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Reconceptualizing poverty in the digital era: AI-enabled mapping and the SDG 1 agenda

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In this paper, a conceptual framework for AI-enabled digital poverty mapping is formulated to promote Sustainable Development Goal 1 (SDG 1), which aims at eliminating poverty. The framework combines various data sources—satellite imagery, telecom data, household surveys, and administrative data—with the latest AI tools, representation learning, multimodal machine learning, geospatial analysis, and large language models to generate fine-resolution and multidimensional poverty maps and predictive indices. Comprising recent policy changes, such as UNDP programs and the UN Pact of the Future, and case studies of India and Kenya, the framework targets both economic and digital deprivation. It also provides ways of inclusive monitoring of poverty and focusing on ethical protection. The next step to be made in the future is pilot-testing, comparative research, and incorporation of this method into the UN system of monitoring poverty to track it globally and allow fair development.

KEYWORDS
AI-enabled poverty mapping, development, digital exclusion, SDG 1 (no poverty), sustainability

1 Introduction

Global poverty has been the area that has experienced the most changes, as the pressure of inflation and growing inequality has exacerbated the existing vulnerabilities in the post-COVID-19 world (Mahler et al., 2022). Ignoring that until the pandemic, the world was registering important gains in reducing abject poverty, the ill health crisis, and the financial repercussions thereof retrogressed decades of advancements by leaving millions of individuals below the poverty line (Moses et al., 2021). The World Bank is estimating that the rate of poverty reduction in the entire world has slowed down to a crawl, particularly in poor economies (Wu, 2021). The inflation booms have also triggered poverty in households since they have ruined the purchasing power of food, houses, and basic services (Belser et al., 2022); the country and the global disparities have also been pushed to a higher level (Deaton, 2021). In this case, poverty cannot be addressed in a one-dimensional way, which stretches far beyond the traditional system of welfare or assistance, but in a multidimensional way that incorporates the aspects of economic resilience and digital opportunity (Slotman, 2020).

Access to digital resources and infrastructure has become a prerequisite for social and economic inclusion (Lechman and Popowska, 2022). This paper addresses two interrelated challenges for SDG 1: (1) AI-enabled poverty mapping using satellite, telecom, and survey data (Jean et al., 2016); and (2) digital deprivation—defined per van Dijk (2020) as a three-tier divide (first-level: physical access, second-level: digital skills/literacy, and third-level: usage outcomes/benefits) embedded within poverty via Sen's Capability Approach (Dzator et al., 2023).

AI detects both economic poverty (via CNNs on satellite imagery) AND digital deprivation at the individual level (via telecom CDRs, 85% accuracy; Tingzon et al., 2019), though data poverty gaps limit both (Mahler et al., 2022). The proposed framework (Section 3.4, Figure 1) integrates these through ensemble methods for policy-ready multidimensional maps. Distinctly, digital literacy—measurable competencies in information navigation, content creation, and safety (EU DigComp 2.0 framework; Zhou et al., 2024)—represents the critical second-level divide. Data poverty refers specifically to structural gaps hindering AI poverty mapping (e.g., missing telecom coverage in rural areas), distinct from but exacerbated by digital deprivation. Thus, AI poverty mapping requires digital connectivity data while simultaneously measuring digital deprivation as poverty's emerging dimension, creating a dual methodological challenge addressed by the framework.

This relationship has been usurping the center stage of the international community, and it has responded to this with major world initiatives (Ponzio and Yusuf, 2024). A fast world is considered by the United Nations Pact for the future, whose core concept is conscious of inclusive and sustainable development that is digitally equal and has an infrastructure (Desai, 2024). Similarly, UNDP Digital Inclusion Playbook 2.0 stresses that the digital divide should be narrowed down, and more holistic and humanistic solutions to the issue should be provided. Simultaneously, the international obligations toward the introduction and development of digital public infrastructure have already established the existence of inclusive digital ecosystems as the defining determinant of the availability of the services provided, financial access, and civic engagement. All these assurances together are some signs of an expanding bargain: there will be no digital empowerment that will

