AD EDUXIAN JOURNAL

A Quarterly Multidisciplinary Blind Peer Reviewed & Refereed Online International Journal

Google Scholar Indexing PIF: 1.048(I2OR), 3.125 (IIFS) & 3.8(SJIF)

Vol (3), Issue (3), July-September 2026 *ISSN: 3048-7951*

Artificial Intelligence and Poverty Alleviation: A Conceptual Framework

Gundappa[1]

DOI: http://doi.org/10.5281/zenodo.22867128

Review: 29/07/2026 **Acceptance: 02/08/2026** **Publication: 21/09/2026**

Abstract: Artificial intelligence (AI) is creating new opportunities to support poverty alleviation by improving productivity, expanding financial inclusion, strengthening social-protection delivery, and improving the targeting of public support. This conceptual paper examines how AI can contribute to poverty reduction in four areas: agriculture, microfinance, social-welfare targeting, and smart subsidy distribution. In agriculture, AI-enabled analysis of satellite imagery, sensor data, and other digital information can support resource-efficient farming, crop monitoring, and risk forecasting. In microfinance, machine-learning techniques and alternative data can complement conventional approaches to credit assessment and customer service. In social protection, AI and data-integration techniques can support poverty mapping, eligibility assessment, and administrative processing. AI can also contribute to more targeted subsidy systems by linking assistance to observed needs and by supporting fraud detection. At the same time, these applications face important limitations, including data gaps, digital exclusion, algorithmic bias, privacy and governance concerns, and inadequate digital infrastructure. The paper therefore presents AI as a complementary tool rather than a standalone solution to poverty. It proposes a conceptual pathway—data → AI analysis → targeted action → poverty outcomes—and highlights the need for transparent governance, human oversight, inclusive digital infrastructure, and empirical evaluation.

Keywords: Artificial intelligence; poverty alleviation; financial inclusion; precision agriculture; social protection; smart subsidies; digital divide.

1. AI in Agriculture: AI-based precision agriculture is creating new ways for smallholder farmers to improve resource management and respond to production risks. The combination of Internet of Things (IoT) sensors, drones, satellite imagery, and AI-based analytics can support decisions concerning irrigation, fertilizer use, pest management, and crop monitoring. Alawode et al. (2024) describe how soil sensors, drones, and satellite-imaging systems can generate timely information that, when combined with AI analytics, supports forecasting, irrigation management, and pest control. The World Bank also highlights applications of AI in crop monitoring, disease detection, predictive analytics, and resource optimization (Jenane, 2025). AI-based computer-vision systems can assist in identifying crop diseases from images, while predictive models can support yield and weather-risk assessment. These applications may reduce input waste, improve the timeliness of farm decisions, and help farmers respond to climate-related risks. However, the benefits depend on the availability and quality of data, connectivity, affordability, and farmers' ability to use digital tools.

Key applications of AI in agriculture include:

Efficient resource use: AI can analyse information on soil conditions, moisture, weather, and crop status to support more efficient use of water, fertilizers, and other inputs (Alawode et al., 2024; Jenane, 2025).

[1] M.A. Economics (2019–2021), Department of Economics, Central University of Karnataka, Kadaganchi, Alan Road, Kalaburagi, 5858-367, India

1. **Yield and risk forecasting:** Satellite imagery and other spatial data can be combined with machine-learning models to estimate crop conditions and identify potential production risks. Early-warning information can support timely responses to drought, pests, and adverse weather (Jenane, 2025).
2. **Supply-chain and market linkages:** Digital platforms can use data and AI to improve logistics, market information, and connections between farmers and buyers. The World Bank describes AI-enabled agricultural applications that can improve market and service access for smallholders (Jenane, 2025).

AI has also been discussed in relation to agricultural subsidy administration. Alawode et al. (2024) describe a model in which soil testing, digital farmer information, IoT, and geospatial analysis could support more targeted allocation of agricultural inputs and subsidies. The authors report reductions in fertilizer input costs of up to 15% in the settings discussed and describe the potential for automated verification to reduce fraudulent claims. These findings should be interpreted as evidence and proposals reported by the cited study rather than as a general causal estimate applicable to all agricultural subsidy programmes.

