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Data-Driven Designs for Poverty Targeting in Social Protection: *A Systematic Review and Meta-Analysis of Evidence from 2020–2025*

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ABSTRACT

The effective targeting of social protection programmes is critical for poverty reduction, yet traditional methods often suffer from high inclusion and exclusion errors. Data-driven approaches, including machine learning and big data analytics, are increasingly proposed as solutions, but their real-world effectiveness and associated challenges require systematic evaluation. This study synthesizes evidence from recent literature (2020–2025) to examine the performance, trends, and limitations of data-driven designs for poverty targeting. A systematic review was conducted following PRISMA guidelines. Searches across Scopus, ScienceDirect, and Google Scholar yielded 47 peer-reviewed studies and high-quality working papers that met the inclusion criteria. Findings were synthesized narratively and presented in a meta-analysis table. Data-driven methods—such as Proxy Means Tests, machine learning algorithms, and novel data sources (mobile phone, satellite)—generally improve targeting accuracy over traditional community-based or categorical methods, particularly in economically diverse contexts. Innovations like Togo's mobile data-driven cash transfer programme demonstrate the potential for rapid, scalable crisis response. However, persistent challenges include data quality decay, algorithmic bias, the systematic exclusion of "invisible" populations (e.g., the phoneless or homeless), and threats to transparency and public trust. While data-driven targeting is a powerful tool for enhancing social protection efficiency, it is not a panacea. Effectiveness is highly context-dependent, and a purely algorithmic approach risks undermining equity and rights. The evidence strongly supports hybrid models that combine data-driven precision with community validation and robust grievance mechanisms. Future research should prioritize long-term impact evaluations, fairness audits, and strategies to reach populations systematically missed by digital data.

Keywords: Algorithmic fairness, Big data, Machine learning, Poverty targeting, Proxy Means Test, Social protection, Social protection

1. INTRODUCTION

Poverty targeting in social protection is the process of identifying and directing limited resources such as cash transfers, food aid, or service subsidies to the individuals or households most in need. The design of such systems is a complex analytical challenge, requiring robust mechanisms for data collection, processing, and eligibility verification. Historically, targeting has relied on methods like community-based selection, categorical eligibility, or simple means tests. However, these approaches are frequently criticized for being subjective, prone to elite capture, and inefficient in differentiating need within heterogeneous populations.

In response, data-driven designs have gained prominence, leveraging empirical data and advanced analytics to guide decision-making. This includes established statistical methods like the Proxy Means Test (PMT), which uses regression models to predict household welfare based on observable assets and demographics. More recently, the field has seen an influx of innovations from data science, including machine learning (ML) algorithms capable of identifying non-linear patterns in poverty data, and the use of novel "big data" sources such as mobile phone call detail records (CDR) and satellite imagery (Aiken et al., 2022; Hall et al., 2023).

The theoretical promise of these data-driven approaches is significant: greater accuracy (reducing inclusion and exclusion errors), increased scalability, and faster, more responsive delivery systems. The COVID-19 pandemic served as a catalyst, forcing governments and aid agencies to rapidly deploy digital and remote targeting solutions, such as Togo's *Novissi* programme, which used mobile phone data to identify and pay informal workers affected by lockdowns (Aiken et al., 2022).

Despite this momentum, the shift toward algorithmic governance in social protection is not without significant controversy. Critics highlight concerns over algorithmic opacity, data privacy, and the potential for these systems to automate and amplify existing social inequalities (Human Rights Watch, 2023). There is a risk that individuals without a digital footprintoften the most marginalized—become invisible to data-driven systems. The effectiveness of these methods also varies widely by context, and their performance can degrade rapidly without continuous data updates (Aiken et al., 2023).