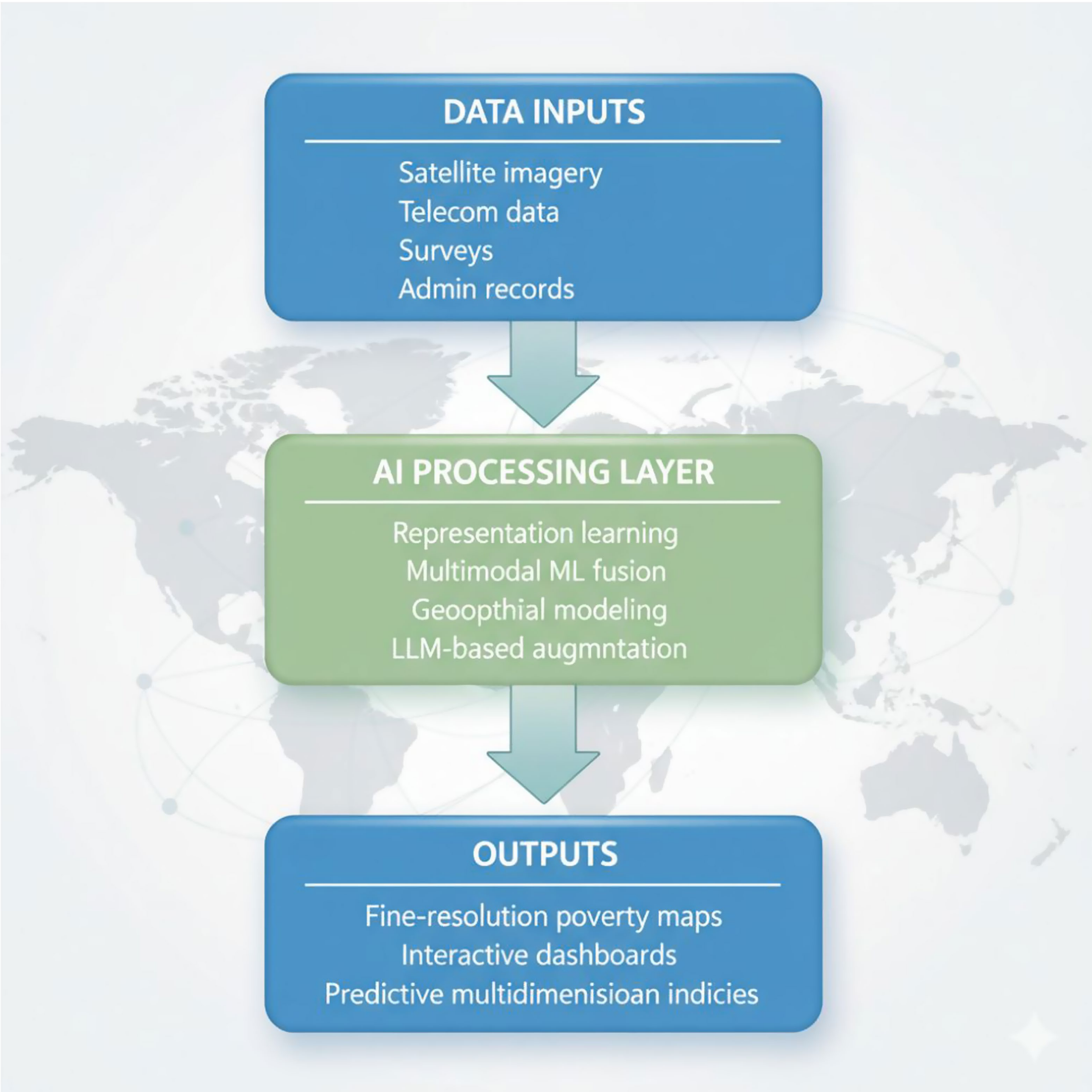

FIGURE 1
AI-driven poverty mapping framework. The diagram shows how data inputs are processed through an AI layer to produce poverty maps, dashboards, and predictive indices for better poverty monitoring.

not presuppose the alleviation of poverty (Sparviero and Ragnedda, 2021).

