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Review Article

Leveraging artificial intelligence and big data analytics for poverty alleviation and social development: a review

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Abstract

Poverty reduction remains one of the most pressing global development challenges, requiring innovative approaches for identifying vulnerable populations, targeting interventions, and monitoring outcomes. Rapid advances in Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics (BDA) have created new opportunities to complement conventional poverty assessment methods, which often rely on costly, infrequent household surveys that are susceptible to measurement errors and reporting biases. AI-driven approaches leverage high-resolution satellite imagery, mobile phone metadata, digital financial transactions, administrative records, and social media data to generate timely and spatially detailed insights into poverty dynamics. This study presents a systematic literature review of publications from 2014 to 2024, supplemented by recent policy reports and selected case studies, to examine the application of AI and BDA in poverty alleviation across finance, agriculture, healthcare, education, and social protection. The review further evaluates ethical, governance, and institutional issues through the World Bank's 4Cs AI readiness framework, comprising connectivity, compute, context, and competency. Findings indicate that AI and BDA have significant potential to enhance poverty measurement, improve service delivery, and support evidence-based policymaking. However, their long-term effectiveness depends on responsible deployment, inclusive governance, robust data protection, investment in digital infrastructure and human capacity, and locally adaptive implementation strategies. Unlike previous sector-specific reviews, this study provides a comprehensive cross-sectoral synthesis integrating technological, ethical, governance, and developmental perspectives for Low- and Middle-Income Countries (LMICs).

Keywords: Digital Inclusion; Ethical AI; Financial Inclusion; Machine Learning; Small AI

1. Introduction

Over 700 million people around the world live in extreme poverty making ends meet on less than US $2.15 per day and millions more are at risk of being pushed back into poverty by economic shocks, conflict and climate change [1]. Poverty is not simply a deficit of income; it is a multidimensional factor that is characterized by poor health, low education, poor housing, susceptibility to shocks and social exclusion [2]. The traditional ways of monitoring poverty include censuses and household surveys that usually take place every few years. These data sources though invaluable, tend to trail behind rapidly shifting realities and are expensive to put up. Poverty estimates based on surveys may also be susceptible to recall bias, under reporting and sampling errors [3]. In the age of big data, the question

is: can newer sources of information like satellites, sensors and smartphones be able to complement or even surpass previous sources of information on where poverty persists and how it can be mitigated?

The unprecedented advancements in computational power and AI algorithms have been accompanied by the exponential growth in digital data generated through remote sensing, telecommunications, financial transactions and online interactions [4]. Machine learning models can process large-scale datasets and identify complex patterns that are often difficult to detect using conventional analytical approaches. Marty and Duhaut [4] have shown that convolutional neural networks trained on daytime satellite images are able to explain even up to 75 percent of the change in local level consumption expenditure and wealth. Analysis of Call Detail Records (CDRs) has demonstrated that such features of individuals as the frequency of calls, purchases of airtime and the structure of a network can predict the wealth of individuals with a correlation of approximately 0.68 and can reconstruct the distributions of national wealth. In Kenya, the mobile money system M-Pesa increased access to formal financial services, which had been 26 % of adult Kenyan households in 2006, to 84 % in 2024, and in the process helped lift an estimated 194 000 households around 2 percent of Kenyan households out of extreme poverty [5].

The transformative potential of AI has stimulated innovation across multiple development sectors. In the agricultural sector, AI-based advisory systems are based on satellite and sensor data to enhance the yields of smallholders. Machine learning models in healthcare can be used to allow remote diagnostics and disease surveillance. Adaptive learning platforms, in the education field, provide individualised content. Predictive analytics are applied in governance to identify fraud and optimise the social protection programmes [6]. Simultaneously, the implementation of AI poses considerable ethical, legal and practical issues. The challenges of privacy, algorithmic bias, digital inequality, data governance, and transparency need to be tackled in order to make sure that the benefits of AI are equitably distributed. The aim of the extended review is to synthesize the state of knowledge about AI and BDA to alleviate poverty, identify best practices and gaps, and suggest responsible innovation pathways.

1.1. Research Gap and Contribution of the Review

Despite the growing body of literature on Artificial Intelligence (AI), Big Data Analytics (BDA), and development, existing review studies remain largely fragmented across individual sectors such as poverty mapping, digital finance, agriculture, healthcare, and AI ethics. Most previous reviews focus on single-domain applications, specific technologies, or regional case studies, thereby limiting broader understanding of how AI-driven systems collectively influence multidimensional poverty reduction and social transformation in Low- and Middle-Income Countries (LMICs).

For example, previous studies have independently examined AI-based poverty mapping using satellite imagery and mobile phone metadata, digital financial inclusion through mobile money systems, AI applications in precision agriculture, and ethical concerns surrounding AI governance. However, limited attention has been given to synthesizing these diverse applications within a unified analytical framework that critically evaluates their interconnections, implementation challenges, governance implications, and long-term developmental impacts.

In addition, earlier reviews often emphasize technological potential without sufficiently examining important cross-cutting concerns such as algorithmic bias, digital inequality, contextual adaptation, institutional readiness, scalability limitations, and sustainability of AI interventions in resource-constrained environments. Many existing studies also adopt descriptive narrative approaches with limited methodological transparency and insufficient integration of theoretical perspectives related to development, innovation, and socio-technical transformation.

This review addresses these gaps by providing a comprehensive and interdisciplinary synthesis of AI and BDA applications across multiple poverty-related sectors, including finance, agriculture, healthcare, education, and social protection. Unlike prior sector-specific reviews, the present study integrates evidence from empirical studies, policy reports, and emerging governance frameworks to develop a broader understanding of how AI systems interact with poverty alleviation strategies in LMICs.

The novelty of this review lies in four major contributions. First, it provides a cross-sectoral synthesis that links technological applications with broader social development outcomes. Second, it introduces

an integrated analytical perspective based on the World Bank's 4Cs framework (connectivity, compute, context, and competency), while also highlighting ethical, institutional, and governance dimensions of AI deployment. Third, the review critically evaluates implementation barriers, scalability constraints, and equity implications rather than merely describing technological applications. Finally, the review identifies future research priorities relating to sustainability, inclusiveness, long-term impact assessment, and responsible AI governance in developing economies.

By combining technological, developmental, and governance perspectives within a single systematic review framework, this study contributes a more holistic understanding of the opportunities and limitations of AI-driven poverty alleviation strategies in the Global South.

1.2. Research Questions

This systematic review was guided by the following research questions:

RQ1. How have AI and BDA been applied across different sectors to support poverty alleviation and social development?

RQ2. What empirical evidence exists regarding the effectiveness of AI- and BDA-driven interventions in improving poverty-related outcomes?

RQ3. What technological, ethical, institutional, governance, and socio-economic challenges constrain the adoption and scalability of AI for poverty alleviation, particularly in LMICs?

RQ4. What policy priorities and future research directions are required to ensure responsible, inclusive, and sustainable deployment of AI and BDA for global poverty reduction?

2. Literature Review

2.1. Theoretical Framework

This review is conceptually grounded in multiple interdisciplinary theories that explain the relationship between technological innovation, inequality, and social development. These theoretical perspectives provide an analytical foundation for understanding both the opportunities and limitations of AI and BDA in poverty alleviation.

First, the Digital Divide Theory explains how unequal access to digital infrastructure, internet connectivity, devices, and technological literacy can reinforce existing socio-economic inequalities. Although AI technologies create new opportunities for service delivery and economic participation, populations lacking digital access may become further marginalized. This theory is particularly relevant in LMICs where disparities in connectivity and digital literacy remain substantial.

Second, the Capability Approach developed by Amartya Sen provides a broader understanding of poverty beyond income deprivation. The theory emphasizes people's capabilities to achieve valued functionings such as education, healthcare, mobility, financial security, and social participation. Within this framework, AI technologies contribute to poverty alleviation only when they expand human capabilities and improve substantive freedoms rather than merely increasing technological efficiency.

