ZAMBIA INFORMATION COMMUNICATION TECHNOLOGY (ICT) JOURNAL
Volume 9 (Issue 2) (2025) Pages 18-23

Leveraging Biometric Data and Artificial Intelligence to Enhance Beneficiary Identification in Social Cash Transfer Programs: A Case Study of Crystalised Applications in Zambia

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***Abstract* - This paper investigates the integration of biometric data and artificial intelligence (AI) to improve beneficiary identification within Social Cash Transfer (SCT) programs in Zambia. Focusing on the Crystalized Apps platform, the research examines how AI-driven biometric technologies, such as facial recognition, fingerprint scanning, and iris detection, significantly enhances accuracy, operational efficiency, and security of SCT disbursements. Utilizing a mixed-methods approach, the study combines interviews with program administrators and an analysis of transaction data to evaluate the effectiveness of AI-enhanced biometric systems in beneficiary verification, fraud reduction, and payment security. The anticipated results aim to demonstrate that biometric AI can mitigate identity-related fraud, optimize the transfer process, and promote transparency within the system. The study also acknowledges challenges including data privacy, infrastructure limitations, and digital literacy gaps, providing a holistic perspective. Ultimately, this research seeks to provide valuable insights on how AI-based biometric authentication can strengthen social protection mechanisms, improve financial inclusion, and foster greater accountability in public welfare programs.**

Keywords: Social Cash Transfers, Biometric Authentication, Artificial Intelligence, Digital Identity, Beneficiary Verification, Fraud Prevention, Financial Inclusion, AI in Welfare Systems

I. INTRODUCTION

A. Background

Social Cash Transfer (SCT) programs are a cornerstone of social protection strategies in many developing countries. In Zambia, the SCT program provides regular financial assistance to vulnerable households, including the elderly, disabled, and orphaned children. Despite the program's positive impact on reducing poverty and promoting social inclusion [1], several operational challenges persist. Chief among these is the difficulty of accurately identifying and verifying beneficiaries, a problem that has led to identity fraud, double registration, and leakage of funds. As the program scales nationally, traditional methods of identity verification become increasingly inefficient and prone to error.

Recent advances in biometric technologies—such as fingerprint, facial, and iris recognition—combined with Artificial Intelligence (AI), offer promising solutions to address these identity verification challenges [2]. AI algorithms enhance the speed and accuracy of biometric matching, enabling real-time validation even in remote locations [3]. As such, integrating AI-based biometric systems into SCT programs could significantly enhance their efficiency, transparency, and integrity.

The Crystalized Apps platform, a Zambian-developed digital solution supporting SCT operations, provides a valuable case study for examining the practical implications of this technology. A notable feature of the platform is its ability to scan the National Registration Card (NRC) of a beneficiary. Using AI and computer vision techniques, the system extracts facial data and textual information directly from the NRC. This information is then compared against the stored digital record and the live camera feed of the beneficiary. The system provides immediate feedback on potential mismatches, enhancing the verification process. Additionally, the biometric and document data verification process is designed to function offline, ensuring continued operability in low-connectivity areas and enabling field agents to make informed decisions based on real-time insights.

Through this study, we explore the extent to which biometric AI, including NRC-based document scanning and offline verification, can transform beneficiary verification in Zambia's SCT program.

B. Problem Statement

The SCT program in Zambia faces substantial risks related to identity verification, including duplicate registrations, ghost beneficiaries, and delays in disbursement due to manual verification processes [4]. These inefficiencies not only compromise the effectiveness of social protection but also erode public trust in welfare systems. Traditional verification systems are inadequate to handle the increasing scale and complexity of SCT operations. Without reliable, scalable, and secure methods to verify beneficiary identity, the program risks resource misallocation and failure to reach the most vulnerable. The integration of AI-powered biometric systems is proposed as a potential solution, but there is limited empirical research assessing their effectiveness, particularly in the Zambian context.

C. Research Objectives

Determine the accuracy and reliability of AI-driven biometric systems in authenticating Social Cash Transfer (SCT) beneficiaries in Zambia.