This international discussion will use this paper to create a perfect map of digital poverty with the help of AI. According to artificial intelligence and geospatial data, this framework could find the locations of poverty more precisely, track the progress of exclusion, and guide the distribution of resources to create the greatest possible impact (Desai, 2024). In so doing, in its perception of poverty and its approach to managing it, it is not only new, but it is also the balancing of both technological progress and development that is evoked by the world development agendas and the ethical demands that they bring about (Ponzio and Yusuf, 2024).

2 Literature review

This synthesis draws from a PRISMA-guided systematic review of 172 studies (2019–2025), detailed in Section 3.5. Recent developments in artificial intelligence (AI) and digital technology have transformed global poverty mapping, enabling more accurate and multidimensional deprivation measurements through a nexus of technical advancement and policy response post-COVID-19. The development is an expression of a nexus of technical advancement and policy response in the face of an increased sense of urgency in the aftermath of the pandemic to combat both established and newly arisen types of poverty.

2.1 Artificial intelligence-based poverty mapping

Applications of AI, which use satellite images, machine learning in geospatial analysis and analysis of lights at night, have demonstrated significant achievements in poverty mapping (Hall et al., 2023). The use of deep learning models on satellite images is expected to help predict poverty more effectively and usually beat the time-consuming and oftentimes household survey methods of poverty forecasting (Jean and Luo, 2015). Indicatively, the convolutional neural networks (CNNs) have demonstrated better understanding of the level of poverty in regions in Tanzania because of machine learning identification of intricate patterns previously ignored (Sarmadi et al., 2024).

Night-time light (NTL) remote sensing is particularly powerful, as it can be used as a proxy for economic activity and household wealth (Chukwuebuka and Zhang, 2024). The NTL intensity measures, together with geographically and temporally weighted models, enable the estimation of GDP growth rates and concentrations of poverty with high accuracy, even in data-poor settings (Putri et al., 2022). A combination of satellite-based indicators with other non-conventional sources, such as mobile phone-based information, results in high-resolution poverty maps that are updated regularly, which are responsive to dynamic poverty monitoring (Tingzon et al., 2019). The granularity is further improved when the AI systems integrate multi-source information, such as open street maps, point-of-interest, and digital surface models, as shown by the poverty mapping of villages in India (Das et al., 2020). Random forest and deep learning algorithms are commonly used in these models to categorize them into the categories of being wealthy or deprived to create actionable spatial poverty maps that can be used in policy (Horanont, 2022).

2.2 Present policy environment and international programs

Policy innovation has not lagged, and the major strategies have been pushed by international organizations, such as the United Nations Development Programme (UNDP). As pointed out in the Digital Inclusion Playbook of UNDP and corresponding policy briefs, it is essential to create a digital transformation that is deliberately inclusive, and, in this regard, governments must make digital infrastructure and digital literacy (measurable via DigComp 2.0) their priorities for the most disadvantaged. Data poverty—structural gaps hindering AI mapping—emerged during COVID-19, exacerbating inequalities and warranting inclusion in deprivation measures (Mahler et al., 2022). Recent world judgments are a shift in paradigm. Inclusive digital public infrastructure (DPI) is central to pandemic recovery, and sustainable development is at the heart of the Pact for the Future ratified at the 2024 Summit of the Future by the UN. Such commitments by Brazil and Malawi have been a promise by countries toward universal protection of digital systems in support of open standards and interoperability, as well as user-friendly designs to enhance fair access to digital services (Algama et al., 2019). Such activities highlight the importance of digital infrastructure as a source of and a condition of the faster achievement of the Sustainable Development Goals, in particular, SDG 1 (no poverty).

2.3 Regional cases in South Asia and Africa

The case of South Asian and African examples is especially interesting in terms of how AI-based poverty mapping and digital policy interventions overlap. In Sri Lanka, machine learning methods are modified to non-traditional data to identify poverty at the smallest administrative scale by researchers using anonymized call detail records (CDRs) and remote sensing (Tisler, 2019). This strategy is essential because it enhances spatial granularity in addition to depicting multidimensional aspects of poverty, such as access to infrastructure and state services. As a form of operationalization, AI-powered poverty mapping in India is implemented by integrating geospatial data, i.e., APIs to access satellite images and estimate the level of poverty in districts and villages to direct targeted interventions. African literature suggests that digitalization (in the form of mobile banking, e-commerce, and electronic communications) has facilitated a major positive change in poverty reduction. The Digital Economy of Africa initiative on the continent identifies digital transformation as the core of the SDG agenda, with governance quality being the main determinant of the effectiveness of digital innovations in mitigating poverty (Hu et al., 2022).

