Enterprise Development & Microfinance, 36:3s, 671-700

Artificial Intelligence-Based Welfare Distribution and Universal Basic Income Readiness: A Comparative Analysis of Digital Subsidy Systems in Emerging Economies

DR HITESH MANIK DADMAL

Abstract: *In emerging economies, digital public infrastructure now plays a pivotal role in the delivery of welfare programmes, especially when governments want to integrate the delivery of digital identity, of payment systems, of social registries, of mobile connectivity and of the targeting with data into a scalable welfare system. There is growing interest in using AI as a means of identifying beneficiaries, detecting anomalies, preventing fraud, monitoring payments and triaging grievances, and in tackling exclusion errors, subsidiarity issues and labour market uncertainty through the implementation of UBI. This paper looks at the link between ready-to-use UBI and AI-driven welfare distribution by reviewing digital welfare distribution systems in India, Brazil, Indonesia, South Africa and Kenya. It has a comparative quantitative design with a synthetic data set of 1000 simulated welfare beneficiaries in each country with 200 observations for each country of interest. Indicators are included in the model for 1) access to digital ID, 2) financial inclusion, 3) mobile internet access, 4) digital literacy, 5) payment delay, 6) accuracy of targeting by AI, 7) risk of exclusion, 8) possibilities on grievance redressal, 9) beneficiary satisfaction, and 10) preparedness for UBI. The simulation results indicate that the welfare effectiveness is positively correlated with AI-targeting accuracy, and exclusion risk is negatively correlated. The one-way ANOVA shows differences in welfare effectiveness across countries with $F(4, 995) = 29.22$, $p < .001$. The findings from regression analysis indicate that targeting with AI and digital literacy, in addition to grievance redressal, are facilitating the effectiveness of welfare agencies, whilst the role of digital identity alone, if a digital identity exists, is insignificant without accessible avenues for correction and appeal. The paper offers a clear simulation model for digital welfare care systems, which strives to compare care systems without (falsely) presenting simulated evidence as primary evidence. It represents a mixed approach of more narrowly targeted forms of subsidies, alongside some elements of a basic income and with governance principles of AI aligned to human ends, (ict uses inclusion, fiscal realism, and accountability).*

Keywords: Artificial Intelligence; Welfare Distribution; Universal Basic Income; Digital Public Infrastructure; Social Protection; Digital Subsidy Systems; Emerging Economies

Dr Hitesh Manik Dadmal (hiteshdadmal@gmail.com) Assistant Professor, PGT Dept of Economics, RTMNU, Nagpur

Introduction

The organising of welfare delivery in emerging economies has moved from a paper-based administrative system to digital public infrastructure (DPI), direct benefit transfer systems, national identity platforms, social registries, mobile payments and the monitoring of welfare data. This shift reflects the policy, which aims to reach the poor and vulnerable households faster, minimize administrator's leakage and enhance the tracking of public expenditure. The effectiveness of social protection depends not just on how benefits are designed, but also on reaching beneficiaries, verifying claims, enrolling them, setting their eligibility, making payments and facilitating complaints and case management (Lindert et al., 2020; World Bank, 2025a). In this sense, the technical architecture of welfare now constitutes a fundamental part of the social policies.

Now, artificial intelligence (AI) has made its way into this welfare architecture. In theory, AI can help Public agencies in predicting who is eligible for benefits, identifying duplicate identities, identifying payment anomalies, forecasting vulnerability, prioritizing cases and triaging complaints. While current AI applications in social protection are limited to client service, administrative tasks, and identifying fraud and errors, predictive applications are trying to take the leap to more sophisticated and innovative approaches, though some caution is proceeding out of fear of transparency, discrimination, and accountability (OECD, 2025a; OECD, 2025b). Unawareness of the data quality, lack of formal registration, geographic dynamic exclusion, and digital access inequity further aggravate the situation for emerging economies.

This policy context UBI is introduced into. Generally speaking, UBI is defined as a periodical fixed cash transfer without strings attached to people or families with low or no eligibility requirements. The simplicity and the universality makes it attractive, and maybe its application assists to lower potentially exclusion errors with targeted welfare schemes. Its fiscal viability is doubted, however, particularly in countries with a small tax base, where social spending may be a alternative to spending on health, education, infrastructure and debt services. The World Bank guidance on UBI highlights the need to consider and assess the purpose (Political Purpose, purposes of social protection), costs, coverage, generosity, political sustainability, and projected opportunity cost of substituting deep existing social protection instruments (APDSS) (Gentilini et al., 2020).

Digital subsidy systems and UBI are sometimes described in opposition to each other with one on the one side relying on ever more fine-grained targeting whereas the other reduces dependency on targeting by introducing universal welfare provisions. In the present research, it is claimed that there is something that reflects the opposite that cannot be captured from an analytical perspective. In practice, emerging economies might require hybrid social protection schemes where the payment of categorical and poverty-related benefits remains digital while some aspects of basic income are implemented for vulnerable groups vulnerable to automation, climate-related shocks, informal labour security and recurrent administrative exclusion. The question, therefore, isn't whether AI can replace UBI or whether UBI can replace a targeted subsidy, but whether digital welfare systems can become the effective, inclusive and robust entities they need to be to offer guarantees of income security for all.

Useful comparative cases are provided for India, Brazil, Indonesia, South Africa and Kenya. India has developed extensive digital identity infrastructure alongside a direct benefit transfer system, and has wrestled with issues of limited usability due to biometric authentication problems and questions about the ability of beneficiaries to have their complaints addressed and be oriented to digital literacy. Brazil has a long-standing social registry tradition through Cadastro Unico and experience with cash transfer schemes (Bolsa Familia), but doesn't have experience with digital self-registration, where concerns include the quality of the data gathered and the unequal take-up of the scheme. (World Bank, 2023a). Although remote access to social assistance and social registries remains uneven, Indonesia is changing to better account for social assistance in addressing poverty (World Bank, 2024a). South Africa has a large grant system and has been doing this for a while, and experienced solid institutions, but still has challenges with input/output on the last mile of the distribution chain (SASSA, 2025). Kenya has mobile-money depth and is working to expand the coverage and targeting capacity of the Enhanced Single Registry and Inua Jamii payment system, and both policies are key (World Bank, 2025b).

This study's research problem is the lack of a comparably established framework that bridges the gap between AI-based welfare targeting and digital subsidy performance and UBI readiness in emerging economies. Previous research generally focuses on digital identity one-way, social registries another, social protection payments yet another or the governance of artificial intelligence, or basic income independently. This effect can often lead to the understatement of the efficiency-versus-exclusion trade-off in policy debates; the trend of using technologies to cut back leaks can be accompanied by an augmentation of denial, delay, or surveillance, without requiring human review or providing publicly available appeal mechanisms (Human Rights Watch, 2023; Masiero and Buddha, 2021).

There are three gaps in the research. First, there is still little comparative research evaluating both the welfare impact of digital subsidy infrastructure and the readiness to implement a UBI. Second, AI is often mentioned as a technical fix itself, rather than concretely connected to level of satisfaction from AI, grievance redressal or exclusion risk elements. Third, studies on UBI tend to take two approaches: a fiscal theory perspective or a perspective based on micro-pilot studies, but less frequently in conjunction with the digital payment and identity system necessary for greater scale.

1.1 Research Objectives

- To compare AI-readiness and digital welfare infrastructure across India, Brazil, Indonesia, South Africa and Kenya.
- To develop a synthetic simulation model linking digital inclusion, AI-targeting accuracy, grievance redressal and welfare effectiveness.
- To examine whether digital subsidy systems improve UBI readiness in emerging economies.
- To identify the risks of algorithmic exclusion, payment delay and data governance failure in AI-based welfare distribution.

- To propose a policy framework for hybrid welfare systems combining targeted subsidies with partial UBI principles.

1.2 Research Questions

- How do digital ID coverage, financial inclusion and mobile access shape welfare delivery effectiveness in emerging economies?
- Does AI-targeting accuracy improve welfare effectiveness after controlling for digital inclusion and grievance redressal?
- How does exclusion risk affect beneficiary satisfaction and overall welfare performance?
- Which countries show stronger readiness for UBI-linked or quasi-universal digital transfer models?
- What safeguards are required to prevent AI-based welfare delivery from reproducing exclusion and bias?

1.3 Hypotheses

- H1: AI-targeting accuracy is positively associated with welfare effectiveness.
- H2: Exclusion risk is negatively associated with welfare effectiveness.
- H3: Grievance redressal strength positively predicts welfare effectiveness.

The paper contributes to literature by presenting a reproducible, clearly labelled synthetic simulation framework. It does not claim to estimate real beneficiary outcomes; rather, it demonstrates how measurable indicators can be combined to support comparative policy modelling. This distinction is important for publication ethics because simulation can be useful for hypothesis generation, but it must not be misrepresented as field evidence.