Third, Innovation Diffusion Theory explains how technological innovations spread across societies through communication channels, institutional systems, and social adoption processes. The uneven adoption of AI technologies across regions highlights the importance of institutional readiness, affordability, trust, cultural acceptance, and local adaptation in determining the success of AI interventions.

Fourth, Socio-Technical Systems Theory emphasizes that technological systems cannot be separated from their broader social, political, economic, and institutional environments. AI systems interact with governance structures, regulatory frameworks, ethical norms, and power relations. Consequently, the developmental outcomes of AI depend not only on technological sophistication but also on governance quality, policy support, and stakeholder participation.

Finally, aspects of Technological Determinism and Development Economics frameworks are incorporated to critically assess whether technological advancement alone can drive poverty reduction. While AI may enhance efficiency and access to services, structural barriers such as weak institutions,

inequality, unemployment, inadequate infrastructure, and governance failures may limit developmental outcomes if not addressed simultaneously.

A complementary perspective is provided by Decolonial and Postcolonial Theory, which argues that digital technologies should not simply transfer solutions developed in high-income countries into LMICs without adequate adaptation to local realities. From this perspective, concerns surrounding data colonialism, unequal ownership of digital infrastructure, and dependence on externally developed AI models may reinforce existing global inequalities. Sustainable AI for poverty alleviation therefore requires locally generated datasets, culturally relevant algorithms, indigenous knowledge integration, and greater technological sovereignty within developing countries. Incorporating decolonial perspectives broadens the analytical framework by emphasizing community participation, equitable data governance, and locally driven innovation rather than technology transfer alone.

Together, these theoretical perspectives provide a multidimensional analytical lens for interpreting the findings of this review and understanding how AI-driven systems influence poverty alleviation, social inclusion, and sustainable development across diverse contexts.

2.2. Remote sensing for poverty measurement

Remote sensing is one of the first and most successful AI-based applications to analyze poverty. Yeh et al. [7] have created a transfer learning model that uses satellite images and night lights to estimate the wealth of households across Africa. Their convolutional neural network accounted up to 75 % of the difference in consumption and asset wealth across five African countries. Extended to India, Latin America and Southeast Asia, studies by Castro and Álvarez [8] and Price and Atkinson [9] and Marty and Duhaut [4] are often enhanced by incorporating multi spectral imagery with socio economic surveys, to enhance spatial resolution. Remote sensing has found special use in the areas where surveys are not frequent or where ground data collection cannot occur due to conflict. The biased estimates can be caused by the saturation of the night lights in the electrified communities and the underestimation of the off-grid communities. Accuracy can also be affected by cloud cover, seasonal variation and resolution constraints. Studies are thus looking at new proxies like spectral indices, road networks and building density. Incorporating remote sensing with other data sources including CDRs, administrative records and crowd sourced information are also gaining interest so as to enhance predictive performance [10].

Mobile phones provide abundant metadata that record communication patterns of users, mobility and network linkages. In a study of Rwandan CDRs (millions of CDRs), Blumenstock et al. [11] found that simple features (such as airtime purchases, call frequency and network centrality) could predict individual wealth with a correlation of 0.68. By combining these forecasts, the researchers could recreate the national distributions of wealth and create fine grained maps of poverty [12]. Due to the accelerated rate of mobile phone penetration even in the low-income context, CDRs are a scalable instrument of monitoring poverty. Nonetheless, their application presents a privacy issue as CDRs are sensitive information that reveals the movement and contacts of individuals. The risk of bias also exists: the ownership of phones is still lower among women and rural population, and some users share phones or buy several SIM cards [13]). Recent work also focuses on these issues, applying privacy preserving computation, weighting models to correct for ownership biases and combining CDRs with other data sources (e.g., satellite imagery or survey data) to improve accuracy [14, 15, 16].

2.3. Digital finance and financial inclusion

Digital financial services have grown at a rapid pace in the developing world, as it has become an essential entry point to the formal economy among millions of people. The pioneer case is the M Pesa, a mobile money platform, launched by Kenya in 2007 that allows its users to store and transfer value using simple phones [17]. In 2024, more than 84.8% of adults had access to formal financial services, an improvement of 26.7 in 2006 [18]. This phenomenal growth can be largely attributed to mobile money and the other related innovations like agent banking and digital credit. According to a study conducted by Suri and Jack [19], access to mobile money has raised 194 000 households out of extreme poverty by increasing household consumption and allowing female headed households to replace farming with business. The study by Batista and Vicente [20] also discovered that mobile money aids users to save more, cope with shocks and enhance resilience. Further examples of how digital finance

can be used to overcome energy, credit and insurance barriers include M Kopa (pay as you go solar home systems) and Oye (pay per use farming services).

Digital finance is improved with AI powering credit scoring, fraud detection and customer support. Credit scores can be produced using machine learning models that use transaction histories and other data to generate credit scores, even in individuals with no formal banking history. Chatbots and voice assistants provide financial services in the local languages [21]. Nevertheless, the growing digital finance raises regulatory and ethical concerns. The users should be safeguarded against over indebtedness, fraud and misuse of data.

2.4. Precision agriculture, health and telemedicine

AI and BDA are transforming the world of agriculture by giving farmers hyper local information of weather, soil conditions and market prices. The Microsoft ICRISAT Sowing App, which was launched in partnership with the Indian government, sends farmers personalised text messages with guidance on the best time to sow, irrigate and apply fertilisers. The field trials demonstrated that farmers who adhered to the AI generated advice increased their yield by approximately 30 % [22]. Digital Green is machine learning based, with local farming practices analysed and providing video-based extension services across multiple languages. Likewise, remote sensing and AI models can project crop yields, identify plant diseases and predict pest outbreaks, and take early action. The tools are especially useful to the smallholder farmers who do not have access to the traditional extension services. However, the adoption is also based on infrastructure, affordability and digital literacy [23]. The uptake in many low-income areas is hampered by poor connectivity and low penetration of smartphones in these areas. The relevance of site-specific adaptation of AI models is highlighted by the fact that trained models on the data of one area may not be applicable to another area [24]. Long term studies are also required to determine the sustainability and cost effectiveness of the AI driven agriculture.

AI has already penetrated healthcare much, and it has implications to reduce poverty by improving health outcomes. Babyl telemedicine platform is a Rwandan platform that uses AI to offer remote diagnostics and connects patients and doctors through mobile phones. This service saves on the cost of travelling as well as the wait time hence making healthcare more accessible to rural and low-income populations [25]. Electronic health records, genomic data and social determinants are also analyzed by machine learning models to predict disease outbreak and customize the interventions. In the case of the COVID 19 pandemic, virus spreading and resources allocation were predicted with the help of AI models [26]. Nonetheless, health data are very sensitive and privacy and security issues are raised. Health algorithm bias can further worsen already existing disparities in case training data fail to adequately represent minority populations. Maintaining fair access to AI can make health services demand an investment in infrastructure and digital literacy, a strong ethical framework, and an open validation of algorithms.

2.5. Human capital and Governance

AI-based personalised learning systems are adaptive services that provide students with dynamic content in regard to their capabilities and development. Kamalov et al. [27] note that one pilot in India applied machine learning to customize mathematics lessons with simple mobile phones, which significantly increased test results. NLP systems are used to translate learning resources into a local language and promote literacy. Chatbots are used to help with homework, career counselling and mental health support. AI has the potential to democratize education by reducing instructional costs, scaling high-quality learning resources, and improving access for underserved populations. But digital inequalities are here to stay: availability of reliable connectivity, devices and electricity is uneven. It is also necessary to provide training to teachers to ensure they can effectively use AI tools. Unless thoughtfully designed, AI has the potential to increase instead of decrease existing inequalities [28]. The studies should look at the long-term results, i.e., whether AI driven education can enhance employment opportunities and social mobility.