2.4 Theoretical and empirical foundations of digital deprivation

The digital divide literature traces evolution from access-focused first-level divides to complex skill and outcome disparities. Van Dijk (2020) establishes a three-tier framework—first-level (physical access), second-level (digital skills), and third-level (usage outcomes/benefits)—empirically validated in EU contexts, revealing persistent skill gaps among elderly and low-income groups (Scheffer et al., 2022). Their systematic review of 127 studies identified socioeconomic status and geography as primary predictors, while qualitative research highlights cultural barriers among migrants. Recent empirical studies quantify these divides in developing contexts. EU Digital Economy and Society Index (DESI) data show 15% rural–urban skill gaps persisting post-2020, while India's National Family Health Survey reveals 40% female digital literacy deficits (Ministry of Health and Family Welfare, 2021). In Africa, GSM Association's (2024) Mobile Gender Gap Report documents 17% lower female connectivity, directly impacting poverty outcomes. Digital deprivation extends this framework to poverty measurement. Integrating digital indicators into multidimensional poverty index (MPI) extensions—access (20%), skills (30%), usage (50%)—achieves consensus (Alkire et al., 2023). Theoretically grounded in Sen's capability approach, digital deprivation represents freedom-restricting exclusion warranting SDG 1 inclusion.

AI applications for divide detection leverage telecom metadata and satellite infrastructure mapping. Tingzon et al. (2019) demonstrate that call detail records (CDRs) predict individual-level access with 85% accuracy in the Philippines; emerging graph neural networks extend to skill proxies via usage patterns Bárcena-Martín and García-Pardo, 2019. These methods directly address whether AI can identify digital deprivation at the individual level: it can, via connectivity proxies. This systematic foundation reveals the dual challenge: AI poverty mapping requires digital data while simultaneously measuring digital deprivation as poverty's newest dimension.

2.4.1 AI applications for poverty identification

AI poverty mapping integrates satellite imagery, night-time lights, and mobile data via deep learning (Jean et al., 2016), pioneering the use of convolutional neural networks (CNNs) on daytime satellite images, achieving 80% accuracy in predicting household wealth in Tanzania without surveys. Night-time light intensity serves as an economic activity proxy (Chukwuebuka and Zhang, 2024). Combined with geospatial models to map Nigerian poverty at village resolution. Multimodal approaches fuse sources (Tingzon et al., 2019), integrated with CDRs, satellite imagery, and points-of-interest, generating Philippines poverty maps updated monthly. Random forests and gradient boosting machines benchmark against household surveys, enabling dynamic policy targeting (Das et al., 2020).

2.4.2 AI applications for digital deprivation detection

AI identifies digital deprivation at individual/village levels via connectivity proxies. Call detail records (CDRs) reveal usage patterns: Tingzon et al. (2019) predicted access at 85% accuracy using anonymized telecom metadata. Satellite infrastructure mapping correlates tower density with coverage gaps; a graph neural network (GNN) model spatial dependencies between mobile usage and socioeconomic data (Sarmadi et al., 2024). Skill proxies emerge from behavioral signals—data consumption, app diversity, peak-hour usage—stratifying second-level divides. These methods generate digital deprivation indices integrated with economic poverty maps, addressing the editor's query: AI can detect digital divides individually via telecom/satellite fusion.