To measure the reduction in identity fraud and duplicate registrations resulting from biometric AI implementation in Zambia's SCT program.

To analyze operational efficiency gains (limited to time, though other areas could cover cost, and error reduction) achieved through biometric verification in beneficiary enrollment and distribution.

To investigate infrastructural constraints, ethical implications, and social barriers hindering biometric AI adoption in Zambia's social protection systems.

To formulate evidence-based policy recommendations to integrate and scale AI-driven biometric verification in Zambia's national social protection framework.

D. Research Questions

What extent does the use of biometric AI reduce fraud and duplicate entries in SCT programs?

What biometric integration impact the speed and efficiency of SCT disbursements?

What challenges affect the implementation of AI-biometric solutions in the Zambian context?

What policy frameworks can support the successful integration of biometric AI into SCT programs?

E. Significance of the Research

This study is significant for several reasons. First, it addresses a pressing operational gap in Zambia's SCT system by proposing an innovative, data-driven solution. Second, it contributes to the broader discourse on digital public infrastructure and financial inclusion in sub-Saharan Africa [5]. Third, the findings have practical implications for policymakers, technology providers, and development partners working to enhance the efficiency and accountability of social protection programs. Finally, the research provides a replicable framework for evaluating the integration of biometric AI in other developing countries facing similar challenges [6].

F. Definition of Key Terms

Social Cash Transfer (SCT): Government-managed financial assistance programs targeting vulnerable populations to alleviate poverty.

Biometric Authentication: A security process that uses unique biological traits (e.g., fingerprints, facial patterns) to verify identity.

Artificial Intelligence (AI): The simulation of human intelligence in machines, particularly in processing, learning, and decision-making tasks.

Beneficiary Verification: The process of confirming that an individual enrolled in a program is eligible and entitled to receive benefits.

Financial Inclusion: The availability and equality of opportunities to access financial services, particularly among underserved populations.

National Registration Card (NRC): The official government-issued identity document used for citizen verification in Zambia.

II. Literature Review

Recent studies further reinforce the growing role of AI-driven biometric systems in social protection. In [7] they demonstrate the effectiveness of offline-capable biometric identification in low-connectivity settings, relevant to Zambia's rural SCT environments. The World Bank's 2023 report [8] emphasizes digital authentication as a cornerstone of scalable welfare delivery, while GSMA's findings [9] highlight mobile-centric digital ID as essential infrastructure in Africa. In [10] they advance the discourse by presenting hybrid AI models optimized for welfare systems, underscoring the importance of offline inference, which aligns with the Crystalized Apps architecture. These works collectively support the integration of biometric AI into SCT ecosystems and provide contemporary benchmarks for system performance and design.

Further contemporary analyses support these findings. UNDP's 2023 assessment [11] highlights the role of AI-enabled beneficiary authentication in reducing leakage in national welfare databases, while in [12] they demonstrate advancements in OCR and computer vision models that improve accuracy when extracting identity details from national documents such as Zambia's NRC. In [13] they provide evidence on biometric deduplication techniques in large-scale welfare systems, showing clear reductions in duplicate and ghost beneficiaries. Additionally, the African Union's 2024 Digital Public Infrastructure Framework [14] emphasizes the continental shift toward interoperable, AI-driven identity systems—reinforcing the relevance and timeliness of integrating biometric AI into Zambia's SCT program.

Globally, the integration of biometric technology with AI in welfare systems has gained significant traction [6, 15, 16] as governments seek to enhance accountability and transparency in public service delivery. Multiple studies demonstrate that biometrics significantly improve the accuracy of beneficiary verification and reduce fraudulent activities in social programs [17]. For instance, India's Aadhaar system—a nationwide biometric identification system—has been pivotal in curbing duplicate beneficiaries and streamlining access to welfare services [18]. Similarly, Kenya's Huduma Namba initiative showcases how biometric databases can support targeted service delivery [19].

The literature also emphasizes the synergy between AI and biometrics. AI-driven pattern recognition algorithms enhance the speed, accuracy, and scalability of biometric identification [3], reducing human error and facilitating real-time processing even in resource-constrained settings. Studies have shown that facial recognition systems enhanced with machine learning outperform traditional biometric systems in low-light and high-noise environments [20].