There is a growing trend of governments using AI and BDA to modernise state services, such as social protection. Frey et al. [29] posit that, in their countries, OECD countries use sophisticated technologies to enhance coverage, efficiency and effectiveness of social programmes. The existing applications of AI in social protection include client support, back-office automation and fraud detection. Potential uses identified in the report include the use of predictive analytics to predict and manage programme demand

and shocks, improved client identification, enhanced outreach to reduce non take up, and better tailored interventions. It reports that, governments are going with care because of privacy concerns, making mistakes in automated decisions making and public mistrust: in 27 countries, only 40 per cent of the surveyed believe that AI is useful in terms of processing social programme applications. This report recommends strong measures to make sure that AI is reliable, transparent and accountable [30]. It also focuses on connecting the administrative data sources to lessen the burden on claimants and enhance service delivery.

LMICs, AI applications in social protection are less advanced but rapidly emerging. Pilot projects use machine learning to detect fraud in cash transfer programmes, target subsidies to vulnerable households and optimise resource allocation [31]. According to Malvasi et al. [31], Brazil has experimented with AI to identify eligible households for its Bolsa Familia programme. Yet these initiatives often face regulatory hurdles, limited capacity and concerns about surveillance. A key challenge is balancing efficiency gains against potential harms: algorithmic decision-making can inadvertently exclude or penalise people if models are biased or the underlying data are incomplete.

2.6. Emerging policy frameworks: the World Bank's 4Cs and Small AI

In its report, 2025 Digital Progress and Trends, the World Bank presents the concept of small AI, which can be described as affordable, locally relevant AI applications running on everyday devices such as mobile phones. The report underscores that while AI opens up opportunities, LMICs face steep challenges to adapt or deploy AI at scale. Small AI provides a bright future since it does not need so much computing power and can be integrated with a minimum infrastructure. The report suggests investment in four pillars (the so-called 4Cs) of connectivity (reliable digital infrastructure and energy), Compute (AI chips, servers, data centres and cloud services), Context (locally relevant data and content) and Competency (digital skills). To ensure that AI establishes and thrives, governments need to ensure that these building blocks are solidified. Inclusive governance, data protection, regulatory reforms and investment in local innovation ecosystems are also called in the report [32].

Although the potential of AI and BDA in helping to alleviate poverty is a widely celebrated fact, researchers and activists warn of the risks. Under representative training data may give rise to algorithmic bias where the model is biased towards overestimating wealth in electrified regions or underestimating off grid households. The lack of access to technology also leads to a digital divide woman, people with disabilities, rural inhabitants and older adults might lack access to smartphones and stable internet [33]. Privacy invasion is harmful to vulnerable communities when personal information is abused. Another issue is that of "data colonialism as companies or governments gather data about low-income communities without properly compensating them or seeking their consent. Ethical guidelines like the OECD AI principles and the AI Act of the European Union demand transparency and accountability, as well as human oversight and respect of privacy [34]. The community involvement and participatory design are necessary to make sure that AI interventions are based on local needs and values.

3. Methodology

3.1. Systematic literature search

The central part of this review is a Systematic Literature Review (SLR) following the guidelines of Preferred Reporting Items of Systematic Reviews and Meta Analyses (PRISMA). The search included peer reviewed articles, conference papers and policy reports published between January 2014 and April 2024 with certain exceptions of late 2024 and early 2025 to include recent developments. Scopus, Web of Science, IEEE Xplore, ScienceDirect and Google Scholar were searched databases. Also, grey literature, including that of organisations like the World Bank, OECD, UNDP and national governments was consulted.

The systematic review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological transparency and reproducibility. The literature identification and screening process involved four major stages: identification, screening, eligibility assessment, and final inclusion.

During the identification stage, 1,856 records were retrieved from Scopus, Web of Science, IEEE Xplore, ScienceDirect, Google Scholar, and selected grey literature sources. Duplicate studies were

removed prior to screening. The screening stage involved title and abstract evaluation to exclude studies unrelated to AI, BDA, poverty alleviation, or social development. Full-text eligibility assessment was subsequently conducted using predefined inclusion and exclusion criteria. Studies that lacked empirical relevance, methodological clarity, or direct linkage to poverty and social development outcomes were excluded.

The final synthesis included 142 studies that met all eligibility requirements. Figure 1 presents the PRISMA flow diagram summarizing the study selection and screening procedure used in this review.

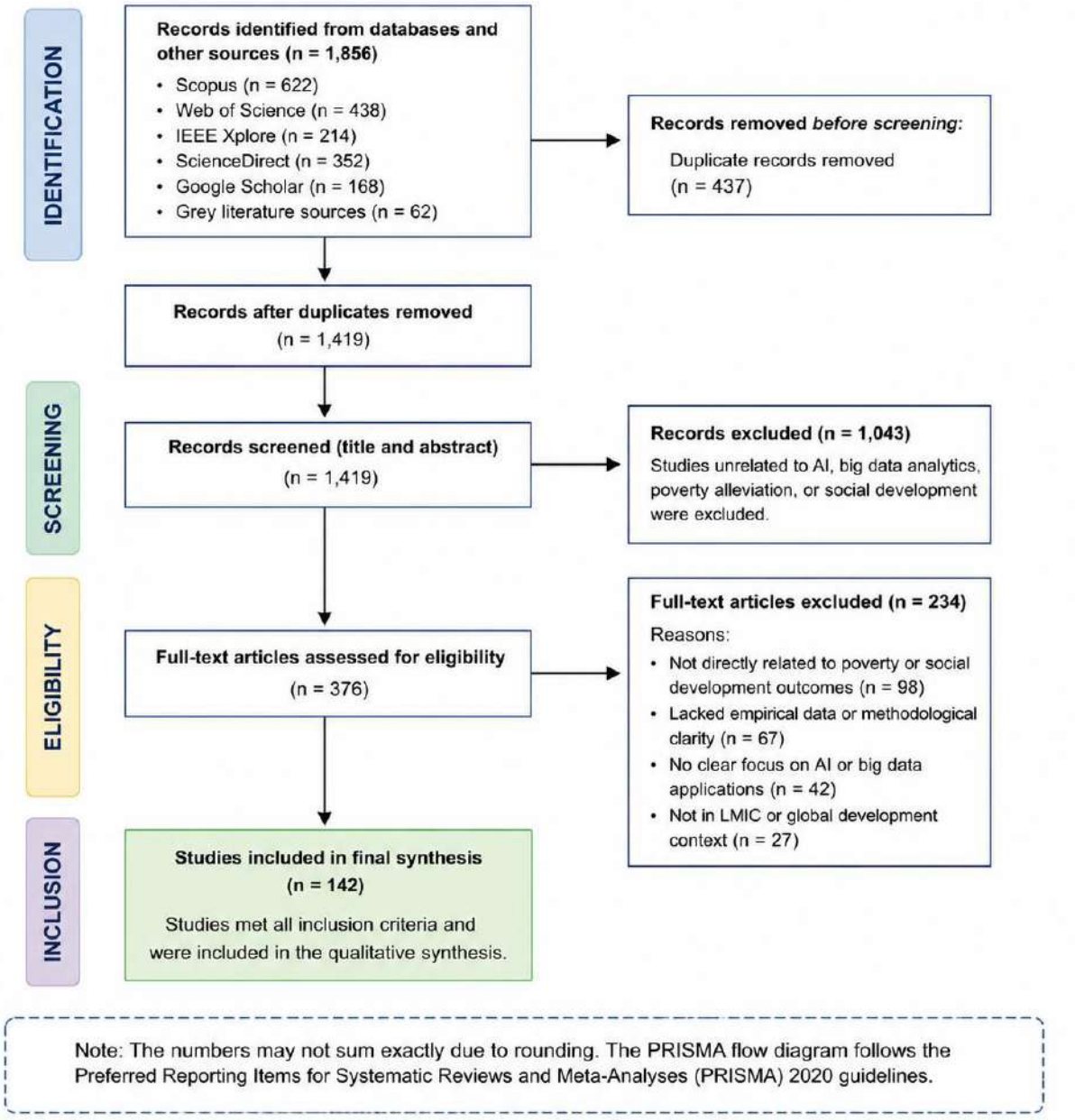


Figure 1: PRISMA Flow Diagram of Study Identification, Screening, Eligibility Assessment, and Final Inclusion Process