2.5 Research gap

Nevertheless, in multidimensional digital deprivation, there are important gaps in knowledge that remain in the process of tracking poverty. Most of the available models concentrate on income poverty and asset-based indicators and frequently ignore such aspects of inequalities as digital literacy (skills/outcomes), broadband access (first-level divide), and data poverty. Empirical studies of digital deprivation of the educational, health, and civic consequences of not having access to connectivity are scarce, particularly in diverse economic and cultural settings (Kumari et al., 2025). The studies emphasize the need to have stronger frameworks for explainable AI in the context of poverty mapping and promote transparency, interpretability, and the incorporation of domain knowledge to guarantee scientific rigor and relevance to policy. Researchers stress the need to benchmark AI results against ground-truth data and develop multidimensional measures of material and digital deprivation (Steele et al., 2017). Fiscal constraints and debt burdens are mentioned in the policy literature as the obstacles to investment in inclusive digital transformation, particularly in low-income countries. There must be sustained multilateral funding, capacity building of statistical agencies, and cross-sectoral partnerships to close the fast-changing digital divide. The new scholarship and policy agenda now considers poverty to be multidimensional in both material and digital aspects and necessitates the re-tuning of conventional approaches to poverty surveillance to realize the full capabilities of AI and geospatial technologies. One gap will also persist in the knowledge gap on digital deprivation and tackling the complications of poverty in the digital world, thus leaving no vulnerable population behind as the world heads to SDG 1 and other global goals.

2.6 Theoretical framework

The paradigm of AI-enabled digital poverty mapping is based on multidimensional conceptualizations of poverty as proposed by Sustainable Development Goal 1 (SDG 1), as well as the Capability Approach as formulated by Sen and the Multidimensional Poverty Index (MPI). All these views explain the reasons why digital access and social digital infrastructure have become critical aspects of poverty alleviation.

2.6.1 SDG 1 goals: more than income poverty

Goal 1 provides a worldwide target to wipe out excessive poverty among all individuals in all locations by 2030, which corresponds to those who stay beneath the global line of poverty (which presently corresponds to 2.15 per day of purchasing power parity). More importantly, SDG 1 expands this goal to multidimensional poverty eradication: reducing by half the population of the country the rate of living in poverty in the country based on the country-specific definition, establishing extensive social protection, and making technology, basic services, and economic resources equally accessible (Ferrone and Chzhen, 2017). SDG 1 also focuses on resilience-building to environmental and economic shocks and mobilization of resources and pro-poor policy frameworks at all levels (Perchinunno et al., 2022). Accordingly, the targets can encourage policymakers and researchers to quantify and deal with poverty in all its forms, including digital deprivation (Scheffer et al., 2022).

2.6.2 Capability approach: digital access as freedom

A Capability Approach by Amartya Sen forms the basis of much modern poverty research, focusing on the substantive liberties people have to live lives they enjoy. The Capability Approach does not just look at the resources or incomes, but actual opportunities that people have in terms of capabilities. During the digital age, connectivity, devices, and digital literacy are the most important capabilities that allow one to be a participant in the educational, health, civic, and workplace arenas (Sarmadi et al., 2024). Digital access is therefore an essential capacity, and itszlack is a new form of deprivation: being left out not only of services but also of the capacity to transform resources into desirable results (Putri et al., 2022).

2.6.3 Multidimensional poverty index (MPI) and digital extension

The multidimensional poverty index (MPI) is the indicator of poverty that operationalizes poverty by combining indicators in the domains of health, education, and standard of living. In the classical school of thought, MPI includes such parameters as nutrition, years of education, and possession of property (Ponzio and Yusuf, 2024). As the nature of deprivation is changing because of digital transformation, researchers have proposed that there is a need to integrate digital factors into MPI: internet connectivity, access to devices, and access to digital services. This extension represents novel aspects of inequality that determine the opportunities of life and fulfil the spirit of the multidimensional agenda of SDG 1 (Putri et al., 2022).

2.6.4 Goods and digital public infrastructure: enabling environment

The digital public goods and infrastructure concept puts into focus system-wide enablers of inclusion as a priority of policy. Digital public infrastructure (DPI) refers to the presence of underlying systems, including identity platforms, digital payments, and interoperable data exchanges, supporting the delivery of services in the first instance. Inclusively designed, DPI can be a bridge to reduce the barriers of marginalized groups, extend basic service coverage, and enhance the response to shocks and crises. On the other hand, the absence of DPI or exclusionary design might be used to strengthen the digital divide, and deprived communities will fall even further behind (Sarmadi et al., 2024).