This study addresses the need for a comprehensive, up-to-date synthesis of the evidence. It systematically reviews and analyses peer-reviewed literature from 2020 to 2025 to answer the following research question: *To what extent have data-driven design approaches improved poverty targeting outcomes in social protection, and what are the principal opportunities, challenges, and context-specific conditions for their success?*

The objectives of this review are threefold:

i. To compare the performance of data-driven targeting approaches against traditional methods.
ii. To identify and analyse emerging trends, innovations, and their implementation across diverse contexts.
iii. To delineate critical gaps in the current literature and practice, providing a clear agenda for future research and policy development.

By consolidating evidence from 47 studies, this review aims to provide policymakers and practitioners with a balanced, evidence-based assessment of data-driven targeting's potential and its pitfalls.

2. METHODOLOGY

This study employed a systematic review methodology adhering to the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure a transparent and replicable process.

2.1 Search Strategy and Data Sources

A comprehensive search was conducted in April 2025 across major academic databases: Scopus, ScienceDirect, and Google Scholar. The search strategy combined keywords related to poverty and social protection with terms for data-driven methods: *("poverty targeting" OR "social protection" OR "cash transfer") AND ("data-driven" OR "machine learning" OR "algorithm*" OR "proxy means test" OR "big data" OR "AI")*. The search was restricted to publication years 2020–2025 to capture the most recent developments. Backward and forward citation tracking of key articles was also performed to ensure completeness.

2.2 Inclusion and Exclusion Criteria

Studies were included if they:

i. Were published (or formally available as working papers) between 2020 and 2025.
ii. Focused on poverty targeting for social protection or humanitarian aid programmes.
iii. Explicitly evaluated or discussed a data-driven targeting method (e.g., PMT, ML models, use of mobile phone or satellite data).
iv. Were peer-reviewed journal articles, conference papers, or high-quality reports from reputable organizations (e.g., World Bank, Human Rights Watch).

Studies were excluded if they:

i. Focused on targeting in unrelated domains (e.g., marketing).
ii. Addressed general social protection impacts without isolating the targeting mechanism.
iii. Were purely theoretical with no empirical application or evaluation.

2.3 Screening and Data Extraction

From an initial pool of over 40,000 identified records, title and abstract screening narrowed the selection to approximately 360 full-text articles for detailed eligibility evaluation, eventually resulting in 47 studies that fulfilled the inclusion criteria (Figure 1).

Data were extracted from each study on: author(s) and year, objective, country/context, methodology, key findings related to targeting, and noted strengths/weaknesses. This information was compiled into a structured meta-analysis table (Table 1 in the Appendix).

2.4 Synthesis Approach

Due to the heterogeneity of study designs and outcome metrics (e.g., error rates, cost-effectiveness, qualitative assessments), a statistical meta-analysis of effect sizes was not feasible. Instead, a narrative synthesis was conducted. Findings were categorized thematically to compare and contrast evidence across studies. The meta-analysis table served as a foundational reference to ensure all key points from each study were captured in the synthesis.

3. RESULTS AND DISCUSSION

3.1 Study Selection

The PRISMA flow diagram as shown in Figure 1details the study selection process. A total of 47 studies were included in the final synthesis.

