Open Access Indonesia Journal of Social Sciences

Vol. 9 · No. 5 · 2026 · pp. 254–273 · Article ID 336

e-ISSN 2722-4252 · *Journal homepage: journalsocialsciences.com/index.php/oaijss*

ORIGINAL ARTICLE

Algorithmic Welfare Gatekeeping and Regressive Digital Administrative Burden: Multi-Tier Econometric and Critical Mixed-Methods Evidence on Informal-Sector and Vulnerable Citizen Exclusion from Social Protection Services in Indonesia

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ARTICLE INFORMATION

Received: September 1, 2026
Revised: September 15, 2026
Accepted: October 15, 2026
Available Online: October 22, 2026
Published: October 30, 2026

Keywords: Administrative burden; Algorithmic welfare gatekeeping; Digital government; Informal sector; Social protection; Indonesia

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DOI: https://doi.org/10.37275/oaijss.v9i5.336

ABSTRACT

Background: States across the Global South place social protection behind digital registries, biometric identity checks, and smartphone applications. Whether this gatekeeping shifts regressive administrative burdens onto informal-sector and vulnerable citizens is insufficiently tested.

Objective: To examine how digital-identity gaps, district exposure to Indonesia's 2017 electronic transfer conversion, and citizen grievances relate to exclusion from social protection.

Methods: A critical mixed-methods design combined 159,399 public records. Tier 1 used World Bank Global Findex (N = 157 economies) and ID4D (N = 58). Tier 2 used INDO-DAPOER panels for 514 Indonesian districts (5,128 district-years, 2011–2020), analyzed with two-way fixed-effects difference-in-differences (TWFE-DiD), augmented inverse probability weighting (AIPW), and recentered influence function (RIF) quantile decomposition. Tiers 3 and 4 applied two-classifier coding (Krippendorff's $\alpha = 0.65–0.99$) and Quasi-Poisson modeling to N = 2,400 citizen reports on four apps.

Results: Primary-educated adults had a −19.21 percentage-point (pp) account deficit and a −17.46 pp online digital-ID deficit. In Indonesia, 16.67% of adults held online digital IDs. After 2017, high-friction informal districts showed a 0.658 pp lower poorest-20% relative expenditure ratio per 1-SD higher baseline friction ($p = 0.0007$), wider Gini inequality (+0.0068, $p = 9.05 \times 10^{-5}$), and slower poverty reduction (AIPW ATE = +0.400 pp). Of the citizen reports, 60.0% described administrative burdens. Replies reached 37.8% on contributory JMO but 0.0%–3.3% on non-contributory portals.

Conclusion: Digital welfare gatekeeping was associated with a 'Digital-to-Analog Boomerang': failed self-service sends claimants back to physical counters. Reform needs offline parity, NIK–DTKS reconciliation, non-biometric fallbacks, and grievance standards.

All authors approved the final version of the manuscript.

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1. Introduction

1.1. Digital welfare transformation and the redistributive politics of administrative burden

The bureaucratic architecture that governs citizen access to social protection has changed deeply over the past decade. Both advanced welfare democracies and rapidly digitalizing states of the Global South show the shift. Paper-based applications, universal commodity subsidies, and community-mediated cash disbursements have increasingly given way to centralized social registries, biometric identity verification, automated proxy-means scoring, and self-service smartphone portals.[1,2] Mainstream international development discourse widely presents digital Government-to-Person (G2P) payment ecosystems and integrated civil-welfare databases as technocratic cures. They are said to eliminate fiscal leakage, bypass rent-seeking local intermediaries, and lower state delivery costs. Yet a growing body of empirical public administration scholarship questions this. Does digitizing public services inherently reduce bureaucratic friction? Burdens do not vanish into code. Administrative burdens, defined along three canonical dimensions (learning costs, compliance costs, and psychological costs), are frequently shifted outward from salaried civil servants onto ordinary claimants, who must act as uncompensated 'accidental caseworkers' and navigate brittle digital interfaces.[3–5]

Recent theoretical and experimental advances show that citizen encounters with bureaucratic rules are neither socioeconomically neutral nor determined solely by formal statutory eligibility, and empirical investigations in leading public administration venues find that structural vulnerability shapes both how often bureaucratic costs arise and how tolerable they feel. Framing matters too. The communicative framing, procedural clarity, and street-level embeddedness of rule enforcement decide whether vulnerable citizens successfully claim public entitlements or exit in frustration.[6–9] Sometimes public agencies replace human front-line discretion with rigid digital forms. Matching investments in citizen usability or empathetic mediation do not always follow. Applications stall. Marginalized claimants then routinely experience 'administrative limbo,' a protracted state of procedural suspension without intelligible explanation, which erodes citizens' sense of institutional recognition, bodily dignity, and emotional capital.[9–13]

1.2. Algorithmic state legibility, biometric gatekeeping, and Indonesia's social protection pivot

Street-level human bureaucracy is giving way to automated digital gatekeeping. This fundamentally alters

how the state 'sees' and classifies vulnerable populations. Automated eligibility checks, mobile authentication protocols, and artificial-intelligence or rule-based scoring engines now recompose front-line administrative discretion. Citizens whose lived livelihoods deviate from standardized formal-sector templates risk becoming illegible to state databases.[2,14,15] Municipal and ministerial open-data dashboards often project an aura of technocratic precision and reformist efficiency through polished data storytelling. Rigid database schemas obscure the exclusions on the ground.[15,16] Recent comparative welfare scholarship names this emerging paradigm 'digital social administration' and warns that automated eligibility cross-checks and multi-layered mobile portals can operate as de facto instruments of welfare retrenchment, building a multi-level digital maze in which authentication failures sever statutory social rights from physical reality.[17–20] Disconnects follow. In populous postcolonial democracies, mandatory biometric and digital-identity linkage has repeatedly generated acute 'digital-physical disconnects' for manual laborers, rural women, the elderly, and poorly documented households, whose fingerprints, facial captures, or civil records fail algorithmic matching.[1,20–22]

Indonesia offers a setting well suited to examining these dynamics at scale. It is home to more than 270 million residents spread across an archipelago of 38 provinces and 514 second-tier regencies (*Kabupaten*) and cities (*Kota*).[23,24] Targeted social protection matters here. It cushions households against macroeconomic shocks, agrarian volatility, and persistent precarity in the informal sector.[25–27] In 2017 the national government began a major structural reform. Community-distributed in-kind rice subsidies (*Raskin/Rastra*) were phased out. Electronic, account- and card-gated Non-Cash Food Assistance (*Bantuan Pangan Non-Tunai* [BPNT]/*Sembako*) took their place, together with a rapid electronic expansion of the Family Hope Conditional Cash Transfer Program (*Program Keluarga Harapan* [PKH]). Eligibility for these non-contributory transfers, and for subsidized National Health Insurance premiums (*Penerima Bantuan Iuran* [PBI-JKN]), was legally tied to the synchronization of two registries. One was the Ministry of Social Affairs' Unified Social Welfare Registry (*Data Terpadu Kesejahteraan Sosial* [DTKS], managed via SIKS-NG). The other was the biometric Single Identity Number (*Nomor Induk Kependudukan* [NIK]) held by the Ministry of Home Affairs. From 2021 to 2026, this digital gatekeeping stack moved directly onto citizens' smartphones. Four flagship national applications carried it. Aplikasi Cek Bansos, from the Ministry of Social Affairs, offers self-nomination and community objection (*Usul–Sanggah*) gated by KTP-selfie liveness and household geotagged photography. *Identitas Kependudukan Digital* (IKD) comes from Ditjen Dukcapil. Mobile JKN, from BPJS Kesehatan, incorporates FRISTA facial recognition. Jamsostek Mobile (JMO), from BPJS Ketenagakerjaan, governs contributory security for formal workers and informal *Bukan Penerima Upah* (BPU) workers. Selective cash and food targeting in developing countries is already known to strain community social cohesion and to produce gendered adequacy gaps.[28–30] What remains unsettled? Social scientists have not yet established whether Indonesia's shift to registry- and app-gated welfare delivery brought equitable poverty reduction across informal rural peripheries or was followed by regressive exclusion.

1.3. Structural stratification, algorithmic agency, and an integrative critical mixed-methods design

Assessing the distributive consequences of algorithmic welfare gatekeeping calls for three bodies of work: macro-structural stratification theory, micro-level digital sociology, and causal econometrics. Contemporary stratification research shows that institutional rules, whether they govern family wealth, tax registries, or state transfers, systematically reproduce gender, educational, and class inequalities across generations. Citizens caught in opaque algorithmic environments respond with creative vernacular tactics. They contest visibility injustices.[31–33] Method matters as well. Isolating causal and distributional policy effects across heterogeneous subnational jurisdictions requires several tools: multi-period Difference-in-Differences designs attentive to treatment-intensity variation and compositional dynamics, principled covariate selection under selection-on-observables, validated computational text measurement, and distributional persistence modeling.[34–40] Neither approach suffices alone. Single-method econometric panels cannot observe the lived bureaucratic encounters through which digital exclusion actually occurs, and isolated qualitative app studies cannot establish population-wide impacts on poverty and inequality. This study follows the latest methodological standards in Critical Mixed Methods Research. Those standards call for explicit integrative research questions, power-conscious reflexivity toward marginalized voices, and formal Joint Displays that synthesize quantitative and qualitative strands into rigorous meta-inferences.[41–44] The study unites four public empirical tiers.

Four linked research questions guide the study. RQ1 (Macro-Comparative Quantitative) asks how civil-documentation deficits, informal employment, and educational/income strata structure access to financial accounts, digital G2P transfers, and online digital IDs across sovereign economies globally. How does Indonesia compare against ASEAN and LMIC peers? RQ2 (Subnational Distributional Econometrics) concerns all 514 Indonesian districts observed from 2011 to 2020. Following the 2017 electronic social protection transition, did baseline informal-labor concentration and analog–digital infrastructure deficits attenuate bottom-quintile welfare gains, widen intra-district inequality, and slow poverty reduction? RQ3 (Computational & Qualitative Grievance Analysis) draws on 2,400 verbatim citizen reports about Indonesia's four flagship digital welfare and civil-ID portals. The question is how learning, biometric/registry compliance, and psychological burdens manifest. Do they garner collective civic endorsement? How do they meet bureaucratic responsiveness or silence? RQ4 (Integrative Critical Mixed-Methods Meta-Inference) closes the set. The last question is this: how do lived citizen experiences of what we conceptualize as the 'Digital-to-Analog Boomerang' explain and expand econometric estimates of regressive welfare exclusion?