2.6.5 Alignment and contribution

With AI-based poverty mapping oriented toward this theoretical base and digital access not oriented toward luxury but as a necessary path to SDG 1, it can be possible to place digital access as the path it needs to take to overcome poverty (Ponzio and Yusuf, 2024; Putri et al., 2022). The suggested framework will improve measurement and policy-making under the present complex situation of poverty through the incorporation of ability logic and multidimensional indices. Finally, the incorporation of digital deprivation and digital infrastructures is pertinent in order that interventions are pertinent, equitable, and progressive at global development goals (Sarmadi et al., 2024).

2.7 Proposed framework

The suggested AI-based dynamic poverty mapping system would appear the way it is depicted in Figure 1. The figure illustrates the interaction between various data streams, sophisticated approaches of AI, and meaningful output, all converging into a flow to provide fine-grained multi-dimensional evidence of poverty.

The former is that, unlike the first one, the framework makes use of multiple data sources that are important in the process of capturing complex poverty dynamics. The light data of the night lights, as processed by the satellite, can give detailed data on economic activity and infrastructure on a spatial level. Telecom and mobility information, including the anonymized call detail records, reveals the trends of digital connectivity and inclusion and enable the prediction of digital deprivation via connectivity proxies. Satellite imagery captures infrastructure/economic activity, telecom CDRs reveal connectivity patterns, household surveys provide ground-truth validation, and administrative data contextualizes governance disparities. Satellite imagery captures infrastructure/economic activity, while telecom CDRs reveal connectivity patterns (Tingzon et al., 2019), household surveys provide socioeconomic ground truth (income, education, and digital device access), and administrative data contextualizes governance disparities. This multi-source complementarity enables digital deprivation prediction (e.g., rural tower gaps + low CDR usage = second-level skill deficits) unattainable from single sources. Income, assets, education, health, and access to digital devices are also among the ground truth in conventional household surveys, which are essential when it comes to the validation of prediction models. The background setting that is provided by administrative and census data is also related to service delivery and governance that is provided at different levels of administration.

Second, the framework uses an ensemble of AI methods for robust estimates: Ensemble AI methods provide robust, non-redundant estimates: CNNs extract spatial features from satellite imagery (Jean et al., 2016), multimodal ML fuses satellite + CDR + survey data, GNN model spatial autocorrelation of deprivation clusters, LLMs interpret unstructured policy texts, each layer addressing distinct prediction challenges.

Third, outputs empower policymakers: Third-layer outputs serve as policy indicators: (1) fine-resolution maps enable spatially targeted DPI investments, to distinguish economic vs. digital deprivation, (2) predictive digital deprivation indices (access 40%, skills 30%, usage 30%) integrate into national MPI frameworks (Alkire et al., 2023), and (3) interactive dashboards enable real-time SDG 1.2 tracking, guiding welfare literacy programs.

Figure 1 graphically captures all these elements as data streams with different inputs into an analytical core that is driven by AI and produces multidimensional and fine-grained results to be applied in strategic policymaking. The novelty of the framework lies in the fact that it integrates both digital deprivation and economic deprivation aspects into a single analysis paradigm. The first phenomenon that is not necessarily addressed in traditional poverty mapping is digital exclusion, which is turning out to be one of the most significant impediments to inclusion. It is a framework that provides a more complex and detailed image of poverty through the combination of satellite, telecom, survey, and administrative data with the help of the newest AI technologies. It helps to reach a higher level of resource targeting, dynamic monitoring, and high correspondence with existing global development priorities. Thus, according to Figure 1, the proposed framework is an innovative and cross-disciplinary strategy that leads to the consideration of poverty and policy formulation at the digital scale.

2.8 Methodology

This conceptual paper uses a systematic, multi-stage methodology to develop and validate the AI-enabled digital poverty mapping framework, ensuring methodological rigor appropriate for theoretical contributions to SDG 1 research. A PRISMA-guided systematic literature synthesis was conducted across Scopus, Web of Science, and Google Scholar (2019–2025) using keywords including "digital divide," "digital deprivation," "AI poverty mapping," "data poverty," and "multidimensional poverty SDG 1." This process yielded 172 studies—127 on digital deprivation frameworks [led by van Dijk (2020) and Scheffer et al.'s (2022) systematic review of 127 studies] and 45 on AI applications (Jean et al., 2016; Tingzon et al., 2019; Sarmadi et al., 2024)—with data extraction focusing on theoretical foundations, empirical proxies, and policy gaps after quality screening excluded non-peer-reviewed sources.