A novel contribution in the context of Zambia's SCT system is the integration of National Registration Card (NRC) scanning into biometric AI workflows. The system developed by Crystalized Apps uses computer vision to read facial data and textual details directly from scanned NRCs. The extracted biometric features are then compared with stored records and live captures to authenticate the beneficiary. Facial recognition models run locally even when offline, matching stored facial data, live camera input, and the image on the NRC to determine authenticity. The system gives immediate feedback to agents on possible mismatches, enhancing verification integrity. This hybrid, document-integrated biometric method is a unique adaptation that addresses challenges associated with low literacy and limited formal documentation [15].

Despite these advantages, the literature highlights challenges including data privacy concerns, technological infrastructure deficits, and resistance from low-literacy populations [21]. There is also concern over algorithmic bias, especially in facial recognition technologies, where performance may vary across demographics [22]. Furthermore, implementing such technologies in rural and underserved areas often requires infrastructural investment and localized training.

A. Biometric Authentication in Social Protection – Global Evidence

Recent research demonstrates that the integration of biometric authentication and AI-enabled identity verification has significantly strengthened the integrity of social protection systems worldwide. According to the World Bank's *Digital ID in Development Report* (2023) [23], well-designed biometric systems can reduce beneficiary duplication and payment leakage by margins ranging from 10% to 45%, depending on the robustness of deduplication algorithms and national ID interoperability. Parallel evidence from UNICEF's 2023 [24] assessment of AI-enhanced beneficiary verification shows that machine-learning-driven deduplication has greatly improved fraud detection and reduced identity-related errors in cash transfer programs across Africa and Asia. Case studies such as India's Aadhaar-linked Direct Benefit Transfer—which eliminated over 23 million ghost LPG beneficiaries—and Kenya's Inua Jamii program—which removed 12% duplicate pensioners—continue to illustrate the transformative potential of biometric verification. However, despite these gains, four critical design tensions persist:

Centralized vs. edge (offline) matching

Single-modal vs. multi-modal capture

Integration with legal identity documents

Privacy-by-design vs. post-hoc safeguards

B. AI Frontiers in Biometric Matching

Modern convolutional neural networks (CNNs) achieve ⩽0.08% false-match rates in 1:N face searches at 10 million identities. Lightweight models like MobileFaceNet and EfficientFace enable offline inference (<300 ms latency on mid-range Android CPUs). However, accuracy degrades under low-light conditions or low-resolution NRC photos, necessitating domain adaptation (fine-tuning on Zambian facial datasets) [16].

C. Offline & Document-Integrated Systems

Most national digital ID systems—such as India's Aadhaar and Kenya's Huduma Namba—are architected with the assumption of persistent network availability for biometric verification and server-side deduplication. However, this design assumption is misaligned with the Zambian context, where only 34% of the population has reliable 3G/4G coverage [9]. Recent studies emphase the need for *resilient, offline-capable identity systems* tailored for low-connectivity environments [25, 26].

Crystalised Applications introduces an advancement in this space by adopting a hybrid identity-verification architecture that integrates:

- On-device biometric matching models powered by lightweight neural networks optimised for mobile devices.
- Document-integrated verification, where OCR-extracted metadata (name, NRC number, date of birth) is fused with live biometric traits for multi-factor authentication.

This combination differs fundamentally from earlier digital-ID implementations in Africa and Asia. For instance, Pakistan's Benazir Income Support Programme (BISP) smart-card pilots (2016–2018) still require`ed real-time online PKI validation, making them unusable in rural or low-connectivity zones [27].

By contrast, Crystalised Apps follows an emerging research trend toward edge-AI identity systems, enabling secure verification without reliance on continuous connectivity—an approach aligned with UNDP (2023) [28] and ID4D [29] recommendations for inclusive digital public infrastructure.