3.2. Data extraction and synthesis

Data were extracted on authors, year, country/region, AI or BDA techniques used, data sources, sector, methodology (e.g. experimental design, observational study, modelling), sample size, main findings, outcomes and limitations. The data that were extracted underwent coding and thematic synthesis was used to analyse the data that had been extracted. Themes were developed around six areas, including measurement and mapping of poverty, digital finance, agriculture, health, education, social

protection/governance. They also identified cross cutting themes, including: algorithmic bias and fairness, privacy and data governance, digital divide and access, scalability and capacity, ethics and regulation, contextual adaptation and small AI. Thematic synthesis enabled the reviewers to synthesize evidence between quantitative and qualitative studies and to identify evidence strengths and gaps.

3.3. Quality assessment

The methodological quality of the included studies was assessed using the Mixed Methods Appraisal Tool (MMAT), Version 2018, which is widely used for evaluating qualitative, quantitative, and mixed-methods studies within systematic reviews. The MMAT was selected because of the interdisciplinary nature of the reviewed literature, which included experimental studies, observational studies, modelling studies, qualitative analyses, mixed-methods research, and policy-oriented investigations.

The appraisal process evaluated studies across five methodological domains depending on study design categories. These domains included: (1) appropriateness of the research questions, (2) adequacy of data collection methods, (3) representativeness and sampling quality, (4) validity and reliability of measurements or analytical approaches, and (5) coherence between data, interpretation, and conclusions.

Each study was independently assessed and categorized according to overall methodological quality. Studies meeting fewer than 50% of MMAT criteria were excluded from the final synthesis due to insufficient methodological rigor. Studies scoring between 50–69% were classified as moderate quality, those scoring between 70–89% were considered high quality, while studies scoring 90% and above were classified as very high quality.

The quality assessment revealed that most included studies demonstrated moderate-to-high methodological quality. Approximately 18% of the studies were categorized as moderate quality, 61% as high quality, and 21% as very high quality. Lower-quality studies were primarily limited by small sample sizes, lack of external validation, insufficient transparency in AI model training, or limited discussion of ethical considerations and contextual limitations.

To enhance the robustness of the review findings, a sensitivity analysis was conducted by comparing conclusions derived from higher-quality studies with those from moderate-quality studies. The analysis showed that the major thematic conclusions regarding the effectiveness, opportunities, and challenges of AI-driven poverty alleviation remained largely consistent across study quality categories, thereby increasing confidence in the reliability of the synthesized findings.

Table 1: Summary of MMAT Quality Assessment Outcomes for Included Studies

Study Category	Number of Studies	MMAT Score Range (%)	Quality Classification	Common Limitations Identified
Qualitative Studies	24	60–90	Moderate to High	Limited sample size, contextual bias, insufficient triangulation, limited generalizability
Quantitative Studies	71	65–95	High to Very High	Lack of external validation, reliance on secondary datasets, correlational designs, sampling bias
Mixed-Methods Studies	31	70–95	High to Very High	Incomplete integration of qualitative and quantitative findings, inconsistent reporting of methodological procedures
Policy/Review Studies	16	50–85	Moderate to High	Limited empirical validation, narrative bias, insufficient methodological transparency
Total	142	50–95	Moderate to Very High	Variability in data quality, contextual limitations, limited longitudinal evidence

Note: Quality assessment was conducted using the Mixed Methods Appraisal Tool (MMAT) Version 2018. Studies scoring below 50% methodological quality were excluded from the final synthesis.

The distribution of methodological quality scores and common limitations identified across study categories are summarized in Table 1.

3.4. Limitations

Despite the exhaustive nature, this review is limited in a number of ways. First, the search might have missed any relevant studies published out of the databases searched or in any other language other than English. Second, the speed of AI development has resulted in the emergence of new applications and evidence every day; the review is current as of April 2024 with some references to early 2025. Third, there is a wide variation in geographic setting, data quality, sample size and intervention design, and it is difficult to conduct cross study comparison. Fourth, most AI applications are proprietary or pilot and thus the published results are limited. Lastly, this review is mainly a synthesis of the existing research without incorporation of original primary data analysis.

4. Results and Discussion

4.1. Study Design Characteristics

Among the 142 studies used, the highest number were carried out in Sub Saharan Africa (39.4 %), followed by Asia (33), and Latin America and the Caribbean (11.3). Fewer of them were oriented towards North America or cross regional comparisons. About 67 percent of the studies were empirical (i.e., field tests, observational tests or model tests), and 33 percent were conceptual or review based. AI techniques included classical machine learning algorithms (linear regression, random forests, support vector machines), deep learning (convolutional neural networks, recurrent neural networks, transformers), natural language processing and rule-based systems. The sources of big data included high resolution satellite imagery and CDRs, social media posts, administrative records, payment transactions, sensor networks and crowdsourced data [35, 36]. The variety of different methodologies indicates that AI and BDA applications in development are multi-faceted.

The two major sources of AI driven poverty measurement continue to be remote sensing and CDRs. The satellite images may be used to map the infrastructure, luminosity and environmental elements which are linked to wealth. The features that can be extracted by AI models include roof type, crop patterns and road density to estimate asset indices [37]. Yeh et al. [7] found that a transfer learning model that takes into consideration the night lights and daytime imagery explained 75 percent of consumption variance. Integrating CDRs with satellite data was also found to be better than either source alone [3, 38]. A model that incorporated phone usage characteristics and variables of remote sensing predicted poverty at the district level with a correlation of 0.85. Cross country models are hopefully promising and usually necessitate retraining because of the socio-economic differences. There is some research that uses social media data to proxy lifestyle indicators and map urban poverty, but these data can be biased toward younger, urban and wealthier users [39].

The debate about measuring poverty highlights the importance of assessing AI estimates with ground truth. Though AI can quickly generate poverty maps, these maps must not substitute but rather supplement household surveys. Surveys offer more detailed data on education, health, housing and subjective wellbeing that AI might fall short of. It is essential to triangulate various types of data [40]. The moral application of remote sensing is another issue that should be considered: photographs may accidentally disclose personal data or infrastructure. The data governance structures should inform the manner in which images are gathered, stored and analysed. Lastly, efforts are underway to democratise AI tools; open-source frameworks to map satellite poverty are also available, enabling local researchers to develop and customise models to their local contexts.

4.2. Digital finance and economic empowerment

Mobile money and digital payments have revolutionised financial inclusion in many LMICs. The Kenyan success story illustrates how basic phone-based platforms can radically increase access to formal services [41]. Other countries have already implemented digital finance innovations: Bangladesh has bKash [42], India has Unified Payments Interface (UPI) [43], China has Alipay and WeChat Pay [44], and Nigeria has eNaira [45]. AI is improving these services by scoring credit, detecting fraud and making personalised recommendations. Credit scoring models that have been trained on transaction histories, mobile top ups and social network data can be used to determine creditworthiness of individuals who lack formal banking records. In China, Zhima Credit, an application by Ant Financial,

uses behavioural and social data to give a score of social credit, yet this raises concerns about surveillance and social control [46]. Fintech firms in Nigeria are employing AI to process loan applications within minutes. Remittances are also supported by digital finance: AI decreases transaction costs predicting currency fluctuations and optimising routing [47].