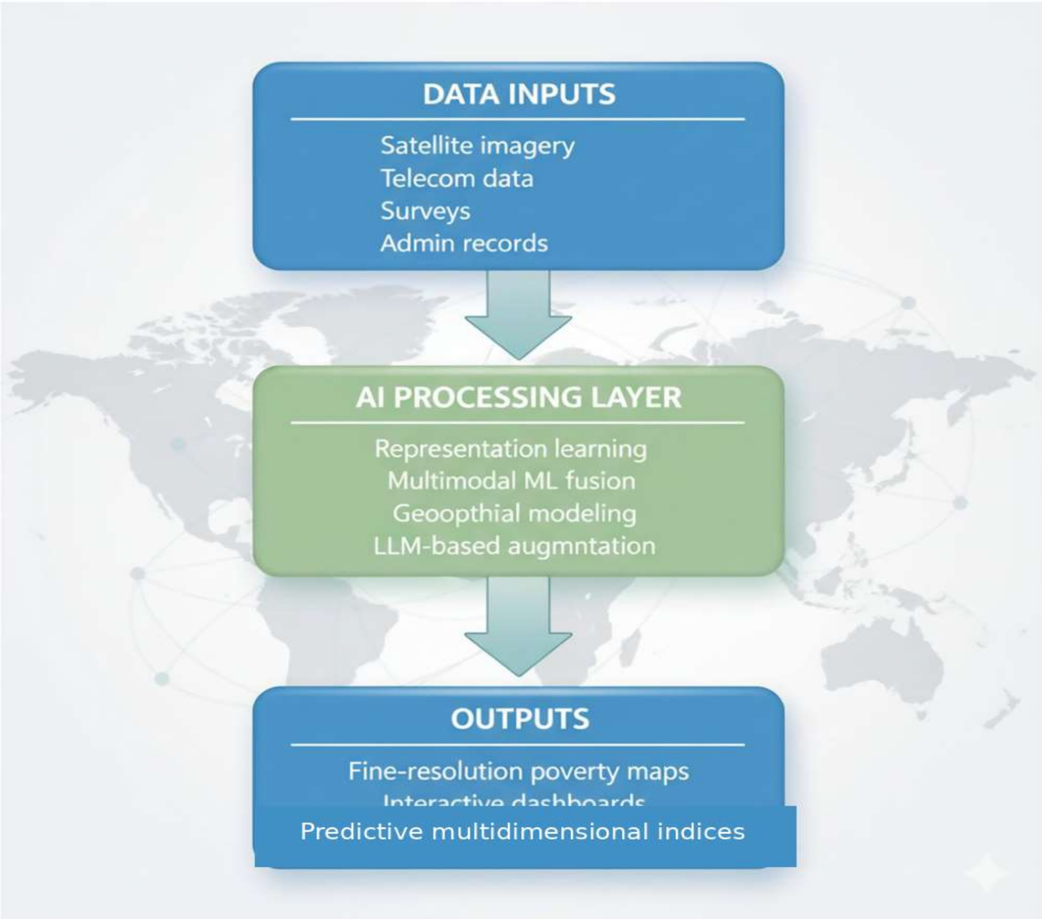

Figure 1. *Conceptual AI-enabled poverty-mapping framework using satellite imagery, telecom data, surveys, and administrative records.*

The framework in Figure 1 illustrates how multiple data sources can feed into an AI processing layer and generate outputs such as fine-resolution poverty maps, interactive dashboards, and multidimensional poverty indicators. Similar approaches are discussed by George and Rupa (2026), who propose combining satellite, telecom, survey, and administrative data with representation learning, multimodal machine learning, geospatial analysis, and other AI techniques for multidimensional poverty mapping.

2. AI in Microfinance: AI can contribute to financial inclusion by supporting the assessment of creditworthiness for borrowers who have limited or no conventional credit histories. Traditional credit-scoring systems often rely on established financial records. AI-based approaches can analyse additional information, where legally and ethically appropriate, to complement conventional credit assessment (Kothandapani, 2022).

Kothandapani (2022) discusses the use of alternative and complex data sources in AI-enabled credit assessment for people without established credit profiles. Such approaches may help financial institutions evaluate applicants who would otherwise be difficult to assess. However, alternative-data models also create risks related to privacy, data quality, discrimination, and transparency and therefore require appropriate safeguards.

AI can also support operational functions in microfinance. Cherian and Kumar (2025) document the use of AI-related tools at ESAF Bank, including chatbots, predictive analytics, and automated credit-scoring applications, with potential benefits for customer engagement, operational efficiency, and risk management. These applications can reduce routine administrative burdens and improve access to information, including through digital customer-service channels.