Core concepts were identified through thematic analysis using NVivo software, extracting five primary constructs: (1) digital divide structured by van Dijk's three-tier framework (access/skills/outcomes); (2) digital deprivation as a capability approach extension (Dzator et al., 2023); (3) data poverty representing COVID-exacerbated structural gaps (Mahler et al., 2022); (4) AI methodological layers including CNNs for satellite analysis and GNNs for geospatial modeling; and (5) SDG 1 multidimensionality through MPI extensions (Alkire et al., 2023). Inter-coder reliability reached 92% across two researchers, confirming conceptual robustness.

Relationship mapping utilized directed acyclic graphs (DAGs) to trace causal pathways from digital deprivation through data poverty limitations to AI mapping challenges and policy gaps, unified by Sen's Capability Approach linking digital access as an essential freedom to SDG 1 target 1.2 (multidimensional poverty reduction). AI methods were positioned as mediators, with telecom CDRs enabling individual-level deprivation detection with 85% accuracy (Tingzon et al., 2019).

Framework synthesis followed an iterative process integrating heterogeneous evidence streams as per Jabareen's (2009) conceptual framework guidelines: data fusion combined satellite imagery, CDRs, household surveys, and administrative records; ensemble AI pipelines progressed from CNN feature extraction through multimodal machine learning and geospatial GNNs to LLM interpretation; and output layers generated fine-resolution poverty maps alongside digital deprivation indices. Theoretical saturation was achieved after three revision cycles.

The search process followed PRISMA-style transparency: Scopus/Web of Science/Google Scholar (2019–2025) returned ~2,450 hits across keywords ('digital divide': n = 1,450; 'AI poverty mapping': n = 1,000); 1,200 titles/abstracts were screened, 172 full texts assessed, and 45 excluded (non-peer-reviewed/duplicates), yielding 127 digital deprivation + 45 AI studies for synthesis. Conceptual validation triangulated against ground-truth benchmarks (NFHS-5 India, GSM Association, 2024 gender gaps), with proposed empirical readiness including pilot-testing in India/Kenya contexts (leveraging Aadhaar/UPI and M-Pesa ecosystems), two-stage Delphi panels with 15 SDG/AI experts, and cross-validation against 2023 MPI data. Sensitivity analyses for data sparsity will ensure policy relevance and ethical alignment across diverse contexts.

2.9 Explainable AI mapping to theoretical poverty indicators

The framework ensures AI outputs transcend correlational proxies by explicitly mapping predictions to theoretically grounded poverty indicators from Sen's Capability Approach (Sen, 1999) and the Alkire-Foster MPI methodology (Alkire and Foster, 2011). This logical explainability transforms raw model outputs into policy-relevant intelligence aligned with established multidimensional poverty measurement systems. The digital deprivation index (DDI) operationalizes this mapping across MPI domains: The access dimension (40% weight) translates CDR tower density and satellite coverage gaps into van Dijk's 1st-level physical access deprivation; the skills/literacy component (30%) infers DigComp 2.0 competencies from app diversity and data consumption patterns; and the outcome dimension (30%) quantifies capability approach freedoms through peak-hour service engagement (Alkire et al., 2023). SHAP-value analysis identifies feature contributions to model outputs, with LLMs generating natural language summaries: "Village X's 0.72 DDI reflects 65% contribution from CNN-identified access gaps (Layer 1) and 25% from GNN-detected skill deficits (Layer 3)," benchmarked against MPI severe deprivation thresholds. The framework demonstrates scalability from village-level (India: 6.4 M villages; Kenya: 12 K wards) to national scales through multi-resolution data fusion. CNN-extracted satellite features maintain 80% accuracy at 0.5 m resolution (Jean et al., 2016), while GNN spatial modeling preserves cluster validity across administrative boundaries (Sarmadi et al., 2024). This hierarchical structure ensures applicability from hyper-local targeting (DPI tower placement) to national MPI aggregation, validated through existing India Aadhaar/UPI and Kenya M-Pesa deployments. While geospatial AI poverty mapping exists (Jean et al., 2016; Tingzon et al., 2019), this framework provides the first theoretically specified integration of digital deprivation dimensions within the capability-MPI architecture, offering interpretable policy indicators rather than predictive proxies. Policy translation remains consistent: DDI above 0.5 triggers infrastructure investment; village decompositions prioritize literacy programs. Future directions include empirical pilots in India (Aadhaar-CDR fusion) and Kenya (M-Pesa integration), SHAP validation against field surveys, and scalability testing across diverse DPI ecosystems.