The effects of M Pesa are evident yet in other cases mobile money is more of a payment system than a savings and investment tool. According to the Kenya Financial Inclusion Strategy, the percentage of adults who use more than one formal financial product is only 44.1 p.c. and insurance use is still low (22 p.c.). The increasing number of over indebted individuals and predatory digital lenders is becoming a concern [48]. In order to tap AI and apply it to inclusive finance, regulators need to safeguard consumers, avert fraud and other malpractices, and ensure that platforms are interoperable. The financial literacy programmes can empower users to use digital credit responsibly. Also, credit algorithms should not discriminate against women, youth or rural residents, which requires developers of AI to incorporate different training data and fairness constraints [49]. The cooperation among governments, fintechs, and civil society is the primary aspect of trust building.

4.3. Precision agriculture and food security

Agriculture is the main livelihood for more than half of the world's poor. The applications of AI and BDA in agriculture include predictive analytics and sensor networks, as well as supply chain optimisation. The area of precision agriculture is concerned with providing personalized advice to farmers [50]. A flagship application is the Microsoft ICRISAT Sowing App: it analyses historical climate data, real time weather forecasts and soil conditions to suggest the best sowing dates, type and amount of fertiliser. Farmers who had sown as per the suggested sowing date would have increased their yield by up to 30%. Digital Green and other nonprofits apply machine learning to interpret videos uploaded by farmers and give them customised advice on extensions [18]. Crop disease detection models involve smartphone images in order to detect pathogens and give advice on treatment.

AI is also beneficial to agricultural supply chains. The machine learning algorithms are used to predict yields of crops enabling governments and traders to plan imports, exports and storage. AI-driven logistics applications pair farmers with buyers and minimize spoilage. Transparency and traceability can be enhanced with the help of blockchain, which helps farmers to get better prices [51]. In addition, AI is applied in designing micro insurance products that will be automatically paid out in case of adverse weather events. Nevertheless, in most areas, the adoption is still low because of low connectivity, high cost and low digital literacy. The report by Future of Life Institute states that in 20-35% of AI interventions, infrastructure limitations are an enabler and a constraint. In order to scale precision agriculture, rural broadband, cheap devices and training of farmers should be invested in [52]. Adoption and sustainability can be enhanced by participating methods that involve farmers in the design of technologies.

4.4. Health and public health surveillance

Applications of AI in health are varied: predictive models are used to predict disease outbreaks, diagnostic tools are used to analyse medical images, chatbots are used to provide triage, telemedicine platforms are used to connect patients and doctors. In Rwanda, the Babyl telemedicine service uses AI to initially diagnose and triages patients to relevant care [53]. In India, AI applications are used to analyse X rays in order to detect tuberculosis and provide the results through mobile devices. The quality of the air, food safety and water pollution, are also monitored by AI models, allowing early interventions [54]. In the case of the Ebola and COVID 19 epidemics, AI-based surveillance systems incorporated mobility data, social media and health records to forecast the spread and allocate resources. The use of AI in health, however, brings up critical ethical questions [55]. Health data are highly sensitive and breach of data can have dire consequences. Also, there is a risk of algorithmic bias; e.g. risk models of heart disease developed in the Western countries might not produce similar results in African populations. The solutions to these problems will be the frameworks such as the guidance on AI ethics offered by the WHO that focus on data governance, human oversight, transparency and accountability. To ensure that AI can be effectively used by health workers, the public health authorities need to invest in digital infrastructure and training health workers to use AI effectively.

4.5. Education, human capital and labour markets

Educational inequalities can be minimised by integrating AI in education to deliver personalised and accessible education. The adaptive tutoring systems provide content at the appropriate level of difficulty; natural language processing tools convert content; and AI-driven chatbots offer tutoring and mentoring [56]. Randomised assessment findings indicate that AI assisted learning might lead to substantial enhancements in test scores in mathematics and reading. The study by Jordan et al. [57] in Kenya used an AI platform that provided interactive lessons through SMS, which led to an improvement in learning outcomes that was 0.2 standard deviations. Another study involved an AI chatbot that was used to help secondary school students with their homework and reported a 30% improvement in the rate of homework completion. Vocational training and upskilling also involve AI: platforms such as Coursera and Udemy use the recommendation algorithm to customize courses.

Automation and AI are transforming labour markets. Although automation does have the risk of displacing low skilled jobs, it equally opens up new opportunities in the gig economy and digital services. It is possible to match jobseekers with vacancies, predict demand of skills and create retraining programmes using AI [58]. It has been indicated that some workers have been able to earn above poverty line incomes through the digital labour platforms. Nonetheless, the issue of job displacement, precarious work and the absence of social protection still persist [58]. Policies are required to see to it that workers enjoy the benefits of AI driven labour market transformations, such as lifelong learning and portable benefits.

4.6. Social protection and governance

The use of AI in social protection by the government is at an initial level but is on the rise. There are four current uses: client support (chatbots that answer questions and guide applicants), back-office automation (process applications and detect fraud), predictive analytics (anticipate demand and identify people at risk) and tailored interventions [59]. The AI models have the capability of identifying anomalies in claims of benefits and identifying possible fraud which helps to reduce leakage. The machine learning can detect those households that are likely to drop out of school or fall into poverty due to shocks, allowing proactive support. The report underlines the fact that governments are wary because of privacy concerns and the necessity of developing trust with the populace. The citizens of OECD countries trust government use of AI to support social programmes, only about 40 percent do. To improve trust, governments must involve the population, release the use cases of AI, and create the clear accountability mechanisms [60].

Some social protection AI initiatives in low-income countries include using mobile money to send cash transfers (e.g. digital cash assistance by World Food Programme), predicting drought impacts to early warning systems, mapping slums to target housing programmes. Nevertheless, gaps in the data and insufficient institutional capacity are obstacles [61]. Not all countries have digital identification systems and it is hard to identify beneficiaries. Other people are politically opposed to the use of algorithms in making decisions. Governments can be assisted by international organisations in providing technical assistance, creation of open-source tools and sharing of best practices. To illustrate, the ID4D program of the World Bank encourages the use of digital identity systems, which can help provide safe and inclusive services.

4.7. Cross-cutting challenges and ethical issues

Based on the synthesis of the literature and policy documents, six cross cutting challenges are identified:

1. Bias and fairness AI models can tend to reproduce or amplify inequalities provided that training data is biased or unrepresentative. Remote sensing models have the propensity to overestimate wealth in electrified regions and under estimate wealth in off grid regions. Models that are based on phones may overlook those who share phones or are unable to afford airtime [23]. Algorithms credit scoring can discriminate against women or rural borrowers. To overcome bias, it is necessary to have various training data, frequently audit and fairness limitations.

2. Privacy and data governance: CDRs, mobile money transactions and health records are sensitive personal data. The abuse may be detrimental to the individuals and the relationships can be ruined. Good legal systems, encryption, anonymisation and privacy preserving computation are essential. The ownership of the data and its consent should be explained.

3. Digital divide: The access to AI-enabled services is a matter of infrastructure, devices, affordability and digital literacy. Older adults and people with disabilities, as well as women might be excluded. In the absence of specific interventions, AI might increase, instead of decreasing, inequality.

4. Scalability and capacity: There are numerous successful pilots who are not able to scale due to regulation barriers, funding and lack of local expertise. Government to government, government to the private sector and government to the NGOs partnerships are required in order to develop capacity. Connection investments, compute and skills investments are crucial. The 4Cs framework created by the World Bank can be used to create the basic infrastructure.

5. Local adaptation: AI products need to be adapted to local languages, cultures and institutions. The fact that the Sowing App is successful is partly due to the delivery of recommendations via SMS and not smartphone apps. Engaging in participatory design and co creating with communities enhances adoption and relevance.