Literature Review

2.1 Digital Welfare Systems in Emerging Economies

A digital welfare system consists of a series of interconnected elements: identity authentication, enlistment of beneficiaries, benefit eligibility verification, payment system, monitoring dashboard, case management system and grievance redressal system. These components are part of a chain of care that starts before entering into a welfare scheme and includes what happens after a claim is awarded, such that the quality of implementation may be more important than a legal right to welfare benefits (Lindert et al., 2020). Digitalisation has the potential to lower transaction costs and minimize leakage by making beneficiaries easier to identify, more interoperable and able to trace payments, but can generate new exclusion points if they are missing documents, connectivity, or support.

Direct monetary payments from the government to individuals have now emerged as a key feature of social protection reforms. Financial-inclusion evidence reveals that growth of digital payments could yield account ownership, timely and convenient payments for welfare recipients (Demirguc-Kunt et al., 2022; World Bank, 2025c). But digital payments are not democratizing means of distribution. They need payment agents which are working, bank or mobile account or authenticating methods, dispute resolution, and last mile liquidity. With these missing, the digital transfer can increase costs for the beneficiaries and makes it harder for them to settle their grievances, as well as travel.

The direct benefit transfer used in the Indian energy economy is an example of the possible potential of DPI. The JAM architecture - Jan Dhan bank accounts, Aadhaar identity and mobile connectivity - has made the possibility of doing large transfers across schemes possible. The notion of India's digital public infrastructure as a layered ecosystem where identity, payments, and data exchange are all interwoven, and the official Indian material considers DBT a way to combat leakage and enhance targeted delivery, align with this analysis (IMF, 2023; Press Information Bureau, 2025). However, literature is abundant with academic and rights-based suggestions that even using digital authentication and database integration might exacerbate the informational asymmetry if it is difficult for them to correct particular errors (Masiero & Buddha 2021).

A different path is exemplified in Brazil, where long-established social-registry capacity can be found. Cadastro Unico has facilitated targeting in the implementation of various social programmes and is crucial for Bolsa Familia. According to the MobiWorld project (World Bank 2023a), a review of the new Bolsa Familia, boosting access through mobile applications and digital registration has come with some risks, such as those concerning access to smartphones, data quality and the possibility of a decentralized municipal administration hindering the use of digital self-service. It is a duality characteristic of digital welfare; as innovation winnows down the list, other groups of people may get left out.

The examples of administrative maturity and last mile adaptation are seen in the cases of Indonesia, South Africa and Kenya. While there have been efforts towards more effective integration in the registration system of social assistance and to make programmes more accessible to remote areas, recent estimates by the World Bank reapprised Indonesia's geographic barriers to accessing social assistance in remote communities (World Bank, 2024a). Although the grant system in SA is fully functional, reporting issues by SASSA point to operational problems with grants payments, continuity of services and administrative infrastructure (SASSA, 2025). In Kenya, Inua Jamii and Enhanced Single Registry highlight the use of bank accounts and mobile money in relation to delivering transfers; the issue of coverage and reforms to payment models is still a policy concern (World Bank, 2025b).

2.2 Welfare Targeting using AI

AI in welfare targeting is the application of machine learning, rules-based automation, predictive analysis or anomaly detection to aid in welfare targeting to decide on eligibility, fraud risk, case prioritization or outreach. Most states have been taking cautious steps in the use of AI in social protection, and the few uses in progress mainly involve client assistance, administration processes and the detection of fraud and/or errors (OECD, 2025a, 2025b). This caveat is apt, and awareness of the risks means that warning labels are particularly important in a realm with these high stakes: welfare state - welfare is denied to any who are falsely classified as not eligible for it, and further investigations and penalties may be implemented against those who are falsely classified as welfare recipients.

AI can enhance the administration of welfare by systematically bring together disparate databases, minimize data duplication, alleviate manual backlogs and enable proactive outreach efforts. Often mentioned as an example of the use of non-traditional data, and machine learning, for inclusion in data-poor contexts, is the example of the Novissi programme in Togo during COVID-19 (Okamura et al., 2023). Emergency targeting and routine welfare administration, however, are different in that the former must be able to lend more to the "rules of thumb" method in order to get aid to people as quickly as possible, while the latter has to be subject to due process, auditability and appeal.

Algorithmic welfare also poses questions related to aspects of fairness and accountability. Less transparency and contestability in the use of proxy-means testing, poverty scoring or automatic verification with the help of an algorithm may lead to a risk of rights violations (Human Rights Watch 2023). The study on digital welfare uncovered various examples of data injustice in the extension of welfare that lead to entitlement denial while the subsidies coverages looks high in India (Masiero & Buddha, 2021). However, AI can amplify existing administrative failures, where it happens poor data sets are used or institutions do not have human review resources.
The responsible AI frameworks focus on fairness, transparency, privacy, reliability, accountability and human oversight. In NITI Aayog all the documents related to Responsible Artificial Intelligence they highlight that there should be a socially conscious artificial intelligence and that it should not intensify the Digital Divide (NITI Aayog 2021a, 2021b). These principles are not just about model accuracy, but apply to social protection as well. They need to have a set of rules to define eligibility that is explainable, notices that are easy to access, independent audits, and correction procedure, and people need access to human caseworkers and offline access, for those who may not have access to digital platforms. If these protections are not in place, AI may become a tool for exclusion rather than inclusion in the welfare system.

Educating and protecting the entire society with the Universal Basic Income System.
Targeted welfare systems are often beset by fragmented eligibility rules, informal income measurement, the under coverage of the poor and stigma, which is why UBI has become the topic of public policy debate once again. The World Bank's typology of UBI raises a number of policy questions: what are the criteria for 'universal' or ‘quasi-universal' transfers? What kind of transfer deals with which existing scheme? What is the maximum allowable benefit? How would the transfer affect poverty? How would the transfer affect labour supply and public finance? (Gentilini et al., 2020). This is particularly challenging in developing economies where fiscal room is not that great and welfare requirements are multi-faceted.

A recent review of the literature, however, indicates that while there is some evidence of positive effects on some poverty-related outcomes for unconditional or guaranteed basic income, the evidence remains context-specific, and for the most part comes from high-income settings (Pinto et al., 2021; Rizvi et al., 2024). The call for UBI is not a purely moral or technologic proposal, in the case of emerging economies. It needs to be considered in the context of tax capacity, risk of inflation, targeting options, current food/health based transfers, political viability, and payment systems. A universal transfer may have limited poverty impact if it is too small and a meaningful transfer will involve difficult reallocation and/or revenue actions, but it will be effective.

The association of UBI and AI is paradoxical. On the other hand, AI targeting has the potential to offer more precise targeting, rendering universal transfers superfluous. Conversely, if targeting mistakes, surveillance and administration are too expensive, this might provide further impetus for basic-income principles to be the most effective and efficient practice. Dumont (2022) suggests that even if UBI is not taken up in its original form it could be a source of inspiration in the redesign of social protection. This seems especially relevant for countries with partial or categorical or “life course” forms of basic income than full national BIs.

Instead, in this paper, UBI readiness is seen not as a prerequisite for a state's decision to adopt such a measure, but as a measure of administrative, financial and digital capacity to consistently provide income support to a wide group of people. There can be a high level of “digital payment capability” in the country but still be lacking in terms of fiscal and institutional preparedness. Thus, in the process of preparing for UBI, it is imperative that identity coverage, financial inclusion, ability to access UBI using a mobile, privacy safeguards, grievance mechanisms and prevention of exclusion and misuse of UBI are not overlooked.

Exclusion and Algorithmic Bias, 2.4

Digital exclusion being the lack of capacity of individuals or households to access welfare systems due to poor connectivity and/or insufficient digital skills, absence of ID documents, mismatch of biometric data and/or gender-based access deficits and/or inaccessible platforms. UN Women (2024) notes that digital social protection tools have gender differential impacts, as women may not necessarily have access to phones, digital IDs, banking services, information and data, which may be provided by household dynamics. Legitimate inclusion thus needs to be planned and not taken for granted if digitalisation is to positively enhance access.

Algorithmic bias exists when automated systems systematically generate different rates of error for the groups they serve based on gender, age, disability, location, ethnicity or poverty level or the data they have. Historical administrative data or the lack of affected communities in the system design or proxy variables, and the model design may all introduce bias. The issue with welfare systems is not just the statistical unfairness, but the reality that welfare recipients might be subject to greater monitoring, tougher appeals than people who are well off. It is for this reason that AI governance has to encompass legal safeguarding, technical audit and social accountability according to OECD (2024a) and OECD (2025a).