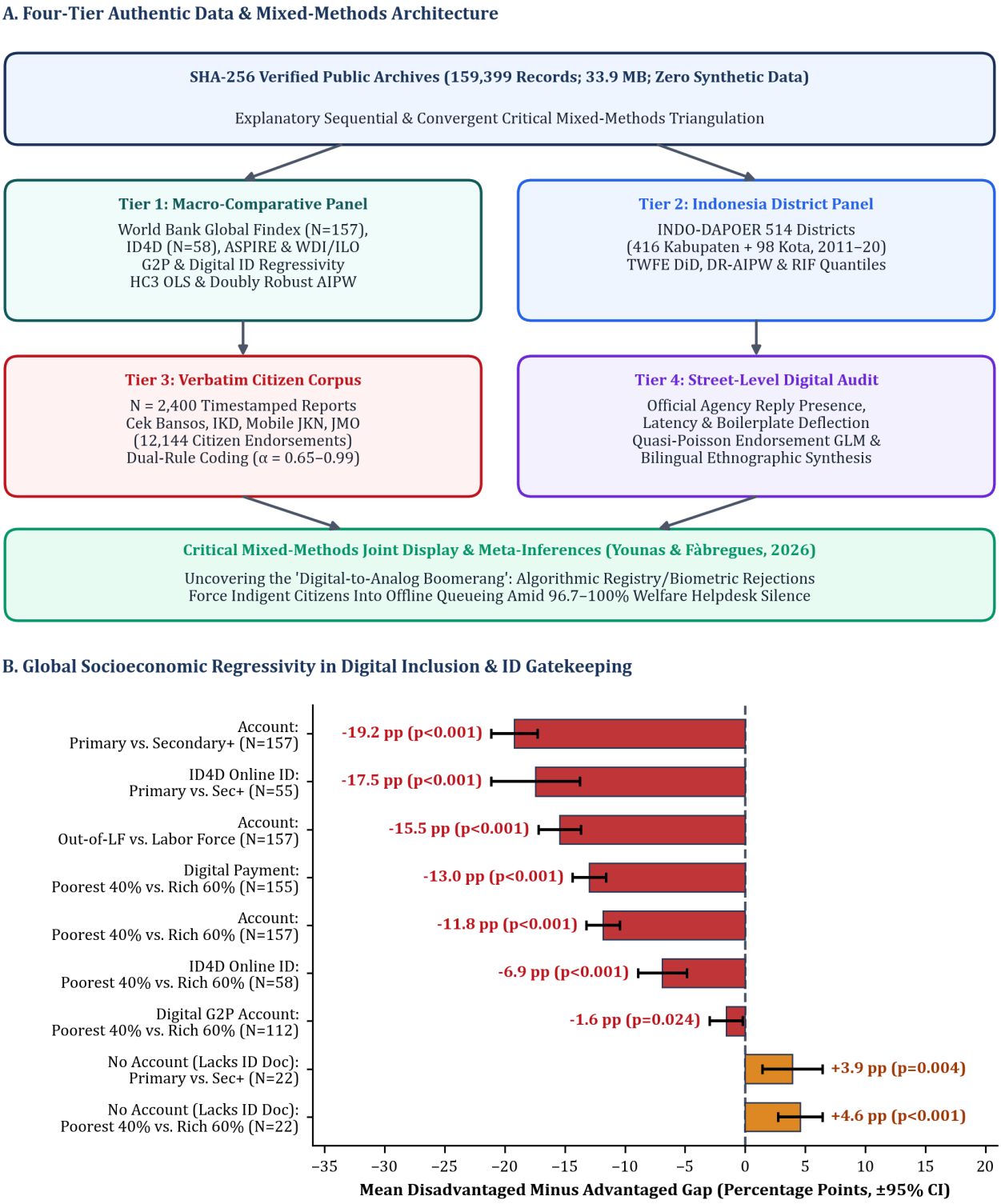


Figure 1. Multi-tier empirical architecture and global socioeconomic regressivity in digital inclusion and identity gatekeeping. (A) Convergent and explanatory sequential Critical Mixed-Methods design uniting 159,399 public records (file integrity checked with SHA-256) across World Bank Global Findex/ID4D/ASPIRE, INDO-DAPOER (514 Indonesian districts), and 2,400 verbatim citizen digital welfare reports. (B) Paired cross-national socioeconomic gaps (percentage points ± 95% confidence intervals) across sovereign economies showing steep class, educational, and labor-force deficits in account ownership, digital payments, and online digital ID possession alongside regressive civil-documentation exclusion.

2. Methods

2.1. Study architecture, institutional timeline, and ethical governance

We implemented a convergent and explanatory sequential Critical Mixed-Methods research architecture.[42,45] It integrates four public evidence tiers. Tiers 1 to 3 supply 159,399 raw records (Figure 1A), and Tier 4 audits the agency replies attached to the Tier 3 reports. No synthetic, simulated, or imputed placeholder observations were used at any stage of analysis. The empirical design exploits the institutional sequence of Indonesia's digital social-protection transformation. Three phases define it. (i) The pre-electronic baseline era (2011–2016). Indonesia's largest food-assistance safety net (*Raskin/Rastra*) then operated through physical community rice allocations, largely decoupled from bank-account ownership or real-time biometric civil-registry matching. (ii) The subnational electronic transition era (2017–2020). It began with Presidential Regulation No. 63/2017, which mandated cashless electronic disbursement of BPNT and PKH transfers via Prosperous Family Cards (*Kartu Keluarga*

Sejahtera [KKS]), strictly cross-validated against SIKS-NG/DTKS and Dukcapil NIK civil records. (iii) The smartphone self-service and biometric verification era (2021–2026). Nationwide deployment of Aplikasi Cek Bansos, *Identitas Kependudukan Digital* (IKD), Mobile JKN facial biometrics, and JMO e-KYC marks this phase.

All quantitative macro-indicators, subnational district panels, and publicly posted citizen application reviews come exclusively from open, de-identified public archives. The World Bank maintains some of them, Statistics Indonesia (BPS) maintains others through INDO-DAPOER, and public software-platform feedback feeds supply the rest. Public pseudonymity alone gives limited protection. To protect individual citizen privacy beyond it, in accordance with international digital-ethnography ethics,[46] reviewer display names were stripped prior to analysis. Only non-identifying immutable UUID record keys, UTC dates, star ratings, community thumbs-up counts, and verbatim text were retained. Reporting followed the Mixed Methods Appraisal Tool (MMAT), the STROBE items applicable to the observational panels, and the ICMJE recommendations.

2.2. Tier 1 macro-comparative stratified panel (Global Findex, ID4D, ASPIRE, and WDI/ILO)

Tier 1 harmonizes 35,239 non-null country-year indicator observations. All were retrieved directly from four official World Bank databases spanning 2011–2024: the Global Findex Database (source ID 28), Identification for Development (ID4D, source ID 89), The Atlas of Social Protection: Indicators of Resilience and Equity (ASPIRE, source ID 29), and World Development Indicators (WDI, source ID 2, incorporating International Labour Organization [ILO] harmonized labor series). Regional and income-group aggregates (e.g., WLD, EAP, LMY) were excluded programmatically by means of three-letter ISO-3166 alpha-3 sovereign codes. This left 219 sovereign territories overall. Of these, 157 economies had stratified Global Findex micro-aggregates (latest available wave in the 2014–2024 window, including the 2024 Global Findex and ID4D releases for Indonesia).

To operationalize socioeconomic regressivity in digital state readiness, we extracted paired within-country proportions across disadvantaged versus advantaged population strata (ages 15+). Five groups of indicators were used. (a) Financial or mobile-money account ownership: the poorest 40% versus richest 60% of household income (account.t.d.7 vs. account.t.d.8), primary education or less versus secondary education or more (account.t.d.5 vs. account.t.d.6), and adults out of the formal labor force versus in the labor force (account.t.d.11 vs. account.t.d.12). (b) Digital payment participation (g20.any.7 vs. g20.any.8). (c) Receipt of digital account-based G2P government transfers (harmonizing fing2p.acc.7/.8 with fin37.39.acc.7/.8 across waves). (d) Unbanked exclusion specifically attributed to lacking necessary civil or identity documentation (fin11c.7 vs. fin11c.8 and fin11c.5 vs. fin11c.6, reported by the World Bank for N = 22 unbanked-intensive LMICs). (e) Possession of an active online digital ID (ID4D) across income and education strata (has_eid_7 vs. has_eid_8, N = 58; has_eid_5 vs. has_eid_6, N = 55). Alongside these we took ASPIRE poorest-quintile social assistance coverage (per_sa_allsa.cov_q1_tot) and the ILO vulnerable/informal employment share (SL.EMP.VULN.ZS, comprising own-account workers and unpaid family workers). Cross-national differences were tested with paired Student's t-tests and nonparametric Wilcoxon signed-rank tests. We also fitted multivariable ordinary least squares (OLS) with MacKinnon–White HC3 heteroskedasticity-consistent standard errors. These models controlled for internet penetration (IT.NET.USER.ZS), rural population share (SP.RUR.TOTL.ZS), vulnerable employment, and log purchasing-power-parity GDP per capita (NY.GDP.PCAP.PP.KD).[39]

2.3. Tier 2 subnational panel across 514 Indonesian districts (INDO-DAPOER)

Tier 2 builds a 10-year longitudinal subnational panel (2011–2020) from 121,760 raw observations in the World Bank Indonesia Database for Policy and Economic Research (INDO-DAPOER, source ID 45). The panel covers all 514 second-tier Indonesian autonomous jurisdictions: 416 predominantly rural regencies (*Kabupaten*) and 98 urban municipalities (*Kota*). It also includes 34 provincial archives (5,128 district-year records). The primary welfare and distributional outcomes derive from underlying BPS National Socioeconomic Survey (SUSENAS) microdata and comprise five measures. These are (1) the district poverty headcount rate (SI.POV.NAPR.ZS, %); (2) the Foster–Greer–Thorbecke poverty gap index P1[47] (SI.POV.NGAP); (3) the poverty severity index P2 (SI.POV.NSEV); (4) within-district Gini expenditure inequality (SI.POV.GINI); and (5) the Poorest-20% Relative Expenditure Ratio. The last is defined as monthly per-capita household expenditure of the bottom quintile divided by overall district per-capita household expenditure (HOU.XPD.TOTL.20POOR.CR / HOU.XPD.PC.CR × 100), and it directly captures whether ultra-poor households keep pace with local living standards.