6. Ethics and accountability: Transparency, explainability and accountability are critical for trust. Governments and companies must publish AI use cases, conduct impact assessments and provide redress mechanisms. Ethical guidelines should be integrated into AI design from the outset. International cooperation is needed to develop global standards.

These challenges underscore that AI is not a panacea; rather, it must be integrated with broader policy reforms, capacity building and inclusive governance.

Table 2: Representative Studies on AI and BDA for Poverty Alleviation

AI Technique	Sector	Data Source	Reported Impact	Representative Studies
Satellite imagery + transfer learning	Poverty measurement	Daytime imagery, night-lights	Models explain up to 75 % of variation in consumption and wealth	[62]
Mobile-phone metadata	Poverty measurement	Call-detail records	Predict individual wealth ($r \approx 0.68$) and reconstruct national wealth distribution	[11]
Digital finance (M-Pesa)	Financial inclusion	Mobile money transaction data	Expanded formal financial services from 26.7 % (2006) to 84.8 % (2024); lifted 194 000 households out of poverty	[19]
Telemedicine (Babyl)	Health	Mobile phone consultations	Improved access to diagnostics and medical advice; scaled nationally	[53]
Social protection analytics	Governance	Administrative records, CDRs	AI used for client support, back-office automation and fraud detection; predictive analytics for targeting	[29]
Small AI & 4Cs framework	Policy	Policy reports	Small AI solutions run on everyday devices; 4Cs emphasise connectivity, compute, context and competency	[63]

Note: The table summarises selected studies and policy frameworks; it is not exhaustive.

Table 2 summarizes the main uses of AI and BDA in different fields that are of importance to poverty reduction. It demonstrates that AI-based methods like satellite images and cell phone metadata can serve as cost-effective and scalable alternatives to traditional methods of measuring poverty, with high predictive accuracy and real-time insights. Digital solutions such as M-Pesa have shown transformative effects through increased access to financial services and alleviation of households out of poverty in financial inclusion [54]. Likewise, precision agriculture and telemedicine (e.g., Babyl) made possible by AI enhance productivity and access to essential services, especially in underserved regions. Governance apps, such as social protection analytics, help to improve the efficiency of targeting and minimize fraud. The fact that the Small AI and 4Cs framework was included, goes further to emphasize the need to have context-appropriate and scalable solutions. Table 2 highlights the multi-sectoral potential of AI and BDA in addressing poverty, and the need to have supporting infrastructure, data quality, and inclusive implementation strategies.

Table 3: Cross-Cutting Challenges and Potential Responses

Challenge	Description	Potential Responses
Bias and fairness	AI models may reinforce existing inequalities by over- or under-estimating poverty due to unrepresentative training data.	Collect diverse and representative data; incorporate fairness constraints; regularly audit models; engage communities in model design.
Privacy and data governance	Sensitive data (CDRs, health records) can be misused, leading to harm and loss of trust.	Implement data protection laws; anonymise data; use encryption and secure storage; adopt privacy-preserving analytics.
Digital divide	Unequal access to devices, connectivity and digital literacy excludes vulnerable groups.	Invest in infrastructure (connectivity); promote affordable devices; deliver services via basic phones; provide digital literacy training; design inclusive interfaces.
Scalability and capacity	Pilot projects often fail to scale due to lack of funding, regulatory barriers and limited local expertise.	Invest in foundational infrastructure and skills (4Cs); form partnerships across sectors; develop open-source tools; create regulatory sandboxes.
Contextual adaptation	Models may not generalise across contexts; interventions must reflect local languages and norms.	Use participatory design; localise content; allow for human oversight and feedback; support community-driven innovation.
Ethics and accountability	Lack of transparency and accountability can erode trust; decisions may harm vulnerable people.	Adopt ethical frameworks (e.g., OECD AI principles); ensure explainability; establish grievance mechanisms; involve ethicists and civil society.

Table 3 identifies the key cross-cutting issues that can be presented when implementing AI and BDA to alleviate poverty, as well as effective response mechanisms. The major concerns are the bias and fairness where unrepresentative data can support the inequalities and privacy concerns are raised due to utilizing sensitive datasets like health and mobile records. The digital divide continues to be a key factor that prevents the marginalized groups to access AI benefits because of insufficient infrastructure and digital literacy [51]. Also, the scalability issues prevent the pilot projects to be scale to large scale implementation often due to funding, regulatory, and capacity limitations. Contextual adaptation is essential whereby solutions should be based on local socio-cultural realities to be effective. The aspect of ethical and accountability also arise, especially on transparency and any harm to the vulnerable groups. The suggested solutions that include comprehensive, accountable, and context-specific attitude to the deployment of AI are important.