Major AI applications in microfinance include:

1) **Alternative credit scoring:** Machine-learning models can analyse additional information to complement conventional credit histories and support assessment of applicants with limited formal financial records (Kothandapani, 2022).
2) **Personalized financial services:** Chatbots and digital advisory tools can provide information about savings, budgeting, and loan applications and can extend customer support beyond normal branch hours (Cherian & Kumar, 2025).
3) **Operational efficiency:** AI can support routine processes such as document handling, customer support, fraud detection, and risk assessment, potentially reducing administrative costs (Cherian & Kumar, 2025).

3. AI in Social-Welfare Targeting: AI and data-integration techniques can support social-protection systems by improving poverty mapping, eligibility assessment, and administrative processing. Conventional targeting systems may rely on information that is incomplete, outdated, or difficult to integrate. AI can process large and heterogeneous datasets, including spatial and administrative information, to support more timely analysis.

Jung et al. (2025) demonstrate how community-informed spatial features, household survey information, satellite imagery, and connectivity measures can be combined with machine-learning methods to predict welfare outcomes in Lusaka, Zambia. Their study reports that the combined approach explained 67.1% of the variance in asset-based wealth scores and improved the targeting potential of social transfers. The authors also note that predicting food insecurity and nutritional outcomes is more challenging than predicting asset-based wealth. This evidence supports the value of combining local knowledge with spatial and household-level data rather than relying on automated models alone.

George and Rupa (2026) similarly propose AI-enabled poverty mapping using satellite imagery, telecom data, household surveys, and administrative data. Their framework is designed to generate fine-resolution and multidimensional poverty indicators. Such approaches may help governments identify geographic concentrations of deprivation and improve the design and monitoring of social-protection interventions.

The OECD (2025) documents AI use cases in social security, including automated eligibility support for energy-poverty benefits in Catalonia and machine-learning-based document classification by the German Federal Employment Agency. These examples show that AI can reduce administrative burdens and support access to benefits, but they also demonstrate the importance of data interoperability, legal safeguards, human oversight, and institutional capacity.

Key applications in welfare targeting include:

1. **Poverty mapping and identification:** AI can combine spatial, survey, telecom, and administrative information to identify areas and populations experiencing different forms of deprivation (George & Rupa, 2026; Jung et al., 2025).
2. **Automated eligibility support:** Algorithms can assist with checking applicant information against programme rules and can reduce repetitive administrative work, while final decisions may still require human oversight (OECD, 2025).
3. **Policy and programme monitoring:** AI-based analysis can help identify gaps in programme coverage, patterns of non-take-up, and areas where social-protection interventions may require further attention (OECD, 2025).

Smart Subsidy Distribution: AI can support more targeted subsidy administration by helping governments match assistance with observable needs, verify eligibility, and identify anomalous or potentially fraudulent claims. Digital identification, geospatial information, and data integration can make subsidy systems more responsive, although such systems also create risks if data are inaccurate or if automated decisions are not subject to review.

In agriculture, Alawode et al. (2024) discuss the potential for AI, IoT, geospatial information, and soil testing to support more targeted fertilizer and input assistance. In a broader supply-chain context, Zheng and Zhao (2025) examine how government subsidies affect the adoption of AI in a dual-channel fresh-produce supply chain. Their modelling results indicate that the effects of subsidies depend on factors such as AI costs, spillover effects, market competition, and the subsidy ratio. The study therefore suggests that subsidy design matters and that excessive subsidies may reduce fiscal efficiency.

Important features of smart subsidy systems include:

A. **Targeted and calibrated support:** Data-driven systems can potentially tailor assistance to observed needs rather than applying identical support levels to all beneficiaries.
B. **Fraud and anomaly detection:** AI can compare information across datasets to flag duplicate, inconsistent, or otherwise suspicious claims for further review.
C. **Real-time monitoring:** Satellite, IoT, and administrative data can support more frequent monitoring than systems based only on periodic manual reporting.

5. Challenges and Limitations: The potential of AI for poverty alleviation should not be separated from its limitations. First, data availability and data quality are major constraints. Remote and poor communities may have limited digital connectivity and may generate fewer digital records. George and Rupa (2026) describe this problem in terms of digital deprivation and data gaps, while Jenane (2025) highlights connectivity, skills, cost, and data-governance barriers in agricultural applications.