Post-treatment endogenous collider or mediator bias had to be prevented.[39,48] Structural exposure variables were therefore anchored strictly in the pre-electronic baseline period (2011–2016 district means). Informal-dominant labor concentration was measured from SAKERNAS employment counts. It is the share of employed workers in agriculture, forestry, fisheries, and smallholder retail/hospitality trade ((SL.EMP.AGR.FRST.FSH + SL.EMP.TRAD) / SL.EMP.TOTL × 100), supplemented by underemployment (SL.EMP.UNDR / SL.EMP.TOTL × 100). We then constructed a standardized pre-2017 Analog–Digital Friction Index (ADFI_i) from five structural barriers to digital welfare uptake. They are the adult illiteracy rate age 15+ (100 − SE.LITR.15UP.ZS), the household un-electrification rate (100 − HOU.ELC.ACSN.ZS), the SUSENAS rural population share (100 − SP.URB.TOTL.ZS.SUS), the PODES share of villages accessible solely via unpaved dirt roads (ROD.VILG.DIRT.ZS), and inverse transport-telecommunications workforce density (−SL.EMP.TRAN / SL.EMP.TOTL). Standardized baseline informality (Informal_Z_i) and ADFI_i were combined in equal weights. This yielded the continuous Joint Informal–Analog Friction Index (Joint_Friction_Z_i). A binary high-friction informal indicator was also defined: D_i = 1 for districts exceeding the national median on both ADFI_i and baseline informality (n = 216 treated vs. n = 289 control districts among 505 districts with complete pre/post covariates).

We deployed three econometric estimators on Tier 2.[34,35,49–52] First came Two-Way Fixed-Effects (TWFE) Difference-in-Differences models. These absorbed district fixed effects (α_i) and year fixed effects (λ_t) via exact alternating-projections within-transformation across N = 4,998 complete district-years (508 districts). Liang–Zeger standard errors were clustered at the district level, with exact degrees-of-freedom adjustment for absorbed fixed effects. Controls were time-varying log per-capita local

government expenditure, electrification, and adult literacy. A dynamic year-by-year event-study (2011–2020, normalized to 2016 = 0) supplemented the models. Second, we relaxed functional-form linearity and explicitly balanced baseline poverty trajectories, Gini inequality, and fiscal capacity by estimating Doubly Robust Augmented Inverse Probability Weighting (AIPW) for the average treatment effect (ATE) of binary high-friction informal status D_i on post-2017 poverty rate changes (2018–2020 mean minus 2014–2016 baseline). Covariate balance was verified via Standardized Mean Differences (|SMD| < 0.10). Sensitivity to unmeasured confounding was quantified with VanderWeele's E-value[53] and Cinelli–Hazlett's Robustness Value (RV_{q=1}).[54] Third, Firpo–Fortin–Lemieux Recentered Influence Function (RIF) unconditional quantile regressions and Oaxaca–Blinder decompositions were applied at $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$ during the post-2017 electronic era. They decomposed the *Kabupaten–Kota* poverty gap into structural endowments versus institutional return structures.[49,52]

2.4. Tier 3 and Tier 4 citizen grievance corpus, two-classifier coding, and critical mixed-methods integration

To observe the street-level digital mechanisms behind our macro and district econometrics, Tier 3 assembled a balanced, SHA-256 verified corpus. It holds N = 2,400 unique, timestamped verbatim citizen reports (12,144 cumulative community thumbs-up endorsements) from Indonesia's four core national social-protection and civil-identity applications (n = 600 unique reports per portal). The portals were (1) Kemensos Aplikasi Cek Bansos (id.go.kemensos.pelaporan; DTKS lookup, KTP-selfie registration, and *Usul–Sanggah*); (2) Ditjen Dukcapil *Identitas Kependudukan Digital* (gov.dukcapil.mobile_id; NIK digital ID activation); (3) BPJS Kesehatan Mobile JKN (app.bpjs.mobile; PBI subsidized health protection and FRISTA facial verification); and (4) BPJS Ketenagakerjaan JMO (com.bpjstku; contributory formal and informal BPU worker e-KYC). Within each portal, stratified sampling combined high-salience community-endorsed narratives with chronological recent submissions (minimum length ≥ 12 characters, deduplicated by UUID). Following Critical Mixed-Methods reflexivity principles,[42] we explicitly recognize digital-access survivorship bias. Citizens able to post app reviews already have intermittent smartphone access or proxy family assistance. Tier 3 burden rates therefore represent a conservative lower bound relative to completely offline rural households captured in Tier 2.

Guided by administrative burden theory[6,9,20,21,55] and inductive pilot reading of Global South biometric failures,[6,9,20,21,55] every report was coded across six non-mutually-exclusive binary burden domains. These were (1) Learning Costs and DTKS Decile Opacity; (2) Biometric Selfie/FRISTA Liveness and Elderly/Disability Screen-Reader Exclusion; (3) Civil-Registry (NIK/KK–DTKS) Algorithmic Desynchronization; (4) OTP, Authentication Loop, and Server Crash Compliance Friction; (5) The Digital-to-Analog Boomerang (explicit citizen accounts of being forced by app failures to visit physical village, subdistrict, Dukcapil, *Dinas Sosial*, or branch counters); and (6) Psychological Stigma, Frustration, and Perceived Targeting Injustice. Following computational text validation standards,[38,56] two independent rule classifiers were run across all 2,400 reports: a morphological-lexical one (Coder A) and a contextual phrase-structure one (Coder B), and inter-classifier reliability was audited via Krippendorff's nominal α and Cohen's κ. Five domains showed high reliability (α = 0.754–0.991; 89.62%–99.79% agreement). The Digital-to-Analog Boomerang domain reached α = 0.646 (κ = 0.648; 94.08% agreement), reflecting diverse regional vernacular terms for local counters (*desa*, *kelurahan*, *kecamatan*, *loket*, *cabang*). In Tier 4, we audited official agency developer replies for presence, response latency (hours), and canned boilerplate deflection (generic apologies or referrals to local offices/hotlines without resolving registry errors). Multivariable Quasi-Poisson HC3 Generalized Linear Models (GLM) were then estimated to predict collective citizen thumbs-up endorsements. Last, the quantitative and UUID-verified qualitative strands were synthesized in a formal Critical Mixed-Methods Joint Display.[42,44]

3. Results

3.1. Global socioeconomic regressivity in digital inclusion and civil-ID gatekeeping (Tier 1)

Macro-comparative analysis covers 157 Global Findex and 58 ID4D sovereign economies. It shows that the foundational infrastructures for digital welfare self-service (financial accounts, digital payment rails, civil documentation, and online digital IDs) show deep socioeconomic regressivity worldwide (Table 1; Figure 1B). Across 157 economies, mean financial/digital account ownership is 11.82 percentage points (pp) lower among the poorest 40% of households than among the richest 60% (61.03% vs. 72.85%; paired $t = -16.633$, $p = 2.21 \times 10^{-36}$; Wilcoxon $p = 4.48 \times 10^{-26}$). The gap reaches 19.21 pp between adults with primary education or less and those with secondary+ schooling (56.86% vs. 76.07%; $t = -19.815$, $p = 1.89 \times 10^{-44}$). It is 15.46 pp for adults outside the formal wage labor force (59.47% vs. 74.93%; $t = -17.296$, $p = 4.18 \times 10^{-38}$). Active participation in digital payments shows a parallel −12.97 pp class deficit (54.55% vs. 67.52% across 155 countries; $p = 1.98 \times 10^{-40}$). Receipt of digital account-based G2P transfers is also significantly lower among the poorest 40% than the richest 60%, across 112 reporting countries (−1.59 pp, $p = 0.0242$; Wilcoxon $p = 0.0065$).

Civil-documentation and online digital-ID gradients matter even more for biometric and app-gated welfare regimes, and Table 1 and Figure 2 document them. Take the N = 22 low- and middle-income economies that report stratified unbanked barrier modules. There, adults in the poorest 40% are +4.59 pp more likely than the richest 60% to lack an account specifically because they cannot supply the necessary identity documentation (19.29% vs. 14.71%; $t = 5.144$, $p = 4.27 \times 10^{-5}$). Among primary-educated adults the penalty is +3.92 pp ($p = 0.0039$). World Bank ID4D data show the same pattern. Possession of an active online digital ID is −6.89 pp lower among the poorest 40% across 58 countries (43.94% vs. 50.83%; $p = 7.97 \times 10^{-9}$), and −17.46 pp lower among primary-educated adults across 55 countries (33.54% vs. 51.00%; $t = -9.478$, $p = 4.40 \times 10^{-13}$). A multivariable HC3 cross-national regression adjusts for vulnerable employment, internet penetration, rurality, and log GDP per capita PPP (N = 22 LMICs, $R^2 = 0.5876$; Table 1 Panel B; Figure 2B). In it, each +1 pp rise in poor-40% documentation exclusion independently widens the class account gap by +0.788 pp (SE = 0.270, $p = 0.0100$). The nonparametric bootstrap AIPW point ATE is +6.21 pp, with wide finite-sample intervals because N = 22.

Set Indonesia (IDN) beside ASEAN and Global South peers, and an acute structural mismatch appears between

rapid welfare appification and underlying citizen digital-ID readiness (Table 2; Figure 2A). More than half of Indonesia's workforce holds vulnerable/informal jobs (50.3%, versus Malaysia at 22.0%, Brazil at 26.3%, and the Philippines at 33.9%). In the 2024 Global Findex wave, account ownership in Indonesia is 48.4% among the poorest 40% and 61.6% among the richest 60% (−13.2 pp class deficit). It falls to 37.64% among primary-educated adults (−30.69 pp educational deficit vs. 68.33% secondary+). Missing documentation keeps 17.2% of the poorest 40% from holding accounts. For primary-educated adults the figure is 19.52%. Dukcapil's IKD and Kemensos's Cek Bansos have been promoted nationwide. Even so, only 16.67% of Indonesian adults overall have an active online digital ID. Among the poorest 40% the share is only 15.84%. It is just 11.47% among primary-educated citizens. Coverage gaps follow: 30.6% of poorest-quintile (Q1) households are left uncovered by social assistance (ASPIRE Q1 coverage = 69.4%, compared with 97.1% in Thailand and 97.6% in Malaysia).