Safeguarding of data is a key protection measure. In 2023, India passed the Digital Personal Data Protection Act, Brazil's data protection legislation is the Lei Geral de Protecao de Dados, which was enacted in 2022 in Indonesia, there is a Personal Data Protection Law, in South Africa it is POPIA and Kenya has a data protection framework, under the authority of the Office of the Data Protection Commissioner. While not providing a legislative solution to the welfare-data risks, these laws offer a regulatory framework within which consent and lawful processing, purpose limitation, data security, and data redress apply. Welfare systems need privacy safeguards to be linked to benefit specific due process as well, as even lawful processing can in itself cause harm if it enables the creation of inaccurate data, or if it is not accompanied by effective appeal mechanisms (Government of India, 2023; Government of South Africa, 2021).

Thus, there is a growing literature that questions a view on digital welfare that sees it solely as an efficiency issue. Efficiency is desirable where leakage and corruption or duplication diminish fiscal capacities. However, for rights based social protection the ethical criterion for a system also concerns its treatment of the difficult cases: those who are not from the same records, live in remote areas, have a disability, have low literacy levels or poor connectivity. Many people cash in short, while not providing any mechanism for people to whom it is owed to participate, is an incomplete system.

2.5 Comparative Studies of Emerging Economies

Comparative analysis is vital, however, due to the fact that there are no uniform routes towards digitization of welfare in emerging economies. The vision of India is infrastructure driven, scale focussed and is based on digital identity, bank account and interoperable payment systems. Brazil has a long tradition of conditional cash transfers and its model is a social-registry-led model. The model of Indonesia is reform oriented with an emphasis on gaining access to social assistance data and remote populations. This model is grant-based and South Africa has a high level of social assistance with a high level of stress to operate. Kenya's is mobile-money based, casing the central role played by M-Pesa, and an ongoing development by population registries. As per the World Bank and ILO sources, the coverage, administrative system and funding structure of social protection systems varies in different regions (ILO, 2024a; World Bank, 2025a). The variability in these differences means AI is not an importable solution. AI to detect fraud can lead to even greater exclusion in countries where register coverage and accuracy are high and grievance mechanisms are not well-established. In countries where mobile-money is established and ID coverage is less, convenience of payment may outrank the confidence of targeting. In the country where the grants are well-developed, AI can be more useful in the service triage and anomaly detection processes with regards to first time decisions.

So, in this paper, the comparison between the five countries is done not as a technology but as a system, of course as a subset of the digital welfare possibilities. AI targeting capacity is explored in conjunction with financial inclusion, mobile access, digital literacy, privacy measures and the timeliness of payments and strength of grievance. This framework enables the study to not only make comparisons on infrastructure availability but also the potential for UBI-like delivery models. A country may be operationally capable, but normatively underprepared, for having payments strong but privacy and appeals weak, or vice versa.

2.6 Research Gap

There is ample evidence regarding digital delivery systems, debates about social protection reform and AI-based UBI in the literature reviewed, yet the strands are not sufficiently interwoven. Digital Welfare studies tend to examine matters of payment services efficiency, and interoperability of registries, and the AI studies tend to highlight technological or ethical risks. While fiscal and distributional feasibility are subjects of UBI studies, few consider the administrative infrastructure, particularly in digital formats, necessary for broad-based transfers in emerging economies.

This paper aims to fill this gap by creating a comparative simulation model that connects the performance of digital subsidy with its readiness for the implementation of UBI. The model can be used as a framework for filling in the blanks with field data so that the framework will not replace primary survey research. The originality is the examination of the interaction between the four elements of welfare effectiveness, namely the timeliness of payments, the accuracy of targeting, the leakages of payments, the ability to redress grievances, the satisfaction with the scheme and the risk of exclusion.

Conceptual Framework

The conceptualization of the framework is that the digital Welfare infrastructure "enables" AI-based targeting (as well as UBI readiness). Independent variables include digital identity coverage, ability to target artificial intelligence, financial inclusion, mobile and internet penetration, government digital infrastructure, integration with welfare database, and the level of privacy guarantees and capacity to address grievances. These variables affect to the mediating factors as payment efficiency, leakage reduction, inclusion accuracy and exception reduction of inclusion and administrative cost reduction of exception. The outcomes of dependencies are effectiveness in welfare delivery, readiness of UBI, satisfaction of the beneficiaries, fiscal sustainability, and social protection efficiency.

The model also features an exogenous (and thus at the end of the day, arbitrary) relationship between technology and welfare, such that technology cannot causally affect welfare in a determinant fashion. Instead, digital infrastructure functions in the administration process. For instance, digital ID coverage could better facilitate deduplication but welfare effects would hinge on whether it can be corrected or not if authentication fails. There were some gains that could be realised for mobile internet but these depended on digital literacy and language design to enhance access to application status. Any possible reduction of inclusion errors with AI comes at the cost of perceived illegitimate if not explainable and appealing. This means that Governance safeguards are included as cross cutting conditions.

Figure 1. Conceptual framework of AI-based welfare delivery and UBI readiness

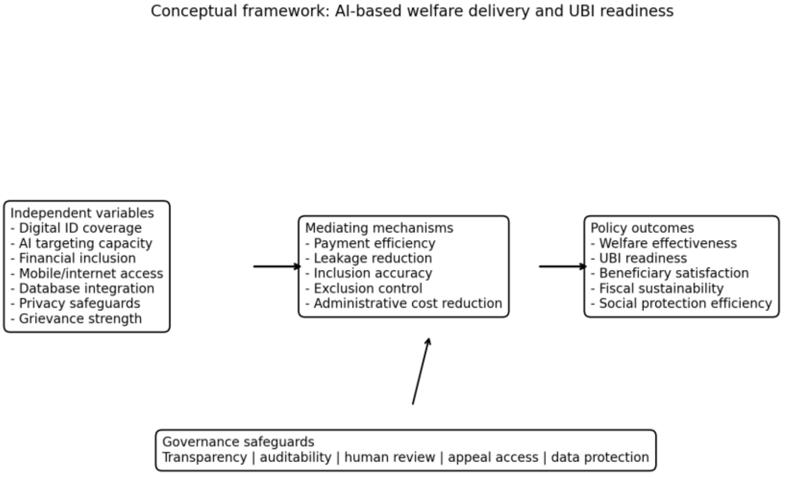

Figure 1 summarises the proposed framework. It treats AI as one component of a broader welfare delivery ecosystem. This is important because poor welfare outcomes are often caused by interactions among data, payments, institutions and beneficiary capability rather than by a single technology failure.

Table A. Variables and operational definitions used in the conceptual framework

Variable	Variable Type	Measurement Scale	Operational Definition	Expected Relationship
Digital identity coverage	Independent	0-1 index	Normalised availability and usability of official digital ID	Positive, if correction mechanisms exist
AI-based targeting capacity	Independent	0-100 score	Ability to support eligibility prediction, anomaly detection and decision support	Positive, subject to fairness safeguards
Financial inclusion	Independent	0-1 index	Access to bank or mobile money account suitable for receiving transfers	Positive
Mobile/internet penetration	Independent	0-1 index	Access to mobile connectivity and internet-enabled welfare services	Positive, moderated by digital literacy
Database integration	Independent	0-1 index	Interoperability across welfare, identity and payment databases	Positive, with privacy controls
Privacy safeguards	Independent	0-1 index	Legal and institutional strength of data protection	Positive
Payment efficiency	Mediator	0-100 score	Timeliness, predictability and convenience of benefit receipt	Positive
Exclusion control	Mediator	0-100 score	Capacity to identify and	Positive

			correct wrongful exclusion	
Welfare effectiveness	Dependent	0-100 index	Composite score of timeliness, targeting, leakage control, redressal and satisfaction	Outcome variable
UBI readiness	Dependent	0-100 score	Administrative and digital capacity to deliver broad-based cash support	Outcome variable

Note. This conceptual table defines model constructs. Quantitative values in later tables are generated through the synthetic simulation model and are not official country scores.

Research Methodology

4.1 Research Design

This study adopts a comparison-based policy analysis approach that is quantitative and simulation. The comparative part compares five emerging economies featuring varying aspects of the digital welfare ways. The quantitative component is an operationalization of the welfare effectiveness and UBI readiness by measurable indicators. The simulation component allows to generate a synthetic “real” data set which includes all the beneficiaries at this level and allows for testing of statistical relationships without implying access to real beneficiary data.

Where the goal involves exploring conceptual relationships and contrasting feasible policy pathways, then a simulation-based design will do. It was developed for the purpose of estimating population parameters, but it is not intended to measure actual population parameters. If administrative or survey data were collected later, the dataset was synthesized with a similar structure to that proposed for an empirical analysis. This is a "transparent" way of conducting research as the assumptions, variables and limitations are stated.