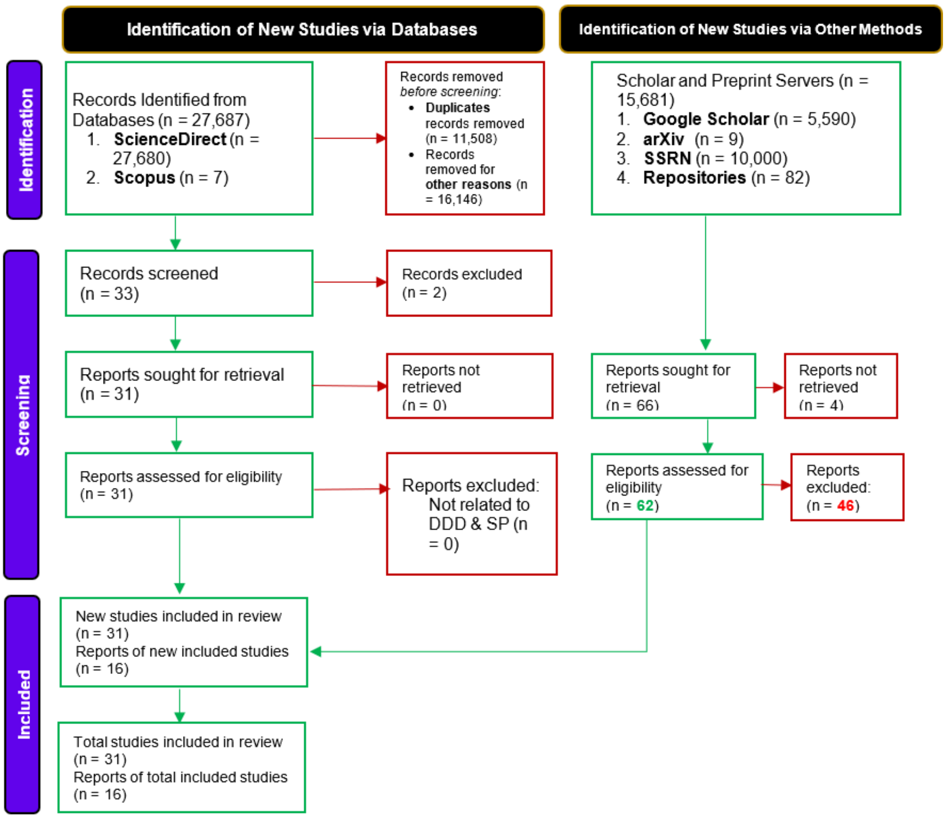

Figure 1: PRISMA 2020 Flow Diagram: Identification of studies

3.2 Meta-Analysis and Summary of Evidence

The meta-analysis as shown in Table 1 synthesizes evidence from 47 diverse studies. Overall, the literature confirms that data-driven innovations—including ML, satellite imagery, and mobile data—enhance targeting precision and efficiency, but they are not immune to challenges like exclusion errors, data bias, and issues of social legitimacy. The evidence strongly supports integrating technological advances with transparent, inclusive, and context-aware design.

Table 1: Meta-analysis table of included studies

SN	Author(s)/Yr	Objective	Methodology	Key Findings	Strengths	Weaknesses
1	Follett & Henderson (2023)	Improve poverty targeting via hybrid PMT-CBT	Bayesian modelling, elite network analysis	Better targeting accuracy and less bias	Tackles political economy issues	Needs technical capacity, limited generalizability
2	Xu et al. (2021)	Predict poverty using NTL and ML in China	SVM on NTL and census data	76.5% accuracy in mapping poverty	High-resolution mapping, ML strength	Ignores non-electrified poor, coarse granularity
3	Nkurunziza et al. (2025)	Classify poverty in Rwanda using ML	EICV5 data, 12 classifiers, 10-fold CV	SVM linear model had 88.5% accuracy	Robust validation, actionable features	Old data, class imbalance
4	Martinez & Cooray (2025)	Spatial ML for targeting in Indonesia	Household survey, spatial clustering	SML reduced targeting errors, esp. in urban areas	Large dataset, spatial insights	Missing data imputation, PCA underperformed