Second, the digital divide can reinforce existing inequalities. People without reliable internet access, smartphones, digital skills, or formal digital identities may be less able to benefit from AI-enabled services. Automated eligibility systems can also produce exclusion if data are missing or if individual circumstances are not captured adequately. Human review and accessible appeal mechanisms are therefore important safeguards.

Third, algorithmic bias and privacy risks require careful governance. Kothandapani (2022) highlights the possibility that biased training data can contribute to biased credit decisions. Similar concerns arise in welfare targeting and public-service delivery. AI systems should therefore be subject to transparency, data-protection rules, monitoring, and appropriate human oversight.

Finally, AI is not a standalone solution to poverty. Electricity, internet connectivity, institutional capacity, education, health services, employment opportunities, and social-protection systems remain essential. AI should complement these broader development interventions rather than be treated as a substitute for them.

6. Conclusion: AI offers several potential pathways for supporting poverty alleviation. In agriculture, it can improve resource management, crop monitoring, and risk assessment. In microfinance, it can complement conventional credit assessment and improve customer-service processes. In social protection, AI can support poverty mapping, eligibility assessment, and administrative processing. In subsidy systems, it can contribute to more targeted allocation, anomaly detection, and monitoring.

The conceptual framework developed in this paper can be summarized as: Data → AI analysis → Targeted action → Poverty outcomes. Satellite imagery, telecom information, IoT data, surveys, and administrative records can be processed to generate information such as yield forecasts, credit assessments, poverty maps, and eligibility indicators. These outputs can then inform policy and programme implementation. However, the quality of outcomes depends on data quality, institutional capacity, inclusive access, transparency, and human oversight.

Future research should move beyond conceptual discussion and evaluate AI-enabled poverty interventions using rigorous empirical designs, including comparative studies and, where feasible, randomized or quasi-experimental evaluations. Such research can help determine whether improvements in prediction or administrative efficiency translate into measurable improvements in income, consumption, financial inclusion, food security, or access to social protection. AI can strengthen anti-poverty programmes, but its contribution should be judged by transparent evidence and inclusive outcomes.

References

Alawode, A., Blessing, A. O., & Chiamaka, O. T. (2024). Integrating IoT and AI in sustainable agriculture to mitigate environmental risk and financial misuse. International Journal of Research Publication and Reviews, 5(12), 2810–2828. https://doi.org/10.55248/gengpi.6.0625.2187

Cherian, A., & Kumar, A. T. T. (2025). Artificial intelligence in microfinance: Enhancing customer experience at ESAF Bank. NPRC Journal of Multidisciplinary Research, 2(3), 164–171. https://doi.org/10.3126/nprcjmr.v2i3.76970

George, A. M., & Rupa, R. (2026). Reconceptualizing poverty in the digital era: AI-enabled mapping and the SDG 1 agenda. Frontiers in Sustainable Cities, 7, 1728240. https://doi.org/10.3389/frsus.2026.1728240

Jenane, C. (2025, March 12). Is artificial intelligence the future of farming? Exploring opportunities and challenges in Sub-Saharan Africa. World Bank Blogs. https://blogs.worldbank.org/en/agfood/artificial-intelligence-in-the-future-of-sub-saharan-africa-far

Jung, W., Stoeffler, Q., Kim, A. H., Goudarzi, S., Benotsmane, R., & Shah, V. (2025). Targeting urban poverty and food insecurity: A community-informed spatial analysis and machine learning approach. Sustainable Cities and Society, 134, 106799. https://doi.org/10.1016/j.scs.2025.106799

Kothandapani, H. P. (2022). Leveraging AI for credit scoring and financial inclusion in emerging markets. World Journal of Advanced Research and Reviews, 15(3), 526–539. https://doi.org/10.30574/wjarr.2022.15.3.0904

OECD. (2025). Harnessing artificial intelligence in social security: Use cases, governance and workforce readiness. OECD Digital Government Studies. OECD Publishing. https://doi.org/10.1787/b52405c1-en

Zheng, Q., & Zhao, P. (2025). Impacts of AI technology and government subsidy on a dual-channel fresh produce supply chain with loss-reduction. Journal of Industrial and Management Optimization, 21(12), 6984–7020. https://doi.org/10.3934/jimo.2025157