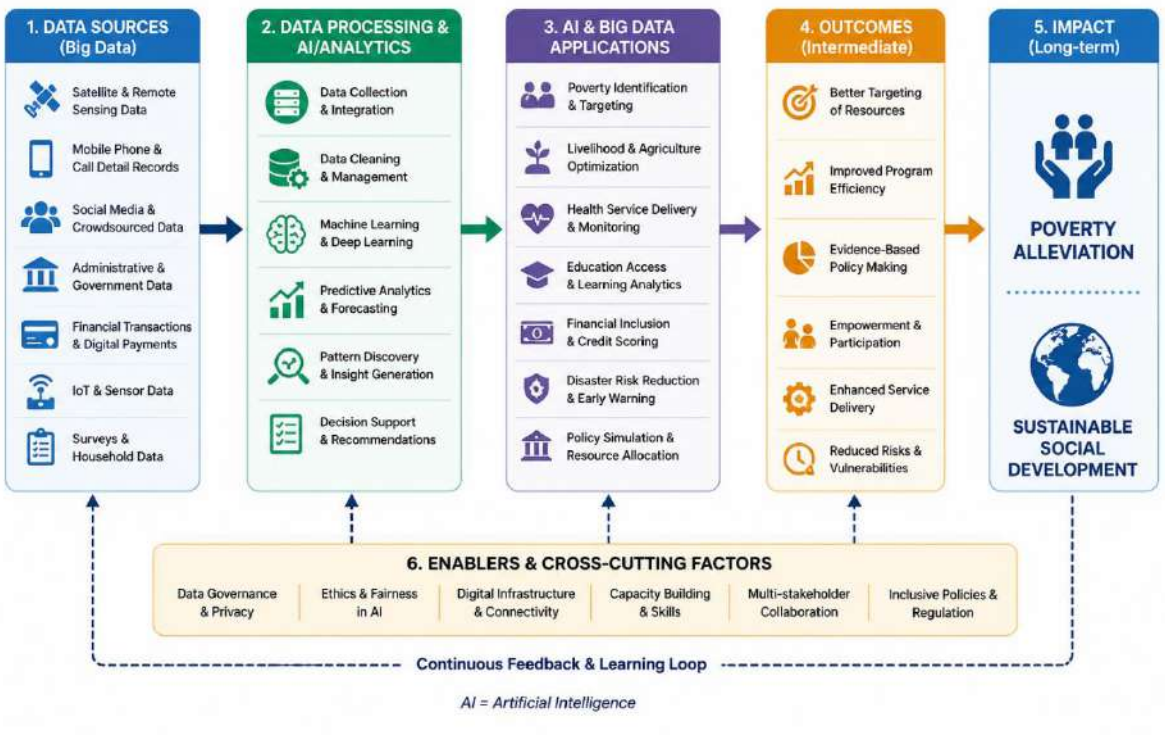


Figure 2: Conceptual Flow Diagram Linking AI and Big Data to Poverty Alleviation

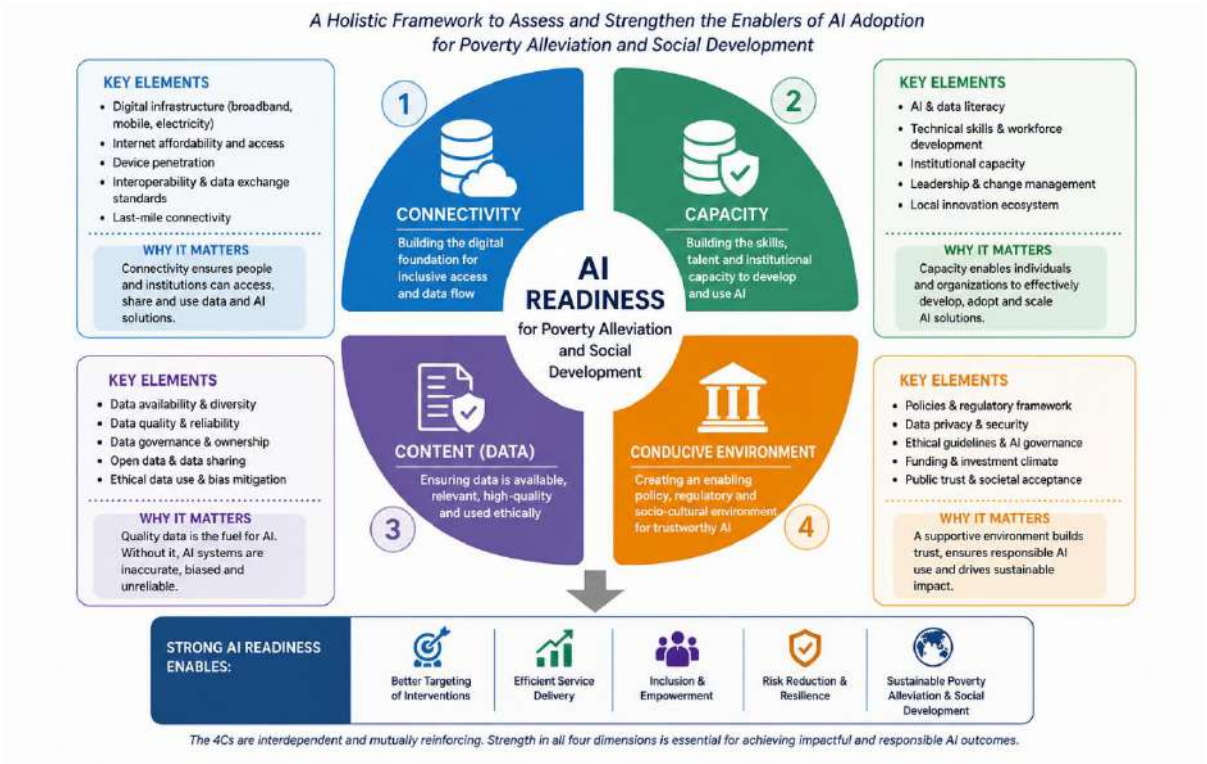


Figure 3: The 4Cs Framework for AI Readiness

Figure 2 illustrates the lineages of how different sources of big data can feed AI models that, in turn, can support interventions in the domains of digital finance, agriculture, healthcare, education and social protection. Satellite, mobile phone, and administrative records are fed into machine learning algorithms to produce insights that can be used in programmes. Figure 2 shows the feedback loops in which better service delivery leads to improved livelihoods, which are used to generate new data, thus refining models. Such cross-cutting enablers as governance, ethics and capacity building are necessary to provide the system with the necessary equity and sustainability.

Figure 3 offers a temporary illustration of the 4Cs model of the World Bank on the topic of AI preparedness. The idea is that solid digital infrastructure (connectivity), sufficient computing resources (compute), locally relevant data and content (context) and a digital-skilled workforce (competency) underpin the foundations of inclusive and effective AI ecosystems [60]. This framework can also help policymakers identify gaps in investments and prioritise actions that can allow them to embrace AI in a manner that suits the context of the country they are in.

4.8. Lessons from Failed and Problematic AI Interventions

Despite the considerable promise of AI and BDA, numerous real-world deployments have demonstrated that AI is not inherently beneficial and may unintentionally reinforce existing inequalities when poorly designed or inadequately governed. Several AI-enabled social welfare systems implemented in both developed and developing countries have produced unintended consequences, including exclusion of vulnerable populations, discriminatory decision-making, privacy violations, and reduced public trust [5, 7].

One widely cited example is the Dutch childcare benefits scandal, where algorithm-assisted fraud detection disproportionately targeted low-income and immigrant families, resulting in wrongful financial penalties and significant social hardship. Similarly, Australia's Robodebt programme relied on automated income averaging to recover alleged welfare overpayments, leading to thousands of incorrect debt notices before the programme was declared unlawful and discontinued [15]. These cases illustrate how algorithmic decision-making without adequate human oversight may amplify administrative injustice.

In developing countries, AI-based beneficiary targeting has also encountered limitations due to incomplete administrative datasets, poor digital infrastructure, and inadequate representation of marginalized populations [7]. Biases in satellite imagery, mobile phone records, and digital financial data may systematically underrepresent rural communities, women, older adults, and individuals without digital access, thereby increasing exclusion errors in poverty identification.

These experiences demonstrate that AI should complement rather than replace human judgement. Transparent governance, regular algorithmic auditing, participatory system design, robust appeals mechanisms, and continuous monitoring are essential to minimize unintended consequences and ensure that AI contributes to equitable and inclusive poverty alleviation.

5. Discussion

Unlike previous sector-specific reviews, this study demonstrates that AI-driven poverty alleviation should be understood as an interconnected socio-technical ecosystem rather than isolated technological interventions. The synthesis reveals that the effectiveness of AI applications depends not only on algorithmic performance but also on governance quality, digital infrastructure, institutional capacity, ethical safeguards, and contextual adaptation. This integrated perspective contributes to the growing discourse on responsible and inclusive AI for sustainable development.

5.1. Synergies and trade-offs across sectors

The evidence provided across sectors shows that there are synergies and trade-offs in taking advantage of AI and BDA to alleviate poverty. Innovations in a certain industry in most instances create data that can be used by other people. Mobile money transactions do not just facilitate finance, but generate behavioural data that can be used to score credit, epidemiological model and disaster response. The monitoring of crops with the help of satellite imagery can also facilitate infrastructure planning and climate adaptation [64]. Nevertheless, the fact that data can be used across sectors makes consent and

purpose questionable. A farmer might be ready to provide yield information to get agricultural advice but not to provide credit risk assessments. Policy frameworks should also make sure that data collected to serve a given purpose do not get repurposed without the informed consent [65].

Scale and depth have trade-offs. The AI models can be used to generate poverty maps of a vast area in no time, but they can overlook the details represented by local surveys. Millions of users can be reached by digital finance, yet personal interaction remains a key to financial literacy and trust [66]. Telemedicine expands access, but certain health issues necessitate physical examination [67]. The most successful results should be expected when a balanced approach is chosen, combining AI with human expertise and community involvement.

5.2. The promise and pitfalls of predictive analytics

A key focus of numerous AI applications being developed is predictive analytics, especially machine learning models. These models are able to predict future events like crop yield, outbreak of diseases or who is most likely to lapse into poverty by identifying the pattern of historical data [68]. These predictions can be used by governments and NGOs to allocate resources in advance, implement specific interventions and prevent crises. To illustrate, predictive models of drought conditions can be used to distribute food aid early [69]). Credit scoring algorithms have the power to offer credit to the unbanked, and open up entrepreneurial opportunities. Models in social protection can be used to forecast the risk of households being affected by the shock and offer assistance prior to the onset of a crisis. Predictive models are, however, not deterministic; based on probabilities and uncertainty. Excessive dependence on predictions may result in unfair decisions in case people are misclassified. Clear communication of the aim and constraints of the predictions is critical [70]. Furthermore, the models that are trained on the historical data can be biased with respect to past injustices and this is where the concept of fairness and constant monitoring comes in.