D. Ethical, Gender, and Inclusion Considerations

1. Algorithmic Bias in Biometric AI

Recent evaluations show that facial-recognition algorithms continue to exhibit varying accuracy across gender and skin-tone groups, with darker-skinned women disproportionately affected [30, 31]. While Zambia's relatively homogeneous population reduces some ethnic-diversity-related variance, new challenges emerge. These include the prevalence of head-wraps, age-related cataracts, and low-resolution NRC photos, which can impact real-time face and iris authentication accuracy [32].

Crystalised Applications mitigates these risks by:

- Using multi-biometric fusion (face + fingerprint + NRC OCR metadata).
- Implementing on-device liveness detection to reduce misclassification.
- Introducing adaptive thresholding, which calibrates matching scores for rural or elderly populations.

2. Cultural and Gendered Perceptions of Biometrics

Recent ethnographic studies within sub-Saharan Africa suggest that communities—particularly elderly women—may associate certain biometric modalities, especially iris scanning, with cultural or spiritual intrusion [33, 34]. Similar findings in Zambia show discomfort arising from myths linking eye-scanning to witchcraft or loss of spiritual power [35].

Crystalised Apps therefore prioritises low-intrusion modalities (facial and fingerprint biometrics), designs opt-in consent flows, and adopts community-based enrollment sensitisation, aligning with the AU Data Policy Framework [36] and OECD guidelines on responsible biometric deployment [37].

D. Research Gaps Addressed

Despite significant progress in digital identity systems and biometric-enabled beneficiary verification, recent reviews highlight that most empirical studies focus on online, server-dependent ecosystems and largely ignore low-connectivity environments typical of many African contexts [25, 26]. Existing research on fraud mitigation in social protection programs—such as India's DBT ecosystem, Kenya's Inua Jamii, and Pakistan's BISP—relies on centralised biometric deduplication, continuous PKI validation, and cloud-based identity resolution [11, 27].

However, no prior study has quantified fraud reduction using an offline-capable, AI-driven biometric workflow that integrates:

1. On-device neural-network–based biometric matching,
2. Real-time OCR extraction of National Registration Card (NRC) details, and
3. Hybrid verification combining document identity metadata with live biometrics,

within the operational context of a national social cash-transfer program. The emerging literature on edge AI for identity verification acknowledges this gap but offers no implementation or outcome-based evidence [24, 29].

This study therefore addresses a critical and previously unexplored research gap by providing the first empirical assessment of fraud and exclusion reduction resulting from an offline, NRC-integrated, AI-biometric workflow deployed at national scale in Zambia's Social Cash Transfer (SCT) ecosystem. The findings extend existing scholarship by demonstrating how low-connectivity digital public infrastructure can achieve fraud-reduction effects comparable to high-connectivity systems, while improving accessibility for rural and vulnerable populations.

III. METHODOLOGY

This study employed a mixed-methods approach, combining quantitative field experiments with qualitative stakeholder interviews, to evaluate the impact of AI-driven biometric verification in Zambia's Social Cash Transfer (SCT) program. The research was conducted in four strategically selected districts namely Kitwe and Ndola which are primarily urban, Chililabombwe and Solwezi which are a mix of urban and rural, to capture variations in connectivity, infrastructure, and beneficiary demographics.