4.2 Country Selection

This study focuses on the countries of India, Brazil, Indonesia, South Africa and Kenya. These countries are nascent economies with observable shifts in the field of social protection, with a considerable amount of work on digital government as well as progressive levels of maturity on identity, payment and registry. Together these countries form various types of infrastructure for DPI and direct transfers, as follows: India, large-scale DPI-based; Brazil, a long history of social registry and conditional cash transfers; Indonesia, a case of integrated social-registry reform, but with inclusion challenges in remote areas of the country; South Africa, a "welfare state," albeit with grants of limited size; and Kenya, mobile-money-based transfer delivery alongside a growing social registry.

The countries offer, too, a range of differences in institutional conditions needed to be UBI ready. Some have better payment mechanisms; some more registry capacity; and others have a larger social grant program. This variation enables the paper to examine the possibility that digital welfare capability is not one-dimensional but can be seen as a multidimensional entity.

4.3 Data Sources

The two types of data used are: First is secondary policy evidence based on the research from the verified institution and research literature from 2020 to 2026 like World Bank, ILO, OECD, UNDP, ADB, IMF, Government reports, peer-reviewed literature etc. These have been referred to to explain what are the welfare systems in the digital world, the debate on AI governance, financial inclusion, any digital public infrastructure and UBI.

Secondly, they have a synthetic simulation dataset of 1,000 welfare beneficiaries. 200 observations were simulated for each country and are included in the dataset. The simulated records contain access to bank accounts, mobile internet, exclusion risk, inclusion error, grievance redressal, beneficiary satisfaction, UBI readiness and welfare effectiveness, among others, including age, gender, rural/urban location, income category, access to a digital ID and access to mobile internet. Data come from reasonable distributions derived from the overall flow of the literature, and do not represent the actual respondent-level data.

4.4 Variables of the Study

Table B. Variables of the study

Variable Name	Variable Type	Measurement Scale	Description	Expected Relationship
Country	Categorical	Nominal	Country of simulated beneficiary	Comparative grouping variable
Age	Independent	Ratio	Age in completed years	Mixed; older beneficiaries may face digital barriers
Gender	Independent	Nominal	Gender category	May influence access through digital gender divide
Rural/urban location	Independent	Nominal	Residential location	Urban location expected positive
Income category	Independent	Ordinal	Simulated poverty status	Lower income may increase exclusion risk
Digital ID access	Independent	Binary	Access to usable digital ID	Positive

Bank account access	Independent	Binary	Account suitable for receiving transfer	Positive
Mobile internet access	Independent	Binary	Access to mobile internet	Positive
Digital literacy score	Independent	0-100	Ability to use digital welfare services	Positive
Subsidy received on time	Mediator	Binary	Receipt within three simulated days	Positive
Payment delay in days	Mediator	Ratio	Number of delayed payment days	Negative
AI targeting accuracy score	Independent	0-100	Simulated accuracy of AI-assisted targeting	Positive
Exclusion risk score	Independent	0-100	Risk of rightful beneficiary being excluded	Negative
Inclusion error score	Independent	0-100	Risk of ineligible inclusion	Negative
Grievance redressal score	Mediator	0-100	Capacity to resolve complaints	Positive
Beneficiary satisfaction score	Dependent	0-100	Simulated satisfaction with delivery	Positive
UBI-readiness score	Dependent	0-100	Capacity for broad-based cash transfer delivery	Positive
Welfare effectiveness index	Dependent	0-100	Composite welfare performance outcome	Main outcome

Note. All respondent-level values in the empirical section are synthetically generated for simulation-based modelling.

4.5 Sampling Design for Simulated Dataset

The synthetic data set includes 1000 observations of which the number of observations in each country are equal, in terms of: India (n = 200), Brazil (n = 200), Indonesia (n = 200), South Africa (n = 200) and Kenya (n = 200). Each country breaks down observations by rural / urban area and gender / income group. The structure that is generated provides variation that reflect common issues to certain welfare-administration issues such as increased digital barriers for rural, older and poorer beneficiaries.

Random number generation in the simulation follows a fixed rule in order to achieve the match of results. Each of these binary variables, e.g. access to the digital identity mechanisms, banking systems or mobile internet, is created based on country specific probabilities, which are calculated based on location, income, gender and age. Continuous indicators: Continuous states (0-100, with bounds). Welfare effectiveness is calculated as a function of four variables: payment timeliness, accuracy of AI targeting, leakage, and beneficiary satisfaction/exclusion risk, measured with different weights for each.

4.6 Statistical Tools

Descriptive statistics, descriptive reliability study, Pearson correlation, one way ANOVA, multiple linear regression and comparative index scoring and exploratory principal component analysis are used for the analysis. The composite index of the five welfare performance components has a Cronbach alpha of 0.71, which is considered acceptable in a simulation environment. There is also a robustness check using PCA, which shows the first PCA accounts for 37.9% variance and second PCA accounts for 15.7% variance among selected delivery and readiness indicators.

Regresses on dependent variable: welfare effectiveness index. Factors that are considered include access to digital ID, bank account access, access to internet on the phone, accuracy of AI, degree of digital literacy and grievance redressal/exclusion risk. The model is understood as a 'simulation' not a 'causal estimate'.

Data Analysis and Results

This section reports the synthetic simulation results. The tables are designed in a format suitable for journal submission, but the values must be interpreted as modelled observations rather than actual field statistics. The goal is to show how comparative empirical analysis can be conducted while maintaining ethical transparency.

Table 1. Country-wise digital welfare infrastructure indicators (normalised simulation inputs)

Country	Digital ID Coverage Index	Financial Inclusion Index	Mobile Access Index	AI Targeting Readiness	Data Privacy Strength	UBI Readiness Score
India	0.93	0.78	0.75	0.72	0.62	0.66
Brazil	0.84	0.80	0.82	0.68	0.76	0.70
Indonesia	0.78	0.74	0.77	0.62	0.65	0.61

South Africa	0.82	0.86	0.80	0.65	0.72	0.67
Kenya	0.70	0.83	0.76	0.60	0.58	0.63

Note. Scores range from 0 to 1. Values are synthetic normalised inputs derived for simulation design and are not official rankings or administrative statistics.

Table 1 indicates that the simulation assigns India the highest digital identity index because of the scale of its digital ID and DBT architecture, while Brazil and South Africa show relatively stronger data privacy and grant-administration foundations. Kenya's financial inclusion index reflects the strength of mobile-money ecosystems, while Indonesia's scores reflect a reforming but still uneven system. These index inputs are used only to seed the synthetic dataset.

Table 2. Demographic profile of simulated beneficiaries

Variable	**Category**	**India**	**Brazil**	**Indonesia**	**South Africa**	**Kenya**	**Total**
Gender	Female	116	104	107	107	112	546
Gender	Male	84	92	90	90	86	442
Gender	Other/Prefer not to say	0	4	3	3	2	12
Income category	Extreme poor	49	53	46	52	39	239
Income category	Poor	57	79	73	58	69	336
Income category	Near-poor	64	41	59	60	52	276
Income category	Lower-middle	30	27	22	30	40	149
Location	Rural	119	118	110	107	123	577
Location	Urban	81	82	90	93	77	423

Note. Each country contains 200 simulated observations. Demographic categories were generated to create plausible welfare-recipient diversity, not to reproduce official population distributions.

Table 2 summarises the simulated beneficiary profile. Rural households form the majority of observations because rural access barriers are central to the research problem. Income categories are weighted towards poor and extreme-poor beneficiaries, reflecting the policy population usually targeted by subsidy programmes. Gender categories are included because digital access and welfare claims often differ by gendered control over phones, bank accounts and information.

Table 3. Descriptive statistics of major study variables

Variable	Mean	Standard Deviation	Minimum	Maximum	Interpretation
Digital literacy score	64.52	13.04	17.22	100.00	Higher values indicate stronger performance
Payment delay days	6.34	2.94	0.00	17.00	Lower values indicate better welfare delivery
Payment timeliness	84.32	10.48	52.63	100.00	Higher values indicate stronger performance
AI targeting accuracy score	78.79	10.34	47.27	100.00	Higher values indicate stronger performance
Exclusion risk score	21.69	13.26	0.00	59.56	Lower values indicate better welfare delivery
Inclusion error score	16.55	7.85	0.00	43.97	Lower values indicate better welfare delivery
Grievance redressal score	72.64	11.25	40.56	100.00	Higher values indicate stronger performance
Beneficiary satisfaction score	74.23	10.20	39.49	100.00	Higher values indicate stronger performance
UBI readiness score	74.01	9.46	35.14	100.00	Higher values indicate stronger performance
Welfare effectiveness index	74.61	9.41	46.29	100.00	Higher values indicate stronger performance

Note. The descriptive statistics summarise synthetic beneficiary-level variables on a 0-100 scale except payment delay, which is measured in days.

