapidly register a large number of potential beneficiaries, and its effectiveness in identifying households with characteristics consistent with urban poverty.

However, challenges remain, including digital exclusion risks, the need for field validation to reduce inclusion errors, and regional disparities in programme participation as mentioned in section 5.1 and 6.2 respectively. Future implementations should address these limitations through complementary registration methods, streamlined validation processes, and targeted outreach to underrepresented regions.

As countries worldwide seek to strengthen their shock-responsive social protection systems, technology-enabled approaches like Nigeria's warrant careful consideration, alongside appropriate measures to ensure inclusivity and data protection. The lessons from this experience can inform the design of more effective, efficient, and equitable social protection responses to future crises.

Declarations

Author Contributions

IA conceptualized and designed the study, led project implementation, provided research tools and resources, critically reviewed the manuscript, and approved the final version for publication. **SN** developed the methodology and data collection instruments, drafted the manuscript, conducted technical reviews, and interpreted the results. **DA** contributed to manuscript editing, provided literature context, and curated references. **MM** was responsible for data collection, analysis, and interpretation.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this study.

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