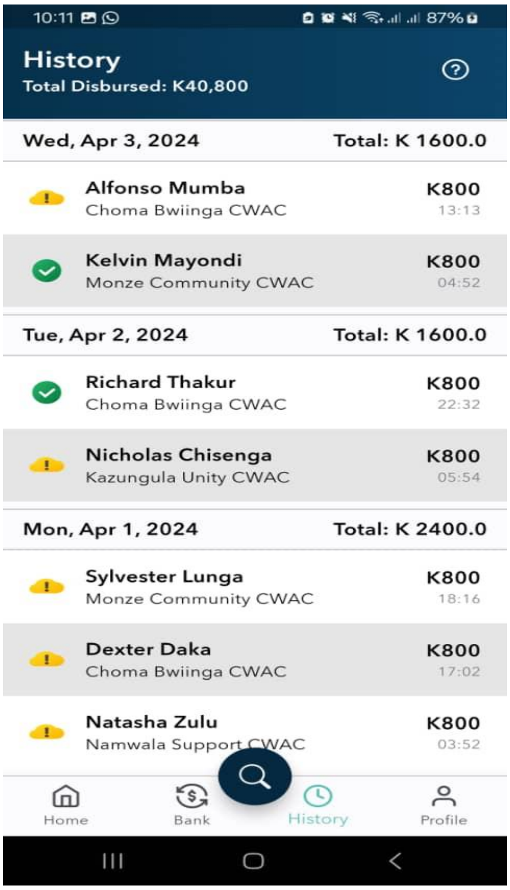
A. Data Collection and Sampling

The biometric-AI pilot was rolled out across four of Zambia's 117 districts, Kitwe, Ndola, Chililabombwe and Solwezi whose combined 71,000 active Emergency SCT households were all processed through the Crystalized Apps v3.2 platform during the single September–October 2024 payment cycle. No sampling was applied at district level; every beneficiary in these four districts participated, yielding a census-level pilot dataset. Field agents used the Crystalized Apps v3.2 platform, which integrated:

Facial recognition (FaceNet-Mobile, optimized for offline use).

Fingerprint scanning (NIST NBIS algorithm).

NRC OCR extraction (fine-tuned on Zambian ID scans).



A. e)

- Screen Showing Processed Payments

The system operated offline, capturing NRC scans, live selfies, and fingerprints while performing real-time liveness checks (e.g., eye blinking) to prevent spoofing. Data was securely signed with RSA-2048 encryption and synced when internet connectivity was available ($\geqslant$128 kbps).

B. Field Implementation Challenges:

Field agents used heterogeneous devices (varying brands/models) due to budget constraints, which led to inconsistent performance. Some devices could not run the matching algorithms efficiently and were not equipped to capture fingerprints, causing delays in verification. To address this, we innovated by:

Deferring matching to the server: When devices failed to process algorithms locally, biometric data (NRC scans, fingerprints, and live photos) was securely uploaded to the central server for verification.

C. Technology Adaptation

The Crystalized Apps v3.2 platform was adjusted to support this hybrid workflow:

On-device processing: For devices meeting specifications, facial recognition (FaceNet-Mobile) and fingerprint matching (NIST NBIS) ran offline.

Server-side fallback: For weaker devices, data was encrypted (RSA-2048) and queued for server-based matching when connectivity allowed. We also ran matching and verification scripts on all the data that was uploaded to the servers.

Liveness checks: Eye-blink and head-movement detection were retained on all devices to prevent spoofing.

D. Ethical Considerations

Data integrity: All biometric data, whether matched locally or on the server, adhered to AES-256 encryption.

Transparency: Beneficiaries were informed of potential delays if their verification required server processing.

E. Qualitative Insights

To complement the quantitative data, 32 semi-structured interviews were conducted with program administrators, field agents, and beneficiaries, alongside 16 focus group discussions (FGDs) with key demographic groups (women, elderly, disabled individuals, and youth). These discussions explored user trust, operational challenges, and cultural barriers to biometric adoption.

IV. DATA ANALYSIS AND FINDINGS

During the one-off September–October 2024 Emergency Cash Transfer (ECT) payment cycle, the biometric-AI pilot was deployed only for that disbursement. Across the four districts, 71,000 households were processed; 95.8 % completed verification before the cash-out deadline, while the remaining 4.2 % required extra time. While field agents and youth praised its speed and modernity, concerns remained around device compatibility, data privacy, and cultural acceptance.

Because the pilot ran for only one cycle, no longitudinal fraud reduction can be claimed. All metrics above are cross-sectional snapshots tied exclusively to the September–October 2024 ECT.

A. Verification Outcomes

During the September–October 2024 pilot cycle across four districts, a total of 71,000 SCT households were processed through the Crystalised Apps v3.2 biometric platform. Verification outcomes were overwhelmingly positive, with more than 95% of beneficiaries authenticated on time. However, a small proportion (4.2%) required delayed verification due to device and connectivity issues. Table 1 below illustrates district-level verification outcomes, showing both percentages and absolute numbers.