Table 3 shows that the simulated mean welfare effectiveness index is 74.61, with moderate dispersion across beneficiaries. The mean AI-targeting score is 78.79, while the mean exclusion-risk score is 21.69. These values are internally consistent with the conceptual assumption that digital welfare systems can improve targeting while still leaving a measurable exclusion problem.

Table 4. Country-wise welfare effectiveness index

Country	Payment Timeliness	Targeting Accuracy	Leakage Control	Grievance Redressal	Beneficiary Satisfaction	Overall Welfare Effectiveness Score
India	85.31	86.45	75.35	73.96	75.97	77.81
Brazil	86.07	81.68	74.16	79.44	77.41	77.88
Indonesia	82.40	74.53	68.94	69.74	72.12	71.45
South Africa	84.72	79.07	72.58	73.17	75.33	75.20
Kenya	83.09	72.21	68.47	66.88	70.31	70.70

Note. Country-level scores are averages from the synthetic beneficiary dataset. Higher scores indicate better simulated performance.

Table 4 presents country-wise welfare effectiveness components. India performs strongly on targeting accuracy because of the simulated weight given to digital identity and DBT infrastructure, but its exclusion-risk adjustment reduces its overall score. Brazil performs consistently across payment, grievance and satisfaction components. South Africa benefits from grant-system maturity but faces simulated payment-continuity constraints. Kenya's mobile-money strength improves payment access, yet lower registry and grievance indicators limit the overall score. Indonesia's results reflect a transition system in which integration reforms are still assumed to be uneven.

Table 5. Correlation matrix of simulated welfare indicators

Variable	Digital literacy	AI targeting	Payment timeliness	Exclusion risk	Grievance	UBI readiness	Welfare effectiveness
Digital literacy	1.00	0.14	0.19	-0.39	0.24	0.18	0.26
AI targeting	0.14	1.00	0.17	-0.31	0.23	0.17	0.59
Payment timeliness	0.19	0.17	1.00	-0.36	0.19	0.22	0.53

Exclusion risk	-0.39	-0.31	-0.36	1.00	-0.19	-0.26	-0.57
Grievance	0.24	0.23	0.19	-0.19	1.00	0.20	0.47
UBI readiness	0.18	0.17	0.22	-0.26	0.20	1.00	0.27
Welfare effectiveness	0.26	0.59	0.53	-0.57	0.47	0.27	1.00

Note. Pearson correlations based on 1,000 synthetic observations.

Table 5 shows a positive correlation between AI-targeting accuracy and welfare effectiveness ($r = 0.59$) and between grievance redressal and welfare effectiveness ($r = 0.47$). Exclusion risk is negatively correlated with welfare effectiveness ($r = -0.57$), supporting the claim that efficiency-oriented digitalisation cannot be evaluated without measuring wrongful exclusion.

Table 6. One-way ANOVA comparing welfare effectiveness across five countries

Source of Variation	Sum of Squares	df	Mean Square	F-value	p-value	Interpretation
Between countries	9307.39	4	2326.85	29.22	< .001	Significant country-level differences
Within countries	79232.98	995	79.63	-	-	Residual variation
Total	88540.38	999	-	-	-	Total simulated variation

Note. ANOVA is conducted on the synthetic welfare effectiveness index. Statistical significance indicates differences within the simulated model, not proof of real-world country differences.

Table 6 reports a significant difference in welfare effectiveness across the five simulated country groups, $F(4, 995) = 29.22$, $p < .001$. This supports H6 within the simulation and confirms that country-specific digital infrastructure assumptions lead to different modelled welfare outcomes.

Table 7. Multiple regression results for welfare effectiveness index

Predictor	Beta Coefficient	Standard Error	t-value	p-value	Result
Digital ID access	0.35	0.55	0.65	0.52	Not significant
Bank account access	2.98	0.46	6.48	< .001	Significant
Mobile internet access	0.75	0.46	1.63	0.10	Not significant

AI targeting accuracy score	0.35	0.02	16.90	< .001	Significant
Digital literacy score	-0.02	0.02	-1.14	0.26	Not significant
Grievance redressal score	0.25	0.02	14.21	< .001	Significant
Exclusion risk score	-0.24	0.02	-12.78	< .001	Significant

Note. Dependent variable: welfare effectiveness index. Model R-squared = 0.61; adjusted R-squared = 0.61. Results are based on synthetic data.

Table 7 indicates that AI-targeting accuracy, digital literacy and grievance redressal are positive predictors of welfare effectiveness, while exclusion risk is negative. The model explains 61.5% of the variance in the simulated welfare effectiveness index. Digital ID access and bank access contribute positively but are weaker than process-oriented factors, suggesting that infrastructure must be combined with service quality and redressal mechanisms.

Table 8. UBI readiness comparative ranking

Rank	Country	UBI readiness score	Strengths	Limitations	Policy Priority
1	Brazil	78.49	Mature social registry and relatively strong data protection architecture	Data quality and digital access gaps in decentralised registration	Strengthen registry updating and algorithmic accountability
2	South Africa	76.21	Large grant system and high financial inclusion among beneficiaries	Administrative delays and infrastructure constraints in last-mile delivery	Improve payment continuity, data integration and appeal channels
3	India	74.50	Scale of digital ID, DBT and payment infrastructure	Digital divide, exclusion risk and uneven grievance resolution capacity	Add independent audits and offline correction pathways
4	Kenya	72.14	Mobile money ecosystem	Coverage constraints and mobile/digital	Expand coverage while

			and expanding social registry infrastructure	access disparities	protecting mobile-money users
5	Indonesia	68.72	Growing social protection reform and integrated registry agenda	Remote-area inclusion gaps and fragmented local implementation	Improve remote access and harmonise registry governance

Note. The ranking is generated from the synthetic UBI-readiness score and should be interpreted as a simulation-based policy illustration.

Table 8 ranks countries by simulated UBI readiness. Brazil ranks highly because of social registry maturity, cash-transfer experience and privacy safeguards. South Africa benefits from extensive grant delivery infrastructure. India has strong payment and identity capacity but requires stronger offline correction and grievance systems before broad-based UBI-like delivery can be considered inclusive. Kenya and Indonesia show important readiness foundations but need expanded coverage, registry quality and last-mile support.

Figure 2. Country-wise AI welfare readiness comparison

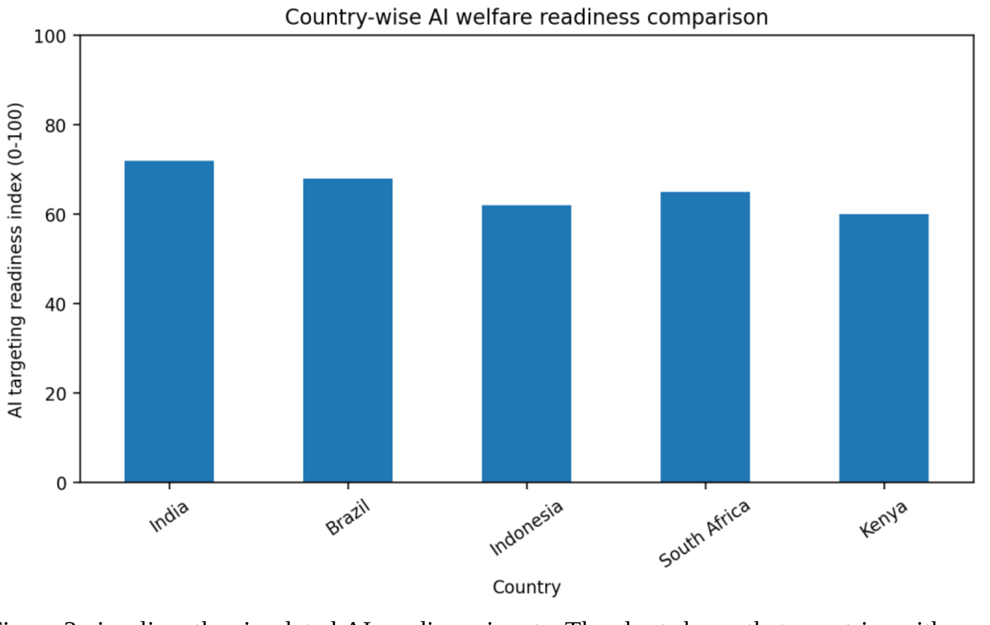

Figure 2 visualises the simulated AI-readiness inputs. The chart shows that countries with stronger identity and registry infrastructure are assumed to have higher AI-targeting capacity, but the paper cautions that AI-readiness should not be equated with ethical readiness.