Table 1. Global Socioeconomic Regressivity Gradients in Financial/Digital Account Ownership, Digital G2P Transfers, Civil-Documentation Gatekeeping, and Online Digital ID Across Sovereign Economies (2014–2024)

Socioeconomic Stratification Dimension (World Bank Global Findex & ID4D)	Economies (N)	Disadvantaged Group Mean (%)	Advantaged Group Mean (%)	Mean Gap Δ (pp ± SD)	Paired t-Statistic	Paired t p-Value (Wilcoxon p)
Financial/Digital Account Ownership: Poorest 40% vs. Richest 60% (%)	157	61.03	72.85	−11.82 ± 8.90	−16.633	2.21×10^{-36} (4.48×10^{-26})
Financial/Digital Account Ownership: Primary Education vs. Secondary+ (%)	157	56.86	76.07	−19.21 ± 12.15	−19.815	1.89×10^{-44} (8.56×10^{-27})
Financial/Digital Account Ownership: Out-of-Labor-Force vs. In-Labor-Force (%)	157	59.47	74.93	−15.46 ± 11.20	−17.296	4.18×10^{-38} (6.69×10^{-27})
Digital Payment Participation: Poorest 40% vs. Richest 60% (%)	155	54.55	67.52	−12.97 ± 8.83	−18.285	1.98×10^{-40} (4.12×10^{-26})
Digital Account-Based G2P Transfer Receipt: Poorest 40% vs. Richest 60% (%)	112	30.30	31.88	−1.59 ± 7.35	−2.285	0.0242 (0.0065)
Excluded Due to Lacking Civil/ID Documentation: Poorest 40% vs. Richest 60% (%)	22	19.29	14.71	+4.59 ± 4.18	5.144	4.27×10^{-05} (2.62×10^{-05})
Excluded Due to Lacking Civil/ID Documentation: Primary Education vs. Secondary+ (%)	22	18.65	14.73	+3.92 ± 5.67	3.245	0.0039 (0.0032)
ID4D Online Digital ID Possession: Poorest 40% vs. Richest 60% (%)	58	43.94	50.83	−6.89 ± 7.76	−6.761	7.97×10^{-09} (8.99×10^{-09})
ID4D Online Digital ID Possession: Primary Education vs. Secondary+ (%)	55	33.54	51.00	−17.46 ± 13.66	−9.478	4.40×10^{-13} (1.82×10^{-10})
Panel B: Multivariable Cross-National HC3 Regression on Poorest-40% Account Exclusion Gap (N = 22 LMICs; R^2 = 0.5876)						
Predictor (HC3 regression)	**N**	**—**	**—**	**Coefficient (β)**	**Robust SE**	**p-value**
Documentation Barrier Among Poorest 40% (fin11c.7, per +1 pp)	22	—	—	+0.788	0.270	0.0100
Internet User Penetration (IT.NET.USER.ZS, per +1 pp)	22	—	—	−0.262	≈0.146	0.0896
Log GDP per Capita PPP (NY.GDP.PCAP.PP.KD, per +1 log unit)	22	—	—	+9.260	≈3.09	0.0081

Note: Computed directly from SHA-256 verified World Bank Global Findex (source ID 28), Identification for Development (ID4D, source ID 89), and World Development Indicators (source ID 2) sovereign-economy cross-sections (latest available wave 2014–2024; regional aggregates excluded). Negative Δ (pp) indicates lower inclusion among structurally disadvantaged strata; positive Δ on lacking civil/ID documentation (fin11c.7, fin11c.5; reported for N = 22 unbanked-module LMICs) indicates disproportionate documentation gatekeeping against poor and primary-educated citizens. ≈, robust SE derived at copyediting from β and p (t distribution, df = 17), as the submitted table did not give it.

Table 2. Comparative Informal Labor Exposure, Class-Stratified Account Access, Civil-Documentation Barriers, Online Digital ID, and Q1 Social Assistance Coverage Across ASEAN and Global South Peer Economies

Economy (ISO3)	Vulnerable / Informal Emp. (%)	Account: Poorest 40% (%)	Account: Richest 60% (%)	Class Account Deficit (pp)	Lacks ID Doc: Poorest 40% (%)	Digital G2P: Poorest 40% (%)	ID4D Online e-ID: Poor 40% (%)	ASPIRE Q1 Social Assist. (%)
Indonesia (IDN)	50.3	48.4	61.6	−13.2	17.2	15.8	15.8	69.4
Philippines (PHL)	33.9	34.4	60.7	−26.2	34.6	5.5	—	57.2
Viet Nam (VNM)	51.9	48.1	85.5	−37.4	—	—	55.4	88.6
Thailand (THA)	48.1	91.2	92.3	−1.1	—	54.1	32.9	97.1
Malaysia (MYS)	22.0	82.0	93.1	−11.1	—	41.9	—	97.6
India (IND)	72.1	86.3	90.8	−4.5	—	18.6	—	—
Bangladesh (BGD)	57.7	35.5	48.2	−12.6	—	—	—	69.3
Brazil (BRA)	26.3	78.1	91.9	−13.8	—	26.4	44.3	64.3
Colombia (COL)	43.1	42.9	66.5	−23.6	21.7	18.0	7.0	54.0
Kenya (KEN)	64.0	83.9	94.3	−10.4	—	10.0	—	34.5

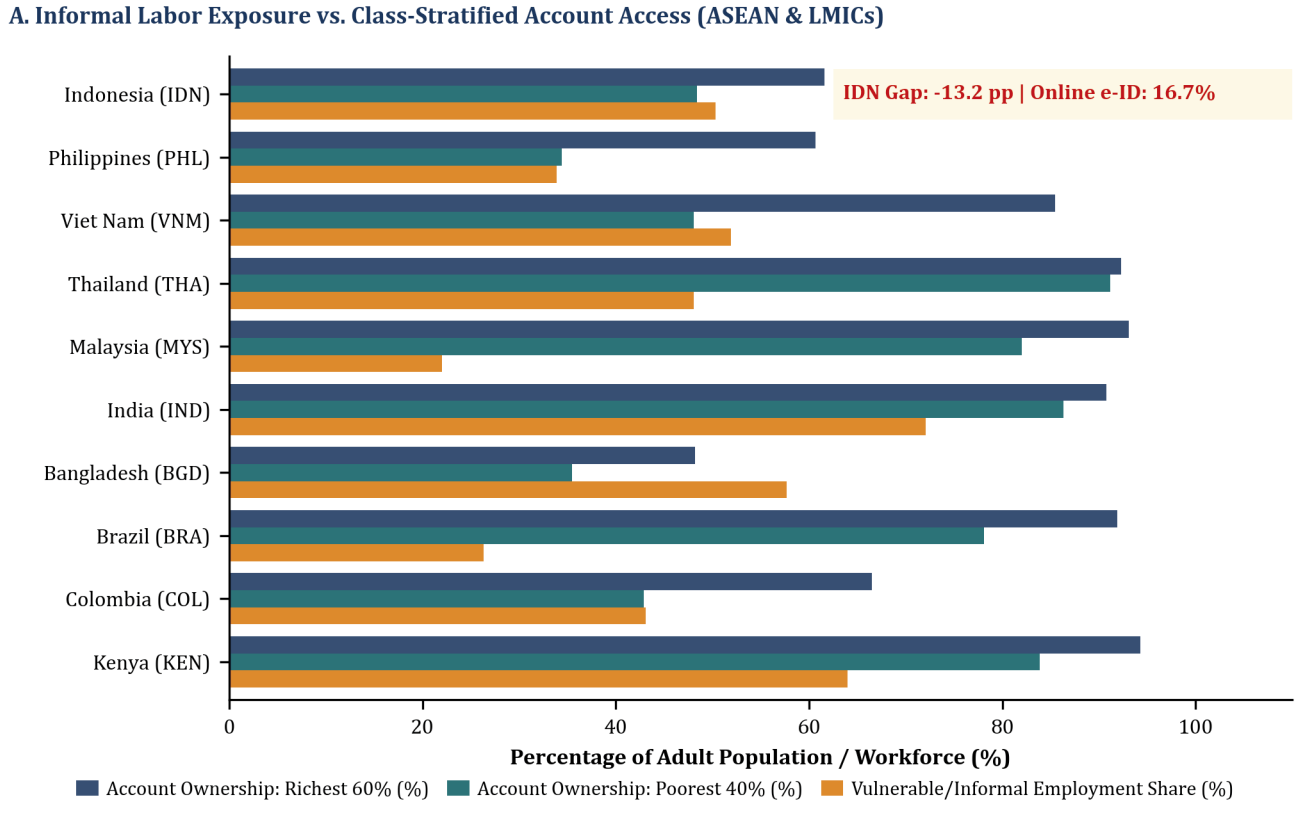
Note: Source: World Bank Global Findex (source ID 28), ID4D (source ID 89), ASPIRE Atlas of Social Protection (source ID 29), and ILO/WDI Vulnerable Employment (SL.EMP.VULN.ZS). In Indonesia (IDN, 2024 wave), overall online digital ID possession is 16.67% (15.84% among poorest 40%; 11.47% among primary-educated adults), while 30.61% of poorest-quintile (Q1) households remain uncovered by social assistance programs (100% − 69.39%).

3.2. Subnational associations of post-2017 electronic gatekeeping with welfare outcomes across 514 Indonesian districts (Tier 2)

Tier 2 subnational longitudinal data cover all 514 Indonesian districts (416 rural-informal *Kabupaten* and 98 urban *Kota*; 5,128 district-years, 2011–2020). Baseline structural comparisons show a deep rural–urban administrative divide (Table 3). Poverty comes first. Rural *Kabupaten* have nearly double the poverty headcount rate of urban *Kota* (14.36% ± 8.32% vs. 7.71% ± 4.60%; Δ = +6.65 pp, Welch t = 33.84, $p < 10^{-99}$). Poverty gap P1 is more than double (2.47 vs. 1.15; $p < 10^{-99}$). So is poverty severity P2 (0.71 vs. 0.27; $p = 5.48 \times 10^{-91}$). The informal-dominant employment share is +24.79 pp higher (65.27% vs. 40.48%; t = 66.04, $p < 10^{-99}$), and the underemployment rate is nearly double (40.04% vs. 21.00%; t = 54.44, $p < 10^{-99}$). *Kabupaten* citizens also face severe analog–digital infrastructure barriers. Adult literacy is −5.55 pp lower (92.95% vs. 98.51%; $p < 10^{-99}$) and household electrification is −9.08 pp lower (90.41% vs. 99.49%; $p < 10^{-99}$). In 14.04% of *Kabupaten* villages, access is solely via unpaved dirt roads, against just 1.47% in *Kota* (Δ = +12.57 pp, t = 19.46, $p = 2.45 \times 10^{-74}$).