5.2.1. Critical Evaluation of AI Effectiveness Across Contexts

Although many studies report positive outcomes associated with AI-driven interventions, the evidence regarding their long-term effectiveness in reducing multidimensional poverty remains mixed and context-dependent. Much of the current literature relies on correlational evidence rather than longitudinal causal analysis, thereby limiting the ability to determine whether AI applications directly alleviate poverty or merely improve short-term service efficiency.

For example, mobile money systems such as M-Pesa have significantly expanded financial inclusion and improved access to digital transactions. However, increased financial access does not automatically translate into sustainable poverty reduction. While some studies report improvements in household consumption, resilience, and entrepreneurial activities, other studies suggest that many users remain financially vulnerable due to over-indebtedness, predatory lending practices, limited savings accumulation, and low uptake of insurance products [8]. This indicates that financial inclusion alone may not sufficiently address broader dimensions of poverty such as healthcare access, educational inequality, food security, and structural unemployment.

Similarly, AI-based precision agriculture platforms demonstrate strong potential to improve productivity among smallholder farmers; however, their effectiveness is often constrained by poor rural connectivity, limited digital literacy, inadequate infrastructure, and high implementation costs. In several LMIC contexts, pilot projects achieved promising results under controlled conditions but encountered scalability challenges during broader implementation. These findings suggest that technological effectiveness is strongly mediated by institutional readiness, governance capacity, and socio-economic context.

Conflicting evidence also exists regarding AI-driven governance systems and predictive social protection models. While predictive analytics may improve targeting efficiency and reduce fraud, concerns persist regarding algorithmic exclusion, surveillance risks, opacity in decision-making, and unintended discrimination against vulnerable populations. In contexts characterized by weak data governance and limited accountability mechanisms, automated decision-making may reinforce rather than reduce social inequalities [19].

The synthesis further demonstrates that AI interventions are most effective when integrated within broader socio-economic development strategies rather than implemented as isolated technological

solutions. Human oversight, participatory governance, digital infrastructure investment, and local contextual adaptation consistently emerge as critical determinants of success across sectors. Consequently, AI should be viewed not as a standalone solution to poverty, but as a complementary tool whose developmental outcomes depend heavily on institutional, ethical, and governance conditions.

5.3. Scaling small AI: opportunities for LMICs

Small AI is especially applicable to LMICs, as connections, computational and data capabilities might be constrained. Small AI is simple, low-cost algorithms that execute on simple hardware like feature phones [71]. Examples are advisory services using SMS based lightweight machine learning models to score credit, offline AI tools to diagnose diseases. These types of solutions are cheaper and simple to sustain compared to large scale AI systems. The World Bank claims that small AI can help countries to overcome some of developmental barriers and jump over into the digital era. Nonetheless, to scale small AI, investment in the 4Cs foundation, namely connectivity (e.g., reliable electricity and network coverage), compute (e.g., local data centres or cloud access), context (locally collected data), and competency (training a digitally literate workforce) [72]. The LMICs can be assisted by multilateral organisations, donors and the private sector, through funding of infrastructure projects, building of data platforms and provision of capacity building programmes. Local collaboration may also assist in the exchange of best practices and technologies.

5.4. Policy implications and recommendations

Based on the evidence and cross cutting challenges observed, the following policy recommendations will be made:

1. Build and enhance reliable power supply, mobile networks and data centres, especially in rural communities. There should be increased access to low-cost smartphones and teaching people digital skills will mean that AI solutions will reach marginalised communities. The infrastructure deployment can be fastened by deploying public private partnerships.

2. establish strong data governance models: Clear instructions on how to collect, share, store and use data are vital in privacy protection and in building trust. The governments should ensure that data protection laws are subject to international standards, informed consent is required and open data initiatives are promoted that would allow research and ensure that personal information is not compromised.

3. Enforce inclusive and equitable AI: Policy makers must enforce fairness testing of AI systems being used in vital sectors such as finance and social protection. The areas of emphasis should be research on bias reduction and constraints of fairness. The explainability of AI algorithms should also enable users and regulators to gain a clearer insight into how decisions are made.

4. Promote participatory design and local innovation: AI solutions are better when co designed with its intended users. Governments and NGOs ought to engage communities in problem identification, intervention and monitoring design, as well as implementation and evaluation. Investing in local startups and researchers encourages the development of innovation specific to localities.

5. Incorporate AI into existing social programmes: AI should not be used to replace existing social programmes. An example is that predictive models may make the decisions of social workers but not substitute the human judgement. Routine tasks can be automated by AI, which will allow the staff to offer personalised assistance. Training on the responsible use of AI should be incorporated into the programmes to educate the staff.

6. Promote regional and international collaboration: Learning, data standards and ethical principles exchange across national borders increases learning and decreases redundancy. The coordinating role can be played by multilateral institutions. Research, infrastructure and capacity building in the low-income countries can be supported by international funding.

5.4.1. Economic Viability of AI Interventions

Although AI technologies have considerable potential to improve poverty alleviation programmes, their long-term sustainability depends on economic feasibility. Initial investments in digital infrastructure,

cloud computing, data centres, cybersecurity, workforce development, and regulatory systems may be substantial, particularly in LMICs with constrained public resources [6]. However, evidence suggests that appropriately designed AI systems can generate significant long-term savings through improved targeting of social protection programmes, reduced administrative costs, enhanced fraud detection, increased agricultural productivity, improved healthcare efficiency, and optimized allocation of public resources.

Consequently, governments should undertake comprehensive cost-benefit assessments before large-scale AI implementation, considering both direct financial costs and broader social returns. Public-private partnerships, international development financing, and open-source AI solutions may substantially reduce implementation costs while improving scalability and long-term sustainability.

5.5. Future research directions

Although a considerable amount of literature has been gathered, a number of research gaps have been identified. To start with, there are limited studies of the long-term effects of AI interventions. The majority of research evaluates short term results; the question remains whether the results are long-term and whether there are any unintended consequences. Second, there is limited research on the impacts of AI on gender equality, disability inclusion and intersectionality. Third, the economic sustainability of AI interventions needs to be worked on more: who funds infrastructure, what business models keep services going? Fourth, scholars ought to examine the interaction between AI and regulatory systems, especially in situations where the quality of governance is low. Fifth, there is a need for comparative studies across countries and sectors to identify which factors enable or hinder success. Lastly, computer scientists, economists, sociologists, ethicists and policy experts must engage in interdisciplinary collaboration in order to come up with holistic solutions.

6. Conclusion

With the advent of AI and BDA, a new era of possibilities to alleviate poverty and develop society has been identified. Utilising satellite, phone, financial transactions, sensors and sensor networks data, AI models can measure poverty with more timeliness and detail than ever, provide personalised services at scale, and support evidence-based policymaking. Examples of Kenya, India and Rwanda show that the combination of inclusive design and supportive policy environments with AI has the potential to transform the healthcare sector. Nevertheless, these technologies also create issues: algorithm bias, privacy issues, digital divisions, capacity gaps and ethical issues. The 4Cs framework of the World Bank emphasizes the necessity of the underlying investments in connectivity, compute, context and competency, whereas the social protection report of the OECD lays emphasis on the importance of transparency, accountability and engagement with the community.

To realise the full potential of AI to alleviate poverty, one would need to look at the whole picture. Civil society, industry and academia, and governments should come together to support the creation of strong data ecosystems, creation of ethical guidelines and development of inclusive programmes. The AI systems must be transparent, fair and accountable, with human supervision and well-developed grievance procedures. The cooperation of the international community can be used to help countries which are resource and expertise deprived. Finally, AI is not a solution, but rather a tool that is used. It needs to be combined with more comprehensive measures to empower communities, strengthen institutions, reduce inequality and enhance sustainable development. When used responsibly, AI and BDA can hasten the achievement of the Sustainable Development Goals and contribute to making the world a place where everyone can achieve their potential.

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