SN	Author(s)/Yr	Objective	Methodology	Key Findings	Strengths	Weaknesses
5	Smythe & Blumenstock (2022)	ML-based poverty maps vs. survey targeting in Nigeria	Compared ML and DHS survey benchmarks using NLSS validation	ML reduced exclusion/inclusion errors; real-world adoption	High-resolution coverage, fairness validated	Validation gaps, asset-only poverty focus
6	Han et al. (2021)	HRRS for predicting poverty in Inner Mongolia	PCA and classification tree using 1m satellite data	Moderate accuracy; building area key feature	Cost/time-efficient, scalable	Limited accuracy, historical data gaps
7	Aiken & Blumenstock (2024)	AI and mobile data for COVID aid in Togo	ML on phone metadata vs. geographic targeting	AI identified more poor households (47% vs. 33%)	Scalable, real-time targeting	Excluded phoneless, privacy issues
8	Aiken et al. (2022)	ML and mobile data in Togo's Novissi program	Satellite + phone data, validation with surveys	ML improved rural targeting, fairness preserved	Practical deployment, reproducible	Phone-less bias, limited stability
9	Aiken, Ohlenburg & Blumenstock (2023)	PMT accuracy decay over time	Panel surveys, decay modeling across 6 LMICs	PMT loses accuracy ~6% yearly	Cost-effective update frequency insights	Limited global generalizability
10	Poulin et al. (2022)	Compare PMT methods for water aid in Ghana	Field-test ML-PMT vs. PPI, CBT, LEAP	ML-PMT most accurate (87%)	Stakeholder feedback, high accuracy	Limited generalizability, high costs
11	Corral, Henderson, Segovia (2023)	ML poverty mapping vs. traditional methods in Mexico	XGBoost vs. parametric models using large census	Traditional models outperformed ML	Robust dataset, simulation rigor	Limited ML generalization, bias in poorest areas
12	Aiken et al. (2025)	Compare PMT, CBT, PBT in Bangladesh	Census, surveys, CBT, phone data comparison	PMT most accurate; PBT more cost-effective at scale	Real-world data, rich policy guidance	Phone exclusion, CBT inconsistencies
13	Schnitzer & Stoeffler (2021)	PMT vs. CBT in Sahel	9 programs, 6 countries, harmonized metrics	PMT better on consumption; CBT improved on food metrics	Cross-country data, multiple metrics	No spillover/legitimacy data
14	Altındağ et al. (2020)	Targeting Syrian refugees via admin data	VASyR + UNHCR data, LASSO validation	Comparable to PMT, cost-effective	Uses existing data, out-of-sample test	Sample not fully representative
15	Hillebrecht et al. (2023)	Dynamic targeting via PMT/CBT in Burkina Faso	Panel data (2006–2009)	CBT improved over time; PMT best at baseline	First dynamic study, robust panel	One-region limit, small impact
16	Zhang et al. (2022)	XAI for deep poverty identification	SHAP, logistic regression on 23k Chinese HHs	XAI outperformed logistic, transparent	Explainability, individual-level insights	China-only, 2019 data

The full meta-analysis is given in S-Table 1.

3.3 Thematic Synthesis of Key Findings

3.3.1 Comparative Targeting Accuracy

The literature consistently demonstrates that data-driven methods, particularly PMT and advanced ML models, offer modest to significant improvements in targeting accuracy over traditional methods (e.g., community-based targeting or simple categorical eligibility). For instance, Aiken et al. (2022) found that ML models applied to mobile phone data in Togo reduced exclusion errors by up to 21% compared to a conventional geographic targeting approach. Similarly, Poulin et al. (2022) reported that an ML-PMT achieved 87% accuracy in identifying poor households for water subsidies in Ghana, outperforming other methods like the Poverty Probability Index (PPI) and community selection.

However, the magnitude of this advantage is highly context-dependent. In areas of widespread, homogenous poverty, the marginal benefit of complex algorithms over simpler universal or categorical approaches is negligible (Kidd et al., 2020). The greatest gains are observed in economically diverse settings where data-driven models can more precisely filter out the non-poor (Figure 2 and Figure 3).