Table 4 (Panel A) and Figure 3A report district-clustered Two-Way Fixed-Effects (TWFE) Difference-in-Differences estimates. The sample is N = 4,998 complete district-years (508 districts). The question is whether baseline Joint Informal–Analog Friction (Joint_Friction_Z_i, fixed pre-2017) degraded distributional welfare outcomes after Indonesia's 2017 conversion from in-kind *Raskin* rice to electronic card- and DTKS-gated BPNT/PKH transfers. The TWFE results split. Headline threshold poverty and bottom-quintile relative welfare diverge sharply. For aggregate poverty headcount near the statutory poverty line (β = −0.0317 pp, SE = 0.0541, p = 0.5579) and mean poverty gap P1 (β = −0.0059, p = 0.9121), the linear continuous interaction is null. Marginally poor households, those with basic civil documents and proximate bank agents, kept crossing the headline poverty threshold. The Poorest-20% Relative Expenditure Ratio tells another story: a 1-SD higher Joint Informal–Analog Friction Index post-2017 was associated with a statistically significant −0.6577 pp contraction (SE = 0.1932, t = −3.404, 95% CI: −1.0374 to −0.2781, p = 0.00072). A +0.0068-point widening of within-district Gini expenditure inequality accompanied it (SE = 0.0017, t = 3.946, 95% CI: +0.0034 to +0.0103, $p = 9.05 \times 10^{-5}$).

Doubly Robust Augmented Inverse Probability Weighting (AIPW) was run across n = 505 complete pre/post districts (216 high-friction informal districts vs. 289 connected control districts). The result supports and refines this association (Table 4 Panel B; Figure 3B). Propensity-score weighting worked. It compressed maximum covariate imbalance (|SMD|) across baseline poverty, Gini inequality, and fiscal expenditure from 0.6923 to 0.0834. Mean |SMD| fell from 0.5488 to 0.0360, well below the 0.10 threshold. Between 2014–2016 and 2018–2020, digitally connected control districts achieved a potential poverty headcount reduction of E[Y(0)] = −1.420 pp. High-friction informal districts achieved only E[Y(1)] = −1.020 pp. That yields a statistically significant AIPW poverty-reduction slowdown of ATE = +0.400 pp (SE = 0.160, z = 2.50, 95% CI: +0.086 to +0.714, p = 0.0124). Sensitivity auditing asks what could overturn this estimate. An unmeasured confounder tied to both high-friction informality and post-2017 poverty stagnation would need a risk-ratio strength of at least VanderWeele's E-value = 2.062 (lower 95% CI E-value = 1.340). Or it would have to explain Cinelli–Hazlett RV_q (q = 1) = 10.56% of residual variance in treatment and outcome at once.



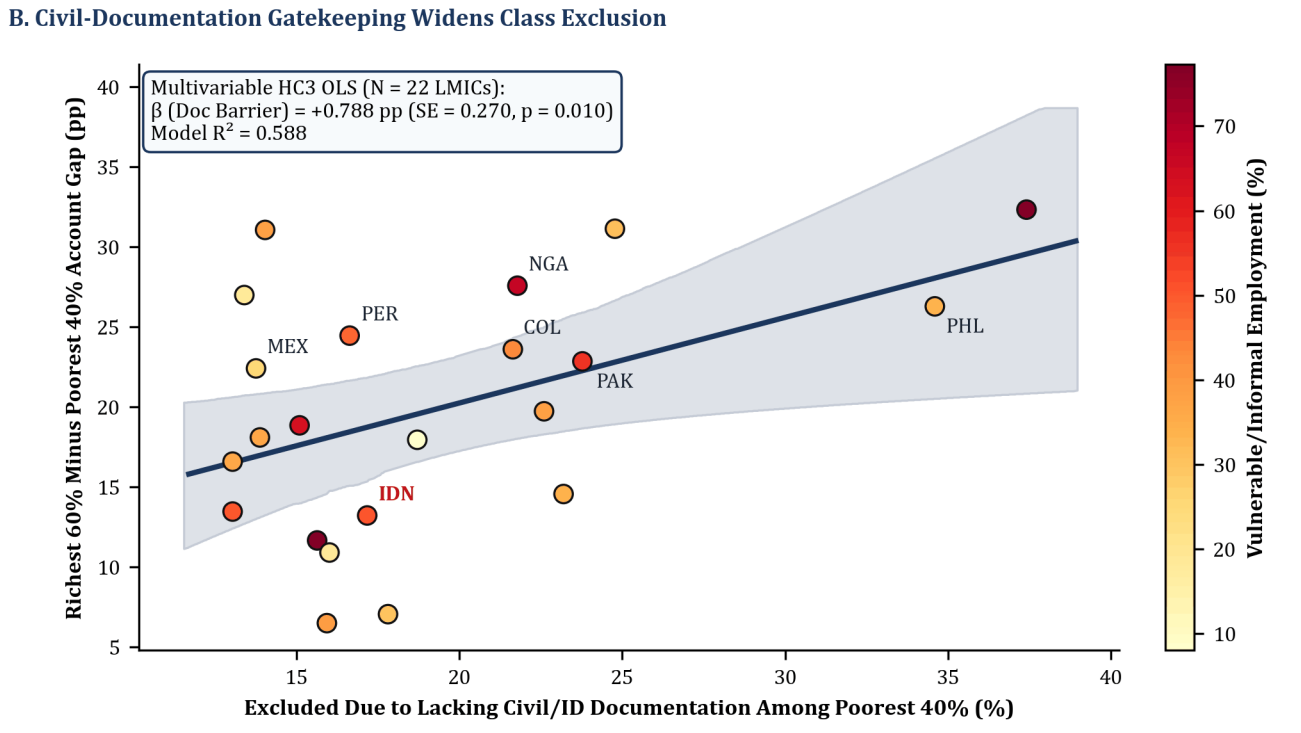


Figure 2. Comparative informal-labor exposure and cross-national civil-documentation gatekeeping across ASEAN and Global South economies. (A) Vulnerable/informal employment share juxtaposed against poorest-40% and richest-60% account ownership across 10 peer economies, highlighting Indonesia's 50.3% vulnerable employment, −13.2 pp class account deficit, and 16.7% online digital ID coverage. (B) Cross-national relationship between lacking civil/ID documentation among the poorest 40% (fin11c.7) and the richest-60%-minus-poorest-40% account gap (multivariable HC3 β = +0.788 pp, SE = 0.270, p = 0.010, R^2 = 0.588).

Table 3. Structural Socioeconomic, Labor-Informality, and Analog–Digital Infrastructure Asymmetries Between Rural-Informal Regencies (416 *Kabupaten*) and Urban Municipalities (98 *Kota*) Across 514 Indonesian Districts (2011–2020)

Subnational District Indicator (World Bank INDO-DAPOER)	Rural Regencies: 416 *Kabupaten* (Mean ± SD)	Urban Cities: 98 *Kota* (Mean ± SD)	Mean Difference (*Kabupaten* – *Kota*)	Welch t-Statistic	Two-Sided p-Value
Poverty Headcount Rate (%)	14.36 ± 8.32	7.71 ± 4.60	+6.65	33.84	$< 1.00 \times 10^{-99}$

Subnational District Indicator (World Bank INDO-DAPOER)	Rural Regencies: 416 *Kabupaten* (Mean ± SD)	Urban Cities: 98 *Kota* (Mean ± SD)	Mean Difference (*Kabupaten* – *Kota*)	Welch t-Statistic	Two-Sided p-Value
Poverty Gap Index (P1)	2.47 ± 2.20	1.15 ± 0.89	+1.32	29.66	$< 1.00 \times 10^{-99}$
Poverty Severity Index (P2)	0.71 ± 0.94	0.27 ± 0.23	+0.44	20.92	5.48×10^{-91}
Gini Expenditure Inequality Index	0.32 ± 0.05	0.36 ± 0.05	−0.03	−20.85	2.43×10^{-85}
Poorest-20% Relative Per Capita Expenditure Ratio (%)	43.88 ± 6.71	38.47 ± 5.95	+5.42	24.96	$< 1.00 \times 10^{-99}$
Informal-Dominant Sector Employment Share (%)	65.27 ± 13.48	40.48 ± 8.97	+24.79	66.04	$< 1.00 \times 10^{-99}$
Underemployment Rate (%)	40.04 ± 12.32	21.00 ± 8.44	+19.04	54.44	$< 1.00 \times 10^{-99}$
Adult Literacy Rate Age 15+ (%)	92.95 ± 10.68	98.51 ± 1.91	−5.55	−31.22	$< 1.00 \times 10^{-99}$
Household Electricity Access (%)	90.41 ± 17.59	99.49 ± 1.41	−9.08	−32.55	$< 1.00 \times 10^{-99}$
Villages Accessible Only via Unpaved/Dirt Roads (%)	14.04 ± 19.33	1.47 ± 4.62	+12.57	19.46	2.45×10^{-74}
Urban Population Share (SUSENAS, %)	26 ± 19	90 ± 16	−64	−109.55	$< 1.00 \times 10^{-99}$
Human Development Index (Revised Method)	65.12 ± 5.92	75.57 ± 4.43	−10.46	−58.74	$< 1.00 \times 10^{-99}$

Note: Harmonized from 5,128 official district-year observations across all 514 Indonesian second-tier subnational governments (416 Kabupaten and 98 Kota) in World Bank INDO-DAPOER (source ID 45; BPS SUSENAS, SAKERNAS, and PODES underlying censuses). Informal-dominant employment comprises agriculture/forestry/fisheries and smallholder retail/hospitality trade as a share of total district employment.