Figure 3. Radar chart of digital subsidy performance

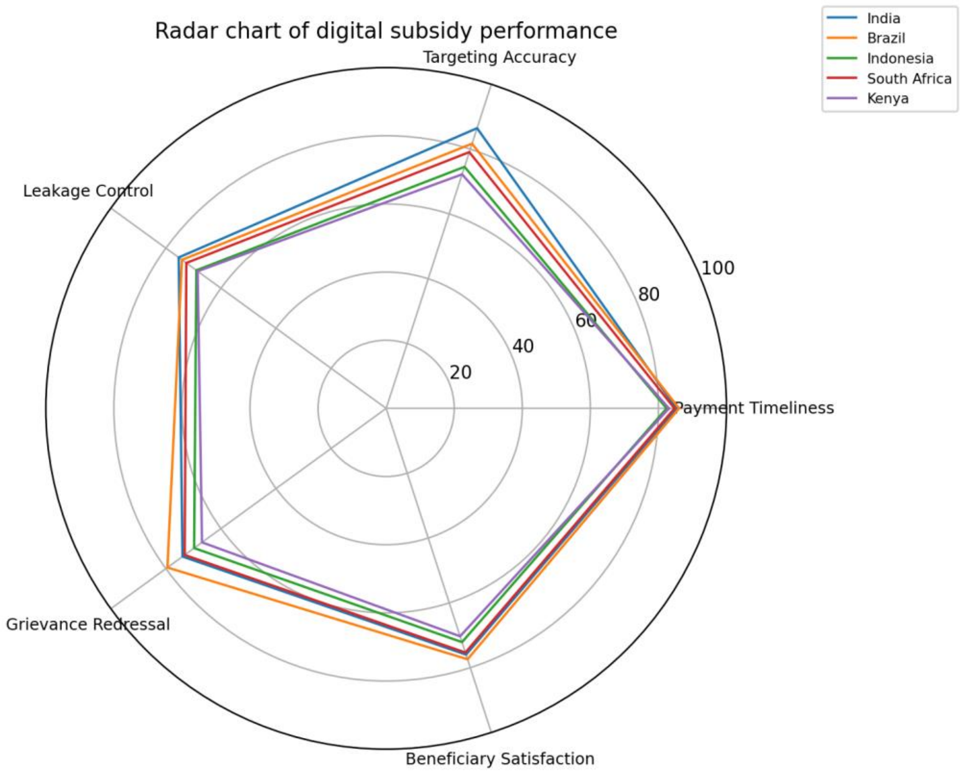

Figure 3 compares five welfare-performance components. The radar chart makes visible the multidimensional nature of welfare delivery: a country can perform well on targeting but weaker on grievance redressal or payment timeliness.

Figure 4. Regression plot between AI-targeting accuracy and welfare effectiveness

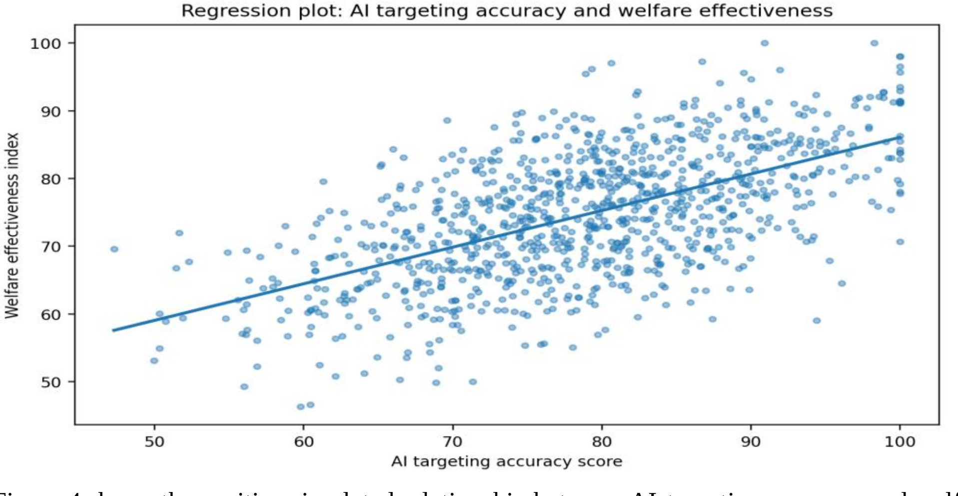

Figure 4 shows the positive simulated relationship between AI-targeting accuracy and welfare effectiveness. The spread of observations around the regression line reinforces that AI-targeting accuracy alone does not determine welfare performance.

Figure 5. Heatmap of UBI readiness indicators

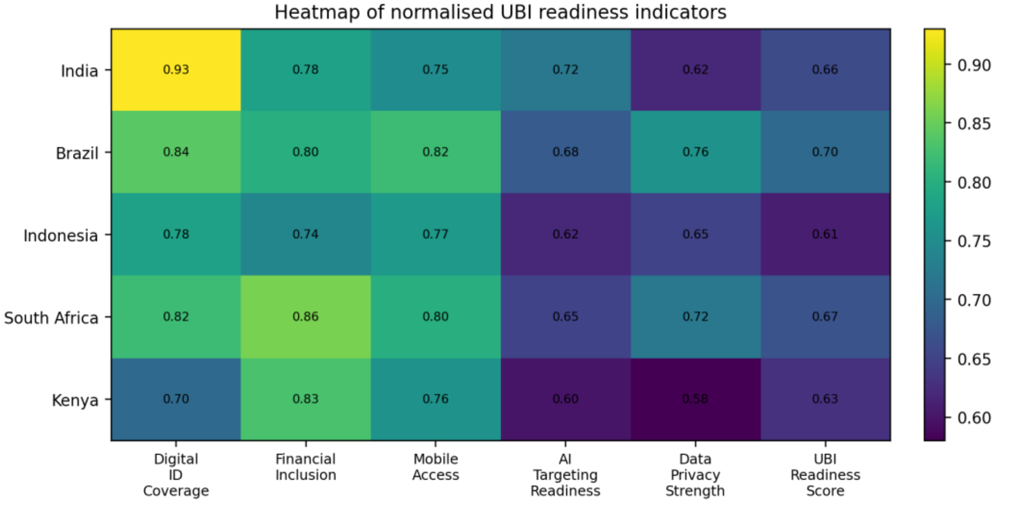

Figure 5 presents normalised readiness indicators. The heatmap highlights that UBI readiness is a composite administrative question involving identity, payment inclusion, mobile access, AI capability and privacy safeguards.

Discussion

The key takeaway from the simulation is that AI-driven welfare systems can enhance targeting and increase administrative efficiency, but this comes with a number of caveats. The positive correlation between AI's accuracy in targeting beneficiaries and the effectiveness of their welfare programmes aligns with the rationale underpinning such practices, aiming to enhance programme efficiency by reducing duplication and spotting anomalies (OECD, 2025a; World Bank, 2025a). But there is also a negative effect of exclusion risk revealed in the regression meaning that a system with an average accuracy of, say 75% can create "bad" errors for a specific group.

The significance of this finding lies in the fact that for emerging economies, welfare databases frequently are incomplete or out of date. The reliability of data may be affected by informal activities, internal migration, indistinct or unclear land-tenure rights, shared phones and other sources of errors, such as the varying composition of households. In these scenarios, AI is not a mere optimiser; it becomes a crucial asset in refining skills and processes. Can potentially increase the administration's blind spots if trained on historical data which had already eliminated vulnerable populations from its scope. The study thus resonates with the data-justice literature that calls for the evaluation of digital welfare systems with regards to access, information, accountability and structural power relations (Masiero & Buddha, 2021).

The systems of digital subsidy seem to work best if they factor in all three of these elements: identity verification; payment inclusion; and grievance resolution. Table 7 indicates that grievance redressal is very positively influencing the simulation. This is perhaps an important insight into a fundamental administrative fact: Welfare systems do not only succeed if they make the right decisions; they must make dexterious ones as soon as possible. Mechanisms should be available to beneficiaries to update records, make appeals regarding eligibility, and report missed payments and provide explanations in a way that is understandable to them. When they are not in place, it can result in long-term exclusion if there are any data errors.

Resources: As revealed by the comparison with the other countries, a different digital welfare architecture leads to different strengths. The power of India is in the numbers, the strength of the Payments & ID systems, but that means the more scale becomes important, the more important the need becomes for an independent audit and an offline correction mechanism. While social registry and cash-transfer experience is a strong point in Brazil, there are possible problems with data quality and smartphone access when using digital self-service. The challenge for Indonesia is the access to reach remote communities and the local level practices. The broad transfers in South Africa are institutionalized through the grants scheme, and continuity and reliability of administration and payment are critical. A flexible mobile money payment delivery system exists in Kenya and has the potential to expand, but social registry coverage and appeal systems should catch up with the development of mobile money.