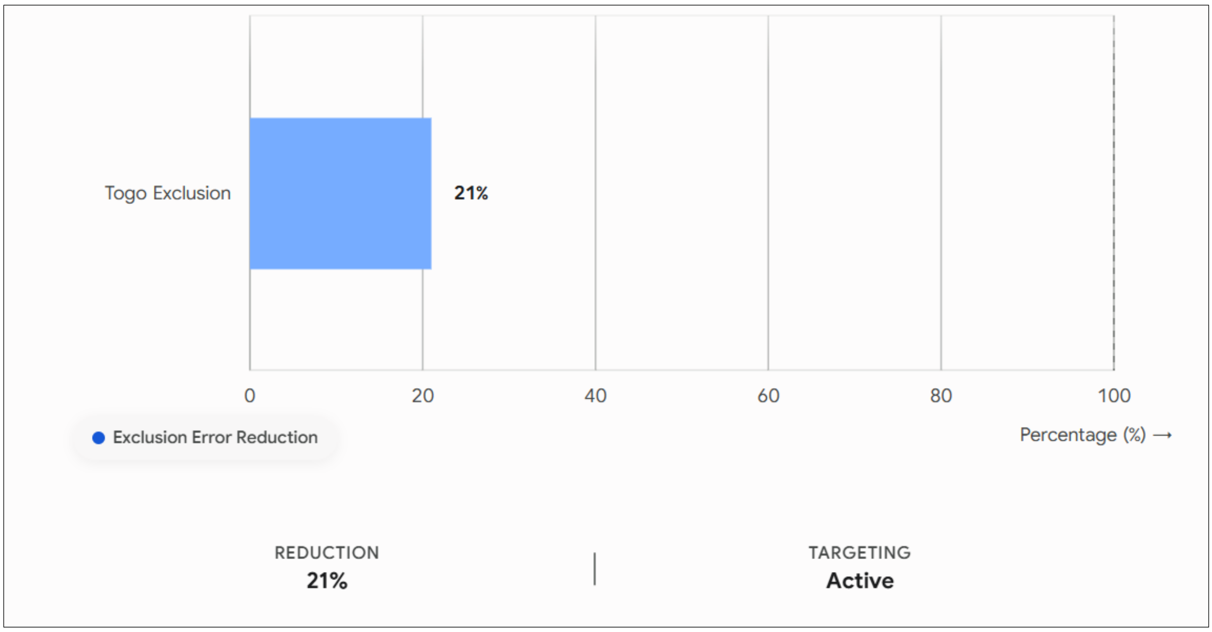

Figure 1: Exclusion Error Reduction in Togo (Adapted from Aiken et al., 2022)