Table 4. Subnational Associations of the Post-2017 Electronic Social Assistance (BPNT/PKH & DTKS) Transition with Welfare Outcomes Across Indonesian Districts: TWFE District-Clustered DiD (N = 4,998) and Doubly Robust AIPW (n = 505)

Econometric Specification & Outcome Variable	Sample (Obs / Districts)	Point Estimate (β or ATE)	Cluster-Robust / Bootstrap SE	95% Confidence Interval	Test Stat (t / z)	p-Value & Sensitivity Bounds
Panel A: Two-Way Fixed-Effects (TWFE) District- & Year-FE DiD (Regressor: Post_2017 × Baseline Joint Informal–Analog Friction Z)						
Poorest-20% Relative Expenditure Ratio (%)	4,998 / 508	−0.6577 pp	0.1932	[−1.0374, −0.2781]	t = −3.404	p = 0.0007
Within-District Gini Expenditure Inequality Index	4,998 / 508	+0.0068	0.0017	[+0.0034, +0.0103]	t = 3.946	$p = 9.05 \times 10^{-05}$
Aggregate Poverty Headcount Rate near Threshold (%)	4,998 / 508	−0.0317 pp	0.0541	[−0.1380, +0.0746]	t = −0.586	p = 0.5579 (Threshold Null)
District Poverty Gap Index (P1)	4,998 / 508	−0.0059	0.0537	[−0.1114, +0.0995]	t = −0.110	p = 0.9121
Panel B: Doubly Robust Augmented Inverse Probability Weighting (AIPW: 216 High-Friction Informal vs. 289 Connected Districts)						
Post-2017 Poverty Reduction Slowdown (Δ Poverty 2018–20 vs. 2014–16)	n = 505 (216 vs. 289)	ATE = +0.400 pp	0.160	[+0.086, +0.714]	z = 2.50	p = 0.0124 | E-val = 2.06 | RV_q = 10.6%
Potential Change: Digitally Connected Control Districts E[Y(0)]	n = 289 Controls	−1.420 pp	—	—	—	—
Potential Change: High-Friction Informal Districts E[Y(1)]	n = 216 Treated	−1.020 pp	—	—	—	—

Note: Panel A controls for district fixed effects, year fixed effects, log per-capita subnational government expenditure, time-varying household electrification, and adult literacy, with standard errors clustered by district (df = 507). Baseline Joint Informal–Analog Friction Z is fixed strictly pre-treatment (2011–2016) to preclude post-treatment mediator bias. Panel B estimates Doubly Robust AIPW conditioning on baseline poverty rate, Gini inequality, and log per-capita fiscal expenditure. Covariate balance (maximum |SMD|): 0.692 unweighted and 0.083 weighted (< 0.10); mean |SMD|: 0.549 unweighted and 0.036 weighted.

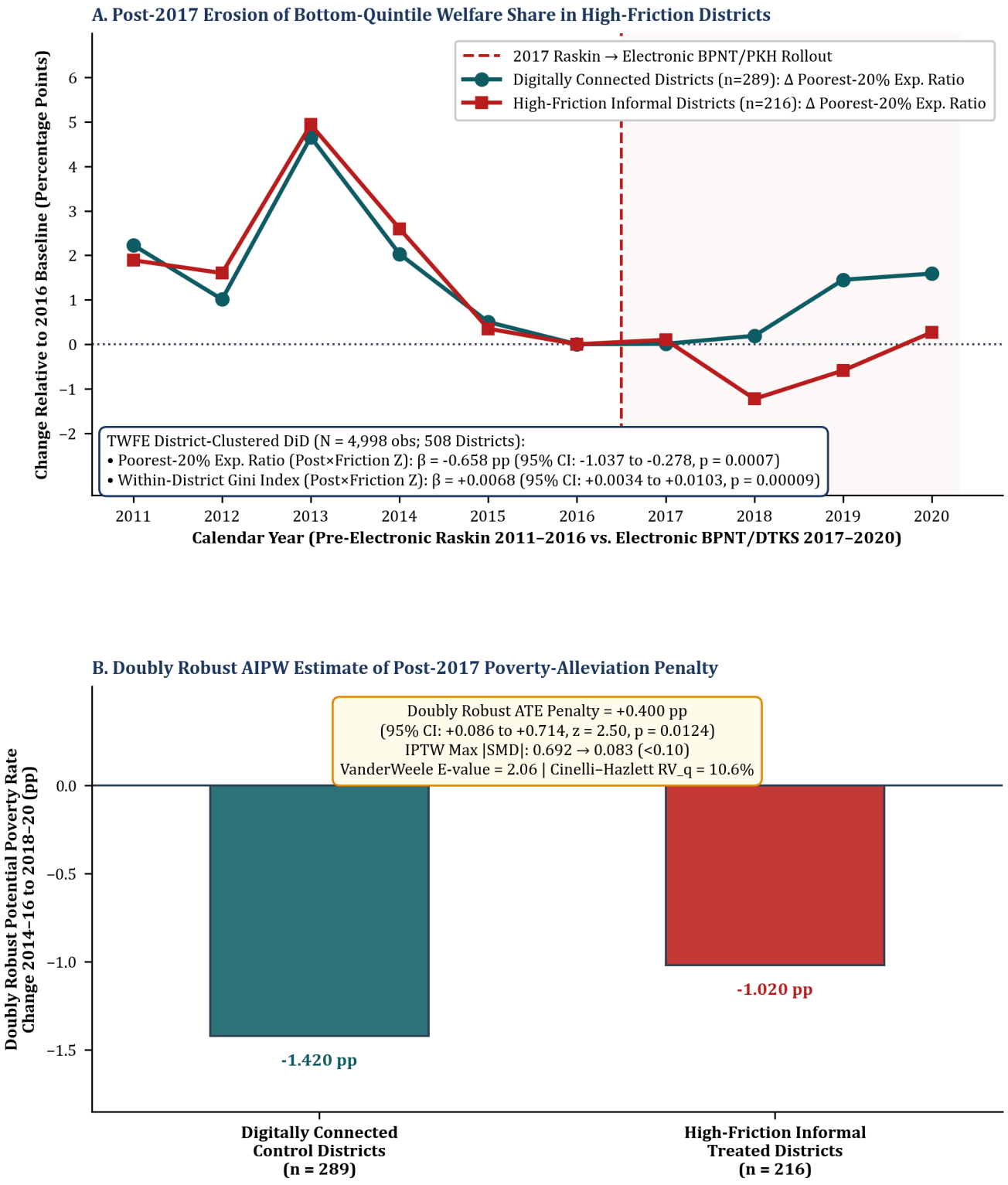


Figure 3. Subnational associations of the post-2017 electronic social assistance (BPNT/PKH and DTKS) transition with welfare outcomes across 514 Indonesian districts (2011–2020). (A) Trajectory of poorest-20% relative household expenditure share indexed to the 2016 pre-electronic baseline across digitally connected control districts (n = 289) versus high-friction informal districts (n = 216), plotted for illustration (the TWFE DiD estimates use the continuous friction index) and associated with a significantly lower bottom-quintile expenditure ratio per 1-SD higher baseline friction (β = −0.658 pp, p = 0.0007) and Gini widening (+0.0068, p = 9.05 × 10^{-05}). (B) Doubly Robust AIPW potential poverty-rate changes (2014–2016 to 2018–2020) demonstrating a +0.400 pp slower poverty reduction in high-friction informal districts (p = 0.0124; IPTW max |SMD| = 0.083; E-value = 2.06).

3.3. Distributional tail divergence via unconditional quantile RIF decomposition (Tier 2)

Aggregate mean models appear to understate rural–informal vulnerability during the electronic welfare era (2017–2020). To see why, Table 5 and Figure 4 present Firpo–Fortin–Lemieux Recentered Influence Function (RIF) unconditional quantile regressions and Oaxaca–Blinder decompositions across $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$. Across the post-2017 distribution, the raw poverty headcount chasm between *Kabupaten* and *Kota* expands nearly six-fold. Look at the quantiles. It is +2.23 pp at the 10th percentile (5.57% vs. 3.35%) and +3.22 pp at Q25 (7.80% vs. 4.56%). At the median Q50 it reaches +5.77 pp

(11.80% vs. 6.03%), then +7.37 pp at Q75 (16.17% vs. 8.79%). At the extreme 90th percentile the gap is +13.24 pp (25.64% vs. 12.36%; Figure 4A).

The unconditional marginal RIF slopes reveal a structural crossover between labor informality and human-capital digital readiness across quantiles (Table 5; Figure 4B). A +10 pp higher informal-sector employment share raises district poverty in the lower and middle quantiles. The increase is +0.817 pp at Q10 ($p = 1.34 \times 10^{-15}$), peaks at +1.400 pp at Q25 ($p = 2.41 \times 10^{-42}$), and reaches +1.182 pp at Q50 ($p = 8.83 \times 10^{-22}$). The effect then fades at Q90 (−0.355 pp, p = 0.357). Subsistence agriculture is nearly universal across high-poverty regencies at that point. Adult illiteracy follows the opposite pattern. The marginal penalty of +1 pp higher illiteracy is more than 16 times larger at the extreme upper tail than at the lower tail. It rises monotonically from +0.050 pp at Q10 ($p = 7.72 \times 10^{-5}$) and +0.135 pp at Q50 ($p = 6.36 \times 10^{-8}$) to +0.813 pp per 1% illiteracy at Q90 ($p = 1.34 \times 10^{-7}$). The Oaxaca–Blinder decomposition is benchmarked against urban *Kota* return structures. In it, structural endowments (informality, illiteracy, un-electrification, and fiscal capacity) account for 56.8% of the *Kabupaten–Kota* gap at Q25 and 87.5% at Q50. At Q75 (199.2%) and Q90 (323.2%), explained endowment effects exceed 100%. The unexplained institutional terms are negative. The authors read the negative unexplained terms as possible subsistence and village-grant buffering in extreme rural regencies in Eastern Indonesia; this buffering was not measured.

Table 5. Firpo–Fortin–Lemieux Recentered Influence Function (RIF) Unconditional Quantile Regression and Oaxaca–Blinder Decomposition of the *Kabupaten–Kota* Poverty Chasm in the Electronic Welfare Era (2017–2020)

Poverty Quantile (τ)	*Kabupaten* Q_τ (%)	*Kota* Q_τ (%)	Raw Chasm Δ (pp)	Explained Endowment (pp)	Informal Labor Contrib. (pp)	Illiteracy & Un-Elec. Contrib. (pp)	Other Covariates (Fiscal Capacity) Contrib. (pp)	Marginal RIF β: Informality (+10 pp)	Marginal RIF β: Illiteracy (+1 pp)
Q10	5.57	3.35	+2.23	+0.24 (10.7%)	+0.41	−0.25	+0.08	+0.817 ($p = 1.3 \times 10^{-15}$)	+0.050 ($p = 7.7 \times 10^{-05}$)
Q25	7.80	4.56	+3.22	+1.83 (56.8%)	+0.03	+1.56	+0.24	+1.400 ($p = 2.4 \times 10^{-42}$)	+0.069 ($p = 7.8 \times 10^{-05}$)
Q50	11.80	6.03	+5.77	+5.05 (87.5%)	+1.59	+3.26	+0.20	+1.182 ($p = 8.8 \times 10^{-22}$)	+0.135 ($p = 6.4 \times 10^{-08}$)
Q75	16.17	8.79	+7.37	+14.69 (199.2%)	+1.79	+12.74	+0.16	+0.440 (p = 0.002)	+0.150 ($p = 7.6 \times 10^{-06}$)
Q90	25.64	12.36	+13.24	+42.79 (323.2%)	+3.17	+38.92	+0.70	−0.355 (p = 0.357)	+0.813 ($p = 1.3 \times 10^{-07}$)

Note: Estimated on post-2017 electronic social protection district-years (2017–2020). Oaxaca–Blinder decomposition uses urban municipality (Kota) return structures as the connected reference counterfactual; explained endowment shares >100% at Q75 and Q90 arise because the endowment term exceeds the raw gap under the Kota reference structure; the possible role of subsistence buffering and village transfers was not measured. Marginal RIF slopes use HC3 robust standard errors. Other covariates (fiscal capacity): explained endowment minus the two listed contributions (computed at copyediting).