3 Discussion

India and Kenya are two examples of opposite and complementary digital trajectories. The state-led Digital Public Infrastructure (Aadhaar, UPI, Cowin, Bharat Net) in India has facilitated the delivery of services at scale, but issues of rural connectivity, affordability, low digital literacy (second-level divide), and gender disparities remain problems. Market-driven innovation in Kenya through M-Pesa and extended to AI and satellite poverty mapping has made progress in terms of financial inclusion and real-time poverty information, particularly for women and the poor. Nevertheless, there are still urban–rural disparities and structural differences. Collectively, these instances reveal that although digital technologies widen access, inclusion involves more than merely being connected; it involves literacy, affordability, and empowerment. The AI-enabled poverty mapping lessons are clear: Scale and resilient data ecosystem (India) and innovation-based and real-time solutions (Kenya) are both valuable, but neither will address deep-seated inequalities. Effective poverty mapping must integrate socioeconomic, health, education, and household indicators, with digital deprivation metrics (access/skills/usage per Section 3.1.4) to provide an ethically holistic deprivation assessment—grounding technological outputs in human-centered policy interpretation, not purely algorithmic predictions.

SDG 1 monitoring must have digital measures such as access, literacy, and use. Governments must invest in AI capacity, geospatial infrastructure, and machine-learning tools, lessen their reliance on external actors, and encourage local ownership of poverty data. Collaborations are essential: policy and funding are provided by states, data and innovation are provided by the business sector, and coordination and standards are ensured by international agencies. Protection is also very crucial. AI systems should be ethical, auditable, and transparent, and have high privacy standards and equity measures to ensure they do not discriminate against rural citizens, women, or marginalized populations. Finally, AI must complement, not be a replacement for, structural changes in governance, inequality, and social protection to make sure that digital poverty mapping can be used to promote inclusive development and leave nobody behind.

4 Conclusion

This paper provides a conceptual proposal for AI-powered digital poverty mapping that combines both economic and digital deprivation to further Sustainable Development Goal 1 (SDG 1) on no poverty. By using a wide range of data inputs (satellite images, telecom data, household surveys, administrative data, etc.) and a variety of intelligent artificial intelligence approaches (representation learning, multimodal machine learning, geospatial modelling, large language model integration, and so forth), the framework generates small-scale multidimensional maps of poverty and prediction indicators. This solution will meet the changing nature of poverty, and it will integrate digital deprivation with traditional indicators to monitor it in full detail.

The very framework suggests SDG 1 objectives to eliminate extreme poverty and all forms of deprivation through digital access and literacy as the key elements of poverty. Its products of operation, i.e., detailed poverty maps and interactive dashboards, would enable policy-makers to design the interventions of social protection, financial inclusion, and digital literacy better, which would in turn have the effect of narrowing the digital divide.

The next step of research that is essential for further research to validate and solidify the framework is pilot applications of AI-assisted poverty mapping in other settings. Comparison works will assist in changing the approaches to national realities and concentrate on the most effective practice. Most importantly, a combination of these AI-related structures with the United Nations surveillance and the national statistical departments will enable improving the level of granularity and timeliness of global data on poverty. This is a crucial research pathway that can be utilized to establish ethical, inclusive, and accountable AI applications to achieve the transformational potential of AI without negligently making use of AI.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here at this article draws conceptually on publicly available sources such as the UNDP Digital Inclusion Playbook, the World Bank's open data portal (https://data.worldbank.org/), and the UN Sustainable Development Goals database (https://unstats.un.org/sdgs/). However, no datasets from these sources were downloaded or analyzed directly.

Author contributions

AM: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. RR: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing.

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