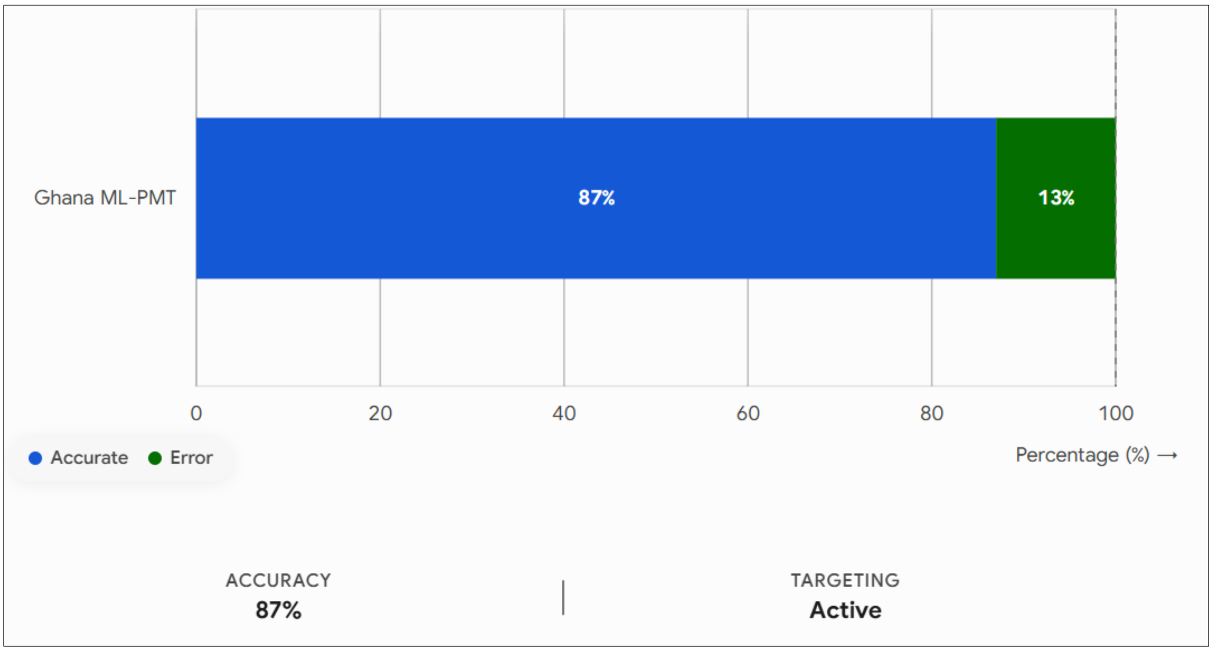

Figure 2: Household Identification Accuracy in Ghana (Adapted from Poulin et al., 2022)

3.3.2 Innovation in Data Sources and Methodologies

A major theme is the rapid adoption and validation of novel data sources. Mobile phone metadata and satellite imagery have emerged as powerful tools, especially for rapid response in data-scarce environments. Togo's *Novissi* programme remains the flagship case study, demonstrating the feasibility of using mobile money transaction history and CDR to identify and pay vulnerable populations during a crisis (World Bank, 2024). Geospatial methods using nighttime lights and high-resolution satellite imagery are also proving effective for creating high-resolution poverty maps, which can improve geographic targeting and resource allocation (Smythe & Blumenstock, 2022; Xu et al., 2021).

Methodologically, there is a clear trend toward using more sophisticated ML algorithms (e.g., random forests, gradient boosting, support vector machines) over traditional linear regression for PMT construction. Studies by Nkurunziza et al. (2025) in Rwanda and Martinez & Cooray (2025) in Indonesia show that these models can capture complex, non-linear relationships between household characteristics and poverty, leading to better predictive performance.

3.3.3 Persistent Challenges: Exclusion, Bias, and Trust

Despite improvements in aggregate accuracy, a critical finding is the persistent challenge of exclusion errors, particularly among the most marginalized groups. Algorithms inherently rely on the data they are fed, making individuals without a digital footprint—such as those without mobile phones, fixed addresses, or formal identification—structurally invisible (Human Rights Watch, 2023). This creates a significant equity risk where data-driven efficiency comes at the cost of excluding the "invisible poor."

Furthermore, the literature highlights concerns over algorithmic opacity and fairness. The case of Jordan's *Takaful* programme, as documented by Human Rights Watch (2023), illustrates how a lack of transparency in algorithmic eligibility can lead to public mistrust and a sense of arbitrary exclusion. This underscores the importance of explainable AI (XAI) and the need for robust grievance and appeals mechanisms as essential components of any data-driven targeting system. The decay of data quality over time is another recurring issue; Aiken et al. (2023) found that the accuracy of a static PMT model can degrade by approximately 6% annually, emphasizing the need for dynamic updating.

3.3.4 The Rise of Hybrid and Dynamic Systems

A clear consensus is emerging around the value of hybrid approaches that blend data-driven algorithms with human judgment and community input. Models like the Bayesian hybrid PMT-Community-Based Targeting (CBT) approach proposed by Follett & Henderson (2023) demonstrate the potential to combine the objectivity of data with the nuanced, tacit knowledge of local communities. Many programmes are adopting a two-stage process: an initial algorithmic shortlist followed by community validation or social worker verification. This approach not only improves accuracy but also enhances social acceptance and perceived fairness (Hillebrecht et al., 2023).

3.4 Discussion

The findings of this systematic review confirm that data-driven designs represent a significant advancement in the technical toolkit for poverty targeting. They offer clear pathways to improve the efficiency and precision of social protection systems, enabling governments and aid agencies to stretch limited budgets further and respond more agilely to shocks. The integration of unified social registries and administrative data systems, as seen in countries like Brazil and Pakistan, forms a foundational infrastructure that amplifies the benefits of these analytical tools (Barca et al., 2023).