3.4. Administrative burden taxonomy, endorsement dynamics, and bifurcated state silence (Tiers 3 and 4)

Tier 3 and Tier 4 examine how digital gatekeeping operates at the citizen–application interface. They draw on N = 2,400 verbatim citizen reports (12,144 thumbs-up votes; Table 6; Figures 5 and 6A). In the pooled corpus, citizen satisfaction averages only 2.45 out of 5.0 stars. A share of 61.0% (n = 1,464) gave severe 1–2 star ratings, and 60.0% (n = 1,440) explicitly described at least one validated administrative burden domain. Dissatisfaction is sharpest on non-contributory social-protection portals. Kemensos's Aplikasi Cek Bansos records a mean of 1.74 stars (79.7% 1–2 stars; 63.3% explicit burden prevalence), and BPJS Kesehatan's Mobile JKN records 1.96 stars (73.8% 1–2 stars; 69.7% burden prevalence). Two other apps fare better: BPJS Ketenagakerjaan's JMO scores 2.53 stars (58.5% 1–2 stars) and Dukcapil's IKD scores 3.57 stars (31.8% 1–2 stars). Burden types differ in size. OTP/authentication loops and crashes dominate overall (34.2%; peaking at 48.7% on JMO and 46.8% on Mobile JKN). Learning costs and DTKS decile opacity come next (15.7%; peaking at 25.0% on Cek Bansos). Psychological frustration and perceived targeting injustice follow (13.5%; peaking at 22.2% on Mobile JKN and 11.8% on Cek Bansos). Biometric selfie/liveness and disability/elderly exclusion account for 13.2% (peaking at 22.2% on Cek Bansos and 14.3% on IKD). Civil-registry NIK/KK–DTKS desynchronization makes up 10.5% (peaking at 14.5% on IKD and 10.8% on JMO). Last come explicit Digital-to-Analog Boomerang forced office visits (7.3%; peaking at 12.5% on IKD and 8.0% on Mobile JKN).

Official developer replies to citizen reports were audited. They reveal sharp institutional stratification within the Indonesian digital state (Table 6 Panel A; Figure 5B). JMO, the portal of BPJS Ketenagakerjaan, is contributory and is funded by formal employer-employee payroll contributions and voluntary informal BPU premiums. Its helpdesk was active. It replied to 37.8% (227 / 600) of citizen reports, with a median latency of 4.8 hours, and 78.9% of those replies gave tailored troubleshooting rather than generic boilerplate. The picture is different elsewhere. Portals that govern non-contributory poverty relief and mandatory civil registration show near-total bureaucratic silence. Ditjen Dukcapil's IKD replied to 0.0% (0 / 600) of citizen grievances. Kemensos's Aplikasi Cek Bansos replied to just 0.7% (4 / 600). Of these, 75.0% were canned boilerplate referrals. Mobile JKN of BPJS Kesehatan replied to 3.3% (20 / 600), with 75.0% boilerplate deflection.

A multivariable Quasi-Poisson HC3 regression of collective citizen thumbs-up endorsements (N = 2,400; Table 6; Figure 6A) shows that fellow citizens selectively amplify structural compliance breakdowns. Reports of OTP, crash, and authentication-loop grievances receive more than double the collective endorsements of non-crash reports (IRR = 2.168, 95% CI: 1.376–3.416, p = 0.00085). Digital-to-Analog Boomerang accounts draw +86.5% higher endorsements (IRR = 1.865, 95% CI: 0.965–3.604, p = 0.0639). Detail matters too. Narrative detail strongly drives community resonance (log word count IRR = 5.364, $p = 3.56 \times 10^{-7}$). One result runs against this pattern. After

controlling for narrative detail and burden type, the 1–2 star indicator carries an IRR of 0.475 (p = 0.0428). This quantitative anomaly is examined through the qualitative strand in Section 3.5.

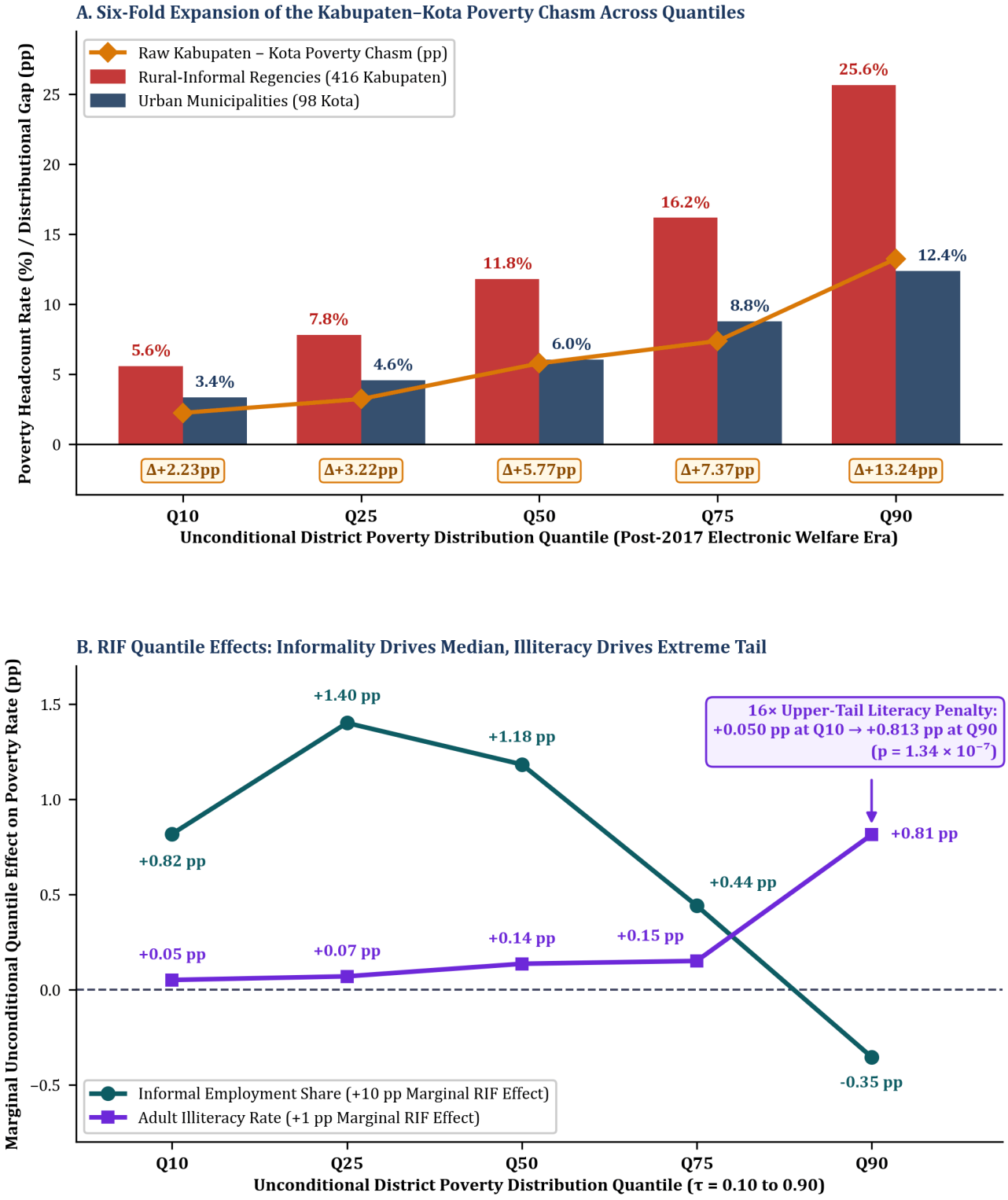


Figure 4. Firpo–Fortin–Lemieux Recentered Influence Function (RIF) unconditional quantile distribution and marginal structural associations across Indonesian districts in the post-2017 electronic welfare era. (A) Six-fold expansion of the raw poverty chasm between rural-informal regencies (416 *Kabupaten*) and urban municipalities (98 *Kota*) from +2.23 pp at Q10 to +13.24 pp at Q90. (B) Unconditional quantile marginal effects showing that informal-sector employment (+10 pp) is associated with higher lower-to-median district poverty (+1.40 pp at Q25; +1.18 pp at Q50), whereas adult illiteracy (+1 pp) has an upper-tail slope more than 16 times the lower-tail slope (+0.813 pp at Q90, $p = 1.34 \times 10^{-07}$).