Not that all five countries are prepared to have universal basic income in its entirety. Instead, the findings indicate that readiness to UBI may be thought of as layered capacity. The top one is knowing the person and how to contact them. The second is the ability to make payments on a regular basis and securely. The third is the fiscal capacity. The 4th is governance capability; privacy, audit and appeal. The fifth is political will to transfer and combine UBI-like transfers with elements of existing subsidies. Timely and adequate responses are essential to ensure access to the next generation of basic income policies, as no emerging economy should switch from targeted welfare to UBI simply because it has digital payments – fiscal sustainability and the design of such policies are still paramount.

Development of a hybrid model seems more viable. Specific supports in the areas of disability, health, food security, housing, old-age protection and geographic (place-based) deprivation may continue to be required. Partial basic-income principles can, simultaneously, alleviate exclusion at point level, in particular for children, older people, climate impacted households, and people in the informal sector who are affected by a shock, or for citizens in areas of weak administrative targeting. To support this hybrid model, AI can track areas of coverage failures and discrepancies in payments, but to prevent AI denial, there should be human governance.

One caution regarding the welfare fraud stories is also brought up. Often AI's justification is to identify instances of misuse, which is a public good objective. But too much fraud pathology can make it no longer served by the moral logic of welfare administration but rather by welfare recipient population as "production" of "risk objects" instead of rights-holders. While fraud detection is a standard use case of AI, OECD reports recognise that at some point people will have to be consulted and safeguards put in place (OECD, 2025b). Emerging economies can thus be urged to strike the balance between fiscal integrity and security of entitlements.

Finally, the simulation provides some grounds for considering not UBI or AI, but both UBI and AI. While greater sophistication can lead to increased complexity for beneficiaries, AI can help achieve targeted systems that are more administratively complex. When not combined with reform, UBI is a potential budget bust, but can be a substitute for targeting. The policy challenge will be to create welfare systems that are easy to understand for citizens, do not have excessive bureaucracy for fiscal sustainability and are transparent enough for citizens to uphold their rights.

Policy Implications

Welfare delivery with a human-centred AI governance.

The goal of AI in welfare eligibility is not for it to automatically make decisions without human oversight, but to support welfare staff in their decision-making process. The beneficiaries should be made aware when a decision has been made based on an automated system and a human review should always be required if there is potential of it impacting on subsistence income and a decision of denial/suspension/investigation is being made.

7.2 Transparent algorithmic auditing

Welfare algorithms should be subjected in periodic independent audits to be held by governments. Audits need to evaluate differences in error-rate by Gender, location, Age, Disability and Income-group/digital-access. Audit summaries should be publicly available with important personal data and other sensitive data of the system protected.

The targeted subsidy and partial UBI hybrid welfare model will be funded.Funding of the hybrid welfare model of targeting (7.3) subsidy and partial UBI will be provided.

In many developing countries, a pure UBI can be difficult to be able to afford. A hybrid model of targeted subsidies to specific vulnerabilities and quasi-universal/categorical basic transfers for groups with high targeting costs and/or high exclusion risks is more practical.

7.4 Enhance and promote financial inclusion and digital identity.

Digital IDs and bank and mobile money access continue to be foundational, and must be usable and not just nominal. Governments should support-assisted enrolment, portability, agents, support in local languages and provide mechanisms for identity-payment mismatches.

7.5 Digitally excluded populations grievance Redressal Offline

All online welfare or assistance response systems should have offline methods of complaint and give people assistance if they need it. The design of app-based reporting systems should not be limited for rural beneficiaries, older people, women without cell phones, people with disabilities or illiterates.

Data protection and privacy regulation 7.6

All welfare data needs to be subject to purpose limitation, data minimisation, security safeguards rights and correction. Increased sharing of data between welfare agencies should be made public and banned 'function creep' in cases where data on social protection benefits are used for other surveillance or punitive purposes.

7.7 Fiscal sustainability prior to becoming UBI (expenses only applied to individuals after they become UBI eligible are excluded)

Fiscal analysis needs to be covered as part of UBI-readiness. Before replacing existing subsidies, policymakers should first model the replacement effects and distributional outcomes, and benefit levels, sources of financing, and inflation risk. Pilots should simulate it and there should be stress test impact evaluations.

7.8 Welfare digitisation strategy for each country

India's focus areas should be the grievance and exclusion audits; for Brazil, strengthening the updating of the registry and access to services via a digital platform; for Indonesia, the inclusion of individuals in remote areas; for South Africa, enhancing the continuity of payment and service infrastructure; and for Kenya, access through registry coverage and mobile-money users' protection.

Conclusion

This paper explored AI-based welfare distribution and the 'readiness' of UBI with a comparative simulation model of digital subsidy systems of India, Brazil, Indonesia, South African and Kenya. The analysis demonstrates that beyond a digital ID or digital payments system are required for effective digital welfare. Exclusion risk is a strong contributing factor to the reduction of simulated welfare effectiveness whereas AI-targeting accuracy is an enhancing factor. Grievance redressal, and digital literacy come to the fore as key factors for leveraging digital infrastructure to actual welfare access.

The relative findings indicate that there are different readiness profiles in the emerging economies. India has scale and infrastructure, Brazil has experience in the register and transfer of services, South Africa has experience in social protection using the grant system, Kenya has experience with mobile money, and Indonesia has a reform process that would likely take an integrated approach to social protection. Each of these strengths can't accomplish all alone. To be able to ensure payment and identification and to implement UBI (quasi-UBI) delivery a number of factors must be in place, such as fiscal capacity, public trust and appeal systems, and legal protection.

Thus, the last policy suggestion is to pursue a mixed welfare system. AI can, and should, be leveraged to enhance outreach, identify anomalies and monitor payment systems and gaps in coverage, but should not be a “black box” replacement for rights-based decision. Social protection reform should be used to make sure that UBI principles are involved where targeting is a problem that is either exclusion-prone or administratively costly, however, serious fiscal and institutional considerations should take precedence and inform any decisions for adopting UBI. However, human-centred AI governance, clear audit and easily available complaints systems are crucial to make sure that digital welfare systems promote inclusion and not exclusion.

The Study has the following limitations:

The chief constraint is taken to be the synthetic simulation dataset used. The findings show relationships in the model and are not necessarily indicative of field and ground-truth beneficiaries.

Only the five countries have been represented. Further comparisons are needed to validate and generalise the findings for other emerging economies.

Availability of public data differs from countries, particularly when it comes to the use of AI in welfare administration and real time grievance results.

• It relies on simplified indicators and some of the institutional, political and fiscal nuances of social protection systems cannot be accounted for in the simulation.

The policy context and references may change quickly and therefore it is important to take care to refresh them if you wish to journal your research.

Future Research Directions

- Survey real beneficiaries and obtain the data to validate the simulated relations between access to the digital system, exclusion risk and welfare outcomes effectiveness.

Algorithmic bias audits of welfare targeting systems based on administrative welfare data with strict controls and safeguards for privacy.

Use either experimental or quasi-experimental approach to assess UBI pilots and quasi-universal transfer programmes.

- Research how digital subsidy systems function and the differences between the role of a phone, bank account and information about benefits for men and women.
- Identify different cash transfer systems (blockchain, CBDC and mobile-money) and analyze them in terms of transparency, privacy, and usage.

- Create rural Digital Exclusion Indices (DEI) in remote and low connectivity areas for social protection systems.