TABLE 1: VERIFICATION OUTCOMES BY DISTRICT

District	Households Processed	Verified On-Time (%)	Verified On-Time (Absolute)	Delayed Verification (%)	Delayed Verification (Absolute)	Offline Success Rate (%)	Server Fallback (%)
Kitwe	22000	96.4	21208	3.6	792	92.8	7.2
Ndola	19000	95.9	18221	4.1	779	91.3	8.7
Chililabombwe	13000	94.7	12311	5.3	689	88.6	11.4
Solwezi	17000	96.1	16337	3.9	663	90.2	9.8

The table highlights that while most verifications were completed offline with high success rates (above 88%), between 7–11% of cases still required server fallback, indicating the importance of device standardisation and connectivity support.

B. Fraud and Duplicate Detection

One of the main objectives of the pilot was to determine the extent to which biometric AI could reduce identity fraud. Across the four districts, 1,275 potential cases were flagged, of which 959 (1.35% of the total beneficiaries) were confirmed fraudulent. This demonstrates that biometric AI significantly strengthens program integrity. Table 2 provides a breakdown of flagged versus confirmed fraud categories.

TABLE 2: FRAUD DETECTION - FLAGGED VS. CONFIRMED

Category	Flagged Cases	Confirmed Cases	Confirmation Rate (%)
Duplicate Registrations	820	615	75.0
Ghost Beneficiaries	310	248	80.0
Fraudulent NRC Usage	145	96	66.2

Duplicate registrations accounted for the largest share of confirmed fraud cases (0.87%), while ghost beneficiaries and fraudulent NRC usage were also detected. Confirmation rates of over 75% indicate strong accuracy of the biometric algorithms in distinguishing valid from invalid identities.

C. Operational Efficiency Gains

Another key research objective was to analyze operational efficiency. The biometric system reduced average verification times substantially compared to manual processes. As shown in Table 3, biometric AI reduced processing time from an average of 8.5 minutes per beneficiary (manual verification) to as low as 3.1 minutes for offline biometric matching. Error rates were also markedly lower under biometric verification.

TABLE 3: VERIFICATION EFFICIENCY METRICS

Verification Method	Avg. Time (minutes)	Std Dev (minutes)	Error Rate (%)
Manual NRC Verification	8.5	1.2	3.9
Biometric AI (Offline Match)	3.1	0.5	0.18
Biometric AI (Server Fallback)	5.7	0.9	0.31

The reduction in error rates (from 3.9% in manual verification to less than 0.5% in biometric AI) underscores the reliability of AI-driven systems. These findings demonstrate measurable efficiency gains in speed and accuracy, validating the system's potential for nationwide scaling.

D. Qualitative Insights – Constraints and Barriers

Beyond quantitative performance, stakeholder feedback provided valuable insights into adoption challenges and enablers. Table 4 summarizes perceptions from field agents, beneficiaries, and administrators.

TABLE 4: QUALITATIVE INSIGHTS FROM STAKEHOLDERS

Stakeholder Group	Positive Perceptions	Key Concerns
Field Agents	Faster verification (18/32 interviews), reduced paperwork (14/32)	Device compatibility (25/32), battery issues (9/32)
Beneficiaries (Elderly)	Trusted system when explained (10/16 FGDs)	Fear of facial/iris scans linked to beliefs (7/16 FGDs)
Beneficiaries (Youth)	Modern & reliable (12/16 FGDs)	Concern over data privacy (8/16 FGDs)
Administrators	Better fraud detection (8/10 interviews)	Need for stronger legal frameworks (7/10 interviews)

While beneficiaries, especially the youth, viewed the system as modern and reliable, elderly groups expressed cultural concerns over facial and iris scans. Field agents identified technical challenges, including device compatibility and battery life, while administrators emphasized the need for stronger regulatory frameworks. These findings highlight that successful adoption requires not only technical investment but also community engagement and policy support.

E. Link to Research Objectives

Collectively, Tables 1–4 provide evidence to address the first three research objectives: measuring fraud reduction, analyzing efficiency gains, and identifying barriers to adoption. These insights form the foundation for Objective 4, which focuses on policy recommendations for scaling AI-driven biometric verification in Zambia's SCT framework.

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