3.4.1 Balancing Efficiency with Equity and Rights

However, the review also issues a strong caution against technological solutionism. The pursuit of ever-more-accurate algorithms must not overshadow the fundamental goals of social protection: reducing poverty and vulnerability in an equitable and rights-respecting manner. The evidence of systematic exclusion among marginalized groups and the potential for opaque algorithms to undermine public trust are not minor implementation glitches; they are central challenges that can determine a programme's ultimate legitimacy and long-term sustainability.

The trade-off between efficiency and equity is a false dichotomy. The most effective systems, as highlighted by the trend toward hybrid models, are those that harness data-driven precision while retaining the flexibility and human-centeredness required to reach the most vulnerable. This requires investing not just in data infrastructure and algorithms, but also in transparency initiatives, accessible grievance redress mechanisms, and ongoing community engagement.

3.4.2 Context as a Critical Determinant of Success

A key insight from the synthesis is that there is no single "best" targeting method. The optimal design is heavily contingent on context. In highly unequal, middle-income settings, the investment in a sophisticated PMT or ML-based targeting system is likely to yield substantial returns in accuracy. In contrast, in a deeply impoverished, homogeneous rural community, the administrative cost and complexity of such a system may not be justified, and a simpler categorical or near-universal approach may be more appropriate and effective. Policymakers must carefully assess their local poverty profile, data availability, and institutional capacity before committing to a specific design.

3.4.3 Limitations and Gaps in the Evidence Base

This review has several limitations. It is restricted to English-language publications and may not capture all relevant grey literature. The heterogeneity of the included studies prevented a formal statistical meta-analysis. Furthermore, the review identifies critical gaps in the current evidence base that warrant urgent attention. There is a dearth of long-term impact evaluations that assess whether data-driven targeting leads to sustained poverty escapes. Comparative cost-benefit analyses of different targeting regimes are also scarce. Most importantly, there is a significant research gap on how to effectively identify and include "invisible" populations who are systematically missed by datadependent systems. Future research must also focus on developing and validating fairness metrics and auditing frameworks specific to the social protection context.

4. CONCLUSION AND RECOMMENDATIONS

Data-driven designs are reshaping the landscape of poverty targeting in social protection. The evidence from 2020–2025 indicates that when implemented thoughtfully and with good data, these methods can significantly enhance targeting accuracy, reduce errors, and improve the speed of programme delivery. They are powerful tools for building more effective, transparent, and shock-responsive social safety nets.

However, these tools are not a substitute for sound policy judgment or a commitment to equity. The future of effective targeting lies not in a binary choice between "algorithmic" and "human" methods, but in the intelligent integration of both. A "progressive universalism" approach, using data to identify different gradations of need and guide broad-based coverage, appears to be a promising way forward.

Recommendations for Policymakers and Practitioners:

i. Adopt Context-Appropriate Strategies: In heterogeneous settings, invest in robust data-driven PMT/ML tools. In homogeneously poor areas, prioritize simpler, more inclusive approaches.
ii. Implement Hybrid Systems: Combine algorithmic targeting with community validation and caseworker verification to improve accuracy and build social legitimacy.
iii. Invest in Foundational Data Infrastructure: Prioritize the creation and continuous updating of unified social registries and robust grievance mechanisms.
iv. Mandate Transparency and Fairness: Develop clear, public explanations of targeting criteria and implement routine algorithmic audits to detect and mitigate bias.
v. Plan for Dynamic Updates: Budget for regular data recertification (every 2-3 years) to prevent the decay of targeting accuracy.

Recommendations for Future Research:

i. Conduct longitudinal studies to evaluate the long-term welfare impacts of data-driven targeting.
ii. Develop and test methods for identifying and including populations without digital footprints.
iii. Perform rigorous cost-benefit and cost-effectiveness analyses comparing different targeting regimes.
iv. Advance interdisciplinary research on algorithmic fairness and public acceptability in the social protection domain.

By pursuing this balanced path, the global community can harness the power of data to build social protection systems that are not only smarter and more efficient, but also fundamentally fairer and more inclusive.

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