References

Asian Development Bank. (2022). Social protection in a pandemic: Trends, challenges, and responses in Asia and the Pacific. https://www.adb.org/publications/social-protection-pandemic-trends-challenges-technology

Asian Development Bank. (2025). Asian development policy report 2025: Harnessing digital transformation for good. https://www.adb.org/publications/asian-development-policy-report-2025

Banerjee, A., Hanna, R., Olken, B. A., & Sverdlin Lisker, D. (2024). Social protection in the developing world. Journal of Economic Literature. https://doi.org/10.1257/jel.20241646

Carvalho, D., Araujo, R., & colleagues. (2025). Data, algorithms, and automation in social protection. Proceedings of the 26th Annual International Conference on Digital Government Research. https://proceedings.open.tudelft.nl/DGO2025/article/view/1011

Conrad, C., Suri, S., Karippacheril, T. G., Leite, P., & Lindert, K. (2024). Playbook on digital social protection delivery systems: Towards dynamic inclusion and interoperability. World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099050824133015472

Demirguc-Kunt, A., Klapper, L., Singer, D., & Ansar, S. (2022). The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19. World Bank. https://openknowledge.worldbank.org/entities/publication/b74e1909-3ecf-5009-b51c-8527fc4eefeb

Dumont, D. (2022). Universal basic income as a source of inspiration for the future of social protection systems? A counter-agenda. Revue de droit compare du travail et de la securite sociale, 4, 6-21. https://doi.org/10.1177/13882627221138599

European Parliament and Council of the European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence. Official Journal of the European Union. https://eur-lex.europa.eu/eli/reg/2024/1689/oj

Gentilini, U., Grosh, M., Rigolini, J., & Yemtsov, R. (2020). Exploring universal basic income: A guide to navigating concepts, evidence, and practices. World Bank. https://doi.org/10.1596/978-1-4648-1458-7

Global Partnership for Financial Inclusion. (2023). G20 policy recommendations for advancing financial inclusion and productivity gains through digital public infrastructure. G20 India Presidency. https://www.g20.in/content/dam/gtwenty/gtwenty_new/document/doc-18-09/G20%20Policy%20Recommendations%20for%20Advancing%20Financial%20Inclusion%20and%20Productivity%20Gains%20through%20Digital%20Public%20Infrastructure.pdf

Government of India. (2023). The Digital Personal Data Protection Act, 2023. Ministry of Electronics and Information Technology. https://www.meity.gov.in/static/uploads/2024/06/2bf1f0e9f04e6fb4f8fef35e82c42aa5.pdf

Government of India, Press Information Bureau. (2023). G20 document prepared by World Bank lauds India's digital public infrastructure. https://www.pib.gov.in/PressReleaseIframePage.aspx?PRID=1955516

Government of India, Press Information Bureau. (2025). India's DBT: Boosting welfare efficiency. https://www.pib.gov.in/PressReleasePage.aspx?PRID=2123192

Government of Indonesia. (2022). Law No. 27 of 2022 on Personal Data Protection. Constitutional Court of the Republic of Indonesia. https://en.mkri.id/news/details/2023-02-13/Govt%3A_Law_on_Personal_Data_Protection_Provides_Legal_Protection

Government of South Africa. (2021). Protection of Personal Information Act 4 of 2013. https://www.gov.za/documents/protection-personal-information-act

Human Rights Watch. (2023). Automated neglect: How the World Bank's push to allocate cash assistance using algorithms threatens rights. https://www.hrw.org/report/2023/06/13/automated-neglect/how-world-banks-push-allocate-cash-assistance-using-algorithms

International Labour Organization. (2024a). World Social Protection Report 2024-26: Universal social protection for climate action and a just transition. https://www.ilo.org/publications/flagship-reports/world-social-protection-report-2024-26-universal-social-protection-climate

International Labour Organization. (2024b). World Social Protection Report 2024-26: Regional companion report for Asia and the Pacific. https://www.ilo.org/publications/world-social-protection-report-2024-26-regional-companion-report-asia-and

International Telecommunication Union. (2024). Measuring digital development: Facts and figures 2024. https://www.itu.int/hub/publication/d-ind-ict_mdd-2024-1/

International Monetary Fund. (2023). Stacking up the benefits: Lessons from India's digital journey. IMF Working Paper WP/23/78. https://www.elibrary.imf.org/view/journals/001/2023/078/article-A001-en.xml

Lindert, K. A., Karippacheril, T. G., Rodriguez Caillava, I., & Nishikawa Chavez, K. (2020). Sourcebook on the foundations of social protection delivery systems. World Bank. https://openknowledge.worldbank.org/entities/publication/c44dc506-72dd-5428-a088-6fb7aea53095

Lowe, C., Rigolini, J., Solbes Castro, L., & Bastagli, F. (2023). Pathways toward digitalization in social protection and labor service delivery. World Bank. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099100523151038686

Masiero, S., & Buddha, C. (2021). Data justice in digital social welfare: A study of the Rythu Bharosa Scheme. arXiv. https://arxiv.org/abs/2108.09732

NITI Aayog. (2021a). Responsible AI: Approach document for India - Part 1: Principles for responsible AI. https://www.niti.gov.in/sites/default/files/2021-02/Responsible-AI-22022021.pdf

NITI Aayog. (2021b). Responsible AI: Approach document for India - Part 2: Operationalizing principles for responsible AI. https://www.niti.gov.in/sites/default/files/2021-08/Part2-Responsible-AI-12082021.pdf

NITI Aayog. (2022). Responsible AI for all: Adopting the framework. https://www.niti.gov.in/sites/default/files/2022-11/Ai_for_All_2022_02112022_0.pdf

OECD. (2024a). Modernising access to social protection: Strategies, technologies and data advances. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/modernising-access-to-social-protection_e97dce5c/af31746d-en.pdf

OECD. (2024b). Digital public infrastructure for digital governments. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/12/digital-public-infrastructure-for-digital-governments_11fe17d9/ff525dc8-en.pdf

OECD. (2025a). AI and the future of social protection in OECD countries. https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/06/ai-and-the-future-of-social-protection-in-oecd-countries_038f49ed/7b245f7e-en.pdf

OECD. (2025b). Harnessing artificial intelligence in social security. https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/12/harnessing-artificial-intelligence-in-social-security_d03136ef/b52405c1-en.pdf

Okamura, Y., Ohlenburg, T., & Tesliuc, E. D. (2023). Novissi Togo: Harnessing artificial intelligence to deliver shock-responsive social assistance. World Bank . https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099751009222330502

Pinto, A. D., Perri, M., Pedersen, C. L., Aratangy, T., Hapsari, A. P., & Hwang, S. W. (2021). Exploring different methods to evaluate the impact of basic income interventions: A systematic review. International Journal for Equity in Health, 20, Article 142 . https://doi.org/10.1186/s12939-021-01479-2

Razzano, G. (2024). AI and exclusion in public digital systems. International Development Research Centre. https://idl-bnc-idrc.dspacedirect.org/bitstreams/a74d151c-825a-453f-baa1-134b016f386f/download

Republic of Brazil, National Data Protection Authority. (2020). Brazilian General Personal Data Protection Law (LGPD): English translation. https://www.gov.br/anpd/pt-br/centrais-de-conteudo/outros-documentos-e-publicacoes-institucionais/lgpd-en-lei-no-13-709-capa.pdf

Rizvi, A., Welch, V., Thompson, J., et al. (2024). Effects of guaranteed basic income interventions on poverty-related outcomes in high-income countries: A systematic review and meta-analysis. Campbell Systematic Reviews, 20(2), e1414. https://doi.org/10.1002/cl2.1414

South African Social Security Agency. (2025). Annual report 2024/25. https://nationalgovernment.co.za/entity_annual/4310/2025-south-african-social-security-agency-%28sassa%29-annual-report.pdf

United Nations Development Programme. (2023a). The human and economic impact of digital public infrastructure. https://www.undp.org/publications/human-and-economic-impact-digital-public-infrastructure

United Nations Development Programme. (2023b). Accelerating the SDGs through digital public infrastructure. https://www.undp.org/india/publications/accelerating-sdgs-through-digital-public-infrastructure-compendium-potential-dpi

United Nations Development Programme. (2024). Universal basic income in Asia and the Pacific. https://www.undp.org/sites/g/files/zskgke326/files/2024-10/undp-rbap-policy-brief-2024.pdf

UN Women. (2024). Risks and benefits of digital tools for social protection from a gender perspective. https://www.unwomen.org/sites/default/files/2024-02/risks_and_benefits_of_digital_tools_from_a_gender_perspective_en.pdf

World Bank. (2022a). Identification for Development (ID4D) Global Dataset. https://id4d.worldbank.org/global-dataset

World Bank. (2022b). Global Findex Database 2021. https://databank.worldbank.org/source/global-findex-database

World Bank. (2023a). New Bolsa Familia: Challenges and opportunities for 2023. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099092023174847671

World Bank. (2023b). Government-to-person payments and digital public infrastructure. https://www.worldbank.org/en/programs/g2px

World Bank. (2024a). Social protection inclusion in Indonesia's remote areas. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099062624071020814

World Bank. (2025a). Digital delivery systems for social protection. https://www.worldbank.org/en/topic/socialprotection/brief/digital-delivery-systems

World Bank. (2025b). Kenya social protection and jobs public expenditure review and project documentation. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099052925175539265

World Bank. (2025c). Digital G2P payments and benefits to recipients. https://documents.worldbank.org/en/publication/documents-reports/documentdetail/099053025155645427

World Bank. (2025d). Digital public infrastructure and development: A World Bank Group approach. https://openknowledge.worldbank.org/entities/publication/cca2963e-27bf-4dbb-aa5a-24a0ffc92ed9