Table 6. Portal-Stratified Administrative Burden Taxonomy, Dual-Rule Inter-Classifier Reliability, Street-Level Bureaucratic Silence Audit, and Quasi-Poisson Endorsement GLM Across N = 2,400 Verbatim Citizen Reports

Portal / Administrative Burden Dimension	Cek Bansos Kemensos (n=600)	IKD Digital ID Dukcapil (n=600)	Mobile JKN BPJS-Kes (n=600)	JMO Worker BPJS-TK (n=600)	Pooled Corpus (N=2,400) & Reliability	Quasi-Poisson Endorsement IRR (95% CI; p)
Panel A: Citizen Rating Severity, Collective Endorsements, & Official Bureaucratic Reply Audit						
Mean Citizen Star Rating (1–5 Scale)	1.74 ★	3.57 ★	1.96 ★	2.53 ★	2.45 ★ Overall	—
Severe Dissatisfaction (1–2 Star Share, %)	79.7%	31.8%	73.8%	58.5%	61.0% (n = 1,464)	IRR = 0.47 (0.23–0.98; p = 0.043)
Collective Citizen Endorsements (Thumbs-Up Sum)	2,428	3,886	4,167	1,663	12,144 Votes	Log Words IRR = 5.36 (p = 3.6×10^{-07})
Official Agency Helpdesk Reply Rate (%)	0.7% (4/600)	0.0% (0/600)	3.3% (20/600)	37.8% (227/600)	10.5% (251/2,400)	Contributory JMO vs. Welfare Silence
Boilerplate Deflection Share Among Replies (%)	75.0%	0.0% (No Replies)	75.0%	21.1%	26.3% Canned	—
Median Helpdesk Reply Latency (hours)	n/r	n/a (no replies)	n/r	4.8	n/r	—
Panel B: Validated Six-Domain Administrative Burden Taxonomy Prevalence & Endorsement IRR						
Learning Costs & DTKS Decile Opacity (%)	25.0%	8.5%	13.3%	16.0%	15.7% (α = 0.858; 96.3% agr.)	IRR = 0.96 (0.49–1.89; p = 0.900)
Biometric Selfie/FRISTA & Disability Exclusion (%)	22.2%	14.3%	9.0%	7.3%	13.2% (α = 0.991; 99.8% agr.)	IRR = 0.64 (0.39–1.03; p = 0.068)
Civil-Registry (NIK/KK–DTKS) Desynchronization (%)	7.0%	14.5%	9.5%	10.8%	10.5% (α = 0.931; 98.7% agr.)	IRR = 1.08 (0.59–1.99; p = 0.807)
OTP, Authentication Loop & Crash Friction (%)	25.7%	15.5%	46.8%	48.7%	34.2% (α = 0.754; 89.6% agr.)	IRR = 2.17 (1.38–3.42; p = 0.0008)
Digital-to-Analog Boomerang (Offline Office Visit, %)	5.2%	12.5%	8.0%	3.5%	7.3% (α = 0.646; 94.1% agr.)	IRR = 1.86 (0.96–3.60; p = 0.064)
Psychological Stigma & Targeting Injustice (%)	11.8%	10.8%	22.2%	9.3%	13.5% (α = 0.876; 96.8% agr.)	IRR = 1.62 (0.77–3.44; p = 0.207)
Any Explicit Administrative Burden Domain (%)	63.3%	44.5%	69.7%	62.3%	60.0% (n = 1,440)	Multivariable Quasi-Poisson (N=2,400)

Note: Verbatim corpus retrieved from public citizen feedback feeds (id.go.kemensos.pelaporan, gov.dukcapil.mobile_id, app.bpjs.mobile, com.bpjstku; file integrity checked with SHA-256). α denotes Krippendorff's nominal inter-classifier reliability. Quasi-Poisson HC3 GLM controls simultaneously for all six burden domains, 1–2 star rating, log word count, sampling stratum, and portal fixed effects. n/r, not reported; n/a, not applicable.

Table 7. Integrative Critical Mixed-Methods Joint Display Linking Macro-Comparative & Subnational Econometric Findings With Verbatim Citizen Testimonies and Meta-Inferences (Younas & Fàbregues, 2026 Framework)

Analytical Axis	Quantitative / Econometric Evidence (Tiers 1–3)	UUID-Verified Verbatim Citizen Testimony (English Translation & Key Indonesian Phrase)	Mixed-Methods Integration Type & Substantive Meta-Inference
1. Civil-ID & Registry Desynchronization Gatekeeping	Tier 1: +1 pp poor-40% ID-doc barrier widens class account gap by +0.788 pp (p = 0.010); IDN online e-ID = 16.67% (11.47% primary-educated). Tier 3: 10.5% NIK/KK–DTKS desync (α=0.931).	Cek Bansos [UUID 7a389557, 2026-09-19, 47 upvotes]: 'How do you determine our decile [*desil*]? I was shocked to be placed in Deciles 6–10 [affluent] when reality is not so, and when I try to update my data an error states it does not match my KK and KTP even though I entered them accurately.'	CONFIRMATION & MECHANISTIC EXPANSION: Macro documentation gaps manifest micro-behaviorally as opaque proxy-means (DTKS decile) misclassifications locked against appeal by false NIK/KK database mismatches.
2. Biometric, Elderly, & Disability Interface Exclusion	Tier 2: Adult illiteracy marginal poverty penalty is 16× larger at Q90 (+0.813 pp) than at Q10 (+0.050 pp) (p = 1.34×10^{-7}). Tier 3: 22.2% biometric/photo failure on Cek Bansos (α=0.991).	Cek Bansos [UUID f09d7bbd, 2026-10-17, 8 upvotes]: 'Still inaccessible for persons with disabilities, especially blind citizens [*tunanetra*]... features cannot be read by a screen reader.' Mobile JKN [UUID f4df0865, 115 upvotes]: 'Users are mostly elderly [*lansia*] who are ill... complex password and OTP rules fail.'	EXPANSION: Explains why low-human-capital tail districts (Q90) suffer severe exclusion—biometric selfie liveness, multi-room photo uploads, and screen-reader-hostile UIs penalize sensory, age, and literacy vulnerabilities.
3. The Digital-to-Analog Boomerang & Spatial Isolation	Tier 2: *Kabupaten* have 14.04% dirt-road villages vs. 1.47% *Kota*; TWFE poorest-20% ratio association β = −0.658 pp (p = 0.0007); AIPW slowdown +0.400 pp (p = 0.0124). Tier 3: Boomerang IRR = 1.865 (p = 0.064).	Cek Bansos [UUID 6bce8724, 2026-10-21, 1★, 26 upvotes]: 'Precisely because I was not registered by the village office [*desa/kelurahan*], I downloaded this app to register independently—yet it forces registration back through the village!' IKD [UUID a5c1b2cc, 62 upvotes]: 'Why must registration face an officer? Pity migrant workers [*perantau*].'	CONCEPTUAL DISCOVERY (BOOMERANG TRAP): Self-service apps fail to bypass local elite capture or spatial distance; instead, mandatory offline QR/PIN resets and village-operator locks double travel and compliance costs.
4. Bifurcated Bureaucratic Silence vs. Citizen Tactical Agency	Tier 3: Agency reply rate = 0.0% (IKD), 0.7% (Cek Bansos, 75% canned), 3.3% (Mobile JKN) vs. 37.8% on contributory JMO (median 4.8h). 1–2★ dummy has IRR = 0.475 (p = 0.043) in endorsement GLM.	Mobile JKN [UUID bf693d05, 2026-09-07, 5★, 839 upvotes]: 'I give 5 stars just so everyone will see this [saya kasih bintang 5 biar pada lihat]: the app constantly crashes, logs out 4 times a day, and fails login—deeply disappointed.'	PRODUCTIVE DISCORDANCE: Reconciles the paradoxical negative 1–2★ endorsement IRR—indigent users strategically deploy '5-star visibility hacking' to amplify grievances when state welfare portals remain 96.7–100% silent.

3.5. Critical mixed-methods joint display and lived mechanics of the 'Digital-to-Analog Boomerang'

Table 7 and Figure 6B bring together the quantitative parameters from Tiers 1–3 and UUID-verified verbatim citizen testimonies. From them we derive four integrative meta-inferences.[41,43,45] The first is Confirmation & Mechanistic Expansion on Registry Desynchronization. Macro documentation barriers (+0.788 pp class gap per 1 pp doc barrier) and Indonesia's 16.67% online e-ID rate show up in lived encounters. There, citizens meet opaque proxy-means (DTKS decile) misclassifications, compounded by algorithmic database lockouts. In Cek Bansos report UUID 7a389557 (2026-09-19; 47 citizen endorsements; 0 agency reply), an indigent citizen writes: 'How do you determine our decile [*melihat desil kita bagaimana ya*]? I was shocked to find myself classified in Deciles 6–10 [deemed affluent/ineligible] when reality is not like that, and when I try to update my data in the app an error occurs stating it does not match my KK and KTP even though I filled everything exactly as instructed.' Corrective self-targeting does not happen here. Instead, asynchronous state databases prevent poor claimants from contesting erroneous algorithmic wealth scores.

The second is Expansion on Biometric and Sensory/Age Exclusion. Tier 2 found that the marginal poverty penalty of adult illiteracy is more than 16 times larger in extreme-poverty districts (Q90) than at Q10 (+0.813 pp at Q90). Uncompromising biometric liveness and accessibility barriers explain it at the micro-behavioral level. On Cek Bansos, citizen reports document multi-step form resets whenever front/interior house or KTP photos are uploaded (UUID 51104ef8; 360 endorsements: '*bukannya mempermudah malah mempersulit*' ['instead of simplifying, this makes life harder']). Other reports describe complete screen-reader exclusion for blind citizens (UUID f09d7bbd, 2026-10-17: '*Aplikasi masih belum akses untuk disabilitas. Khususnya bagi tunanetra*' ['Still inaccessible for persons with disabilities, especially blind citizens... features cannot be read by a screen reader']). Mobile JKN shows a similar pattern. Caregivers report that ill elderly claimants (*lansia*) cannot get through alphanumeric-symbol password resets or failing facial liveness checks, all while they wait for acute clinical care (UUID f4df0865; 115 endorsements). The barrier is practical, not abstract.

The third is Conceptual Discovery of 'The Digital-to-Analog Boomerang'. Our Joint Display shows how failed digital self-service adds a second layer of compliance costs for informal, rural, and migrant citizens. On Cek Bansos, a claimant excluded by village officials downloaded the self-nomination app specifically to bypass local gatekeeping. The claimant then hit an algorithmic catch-22 (UUID 6bce8724, 2026-10-21, 1 star, 26 endorsements): 'Precisely because my family was not registered by the village/subdistrict [*desa/kelurahan*], I downloaded this app to register independently—yet I cannot register and am told it must go through the village! Please respond to the grievances of poor citizens [*keluhan masyarakat miskin*].' On Dukcapil's IKD, the same complaint comes from internal migrant workers (*perantau*; UUID a5c1b2cc, 62 endorsements) and locked-out account holders (UUID 17eae528, 221 endorsements; UUID 231eddc5, 86 endorsements). They protest that forgotten PINs or initial QR activations force them to take unpaid time off informal work and queue physically at subdistrict counters ('*sudah pake aplikasi masih aja harus datang ke kecamatan atau ngantri di lapangan*'). The fourth is Productive Discordance on Tactical Citizen Agency. Qualitative inspection suggests why 1–2 star ratings had IRR = 0.475 in Table 6. Facing 96.7%–100.0% bureaucratic silence, frustrated claimants deliberately assign 5-star ratings to scathing critiques so that their warnings rise to the top of public feeds (Mobile JKN UUID bf693d05, 5 stars, 839 endorsements: '*saya kasih bintang 5 biar pada lihat, aplikasi sering error, sering keluar sendiri...*' ['I give 5 stars so people will see this: the app constantly crashes...']). This is one form of vernacular algorithmic agency.[57,58]

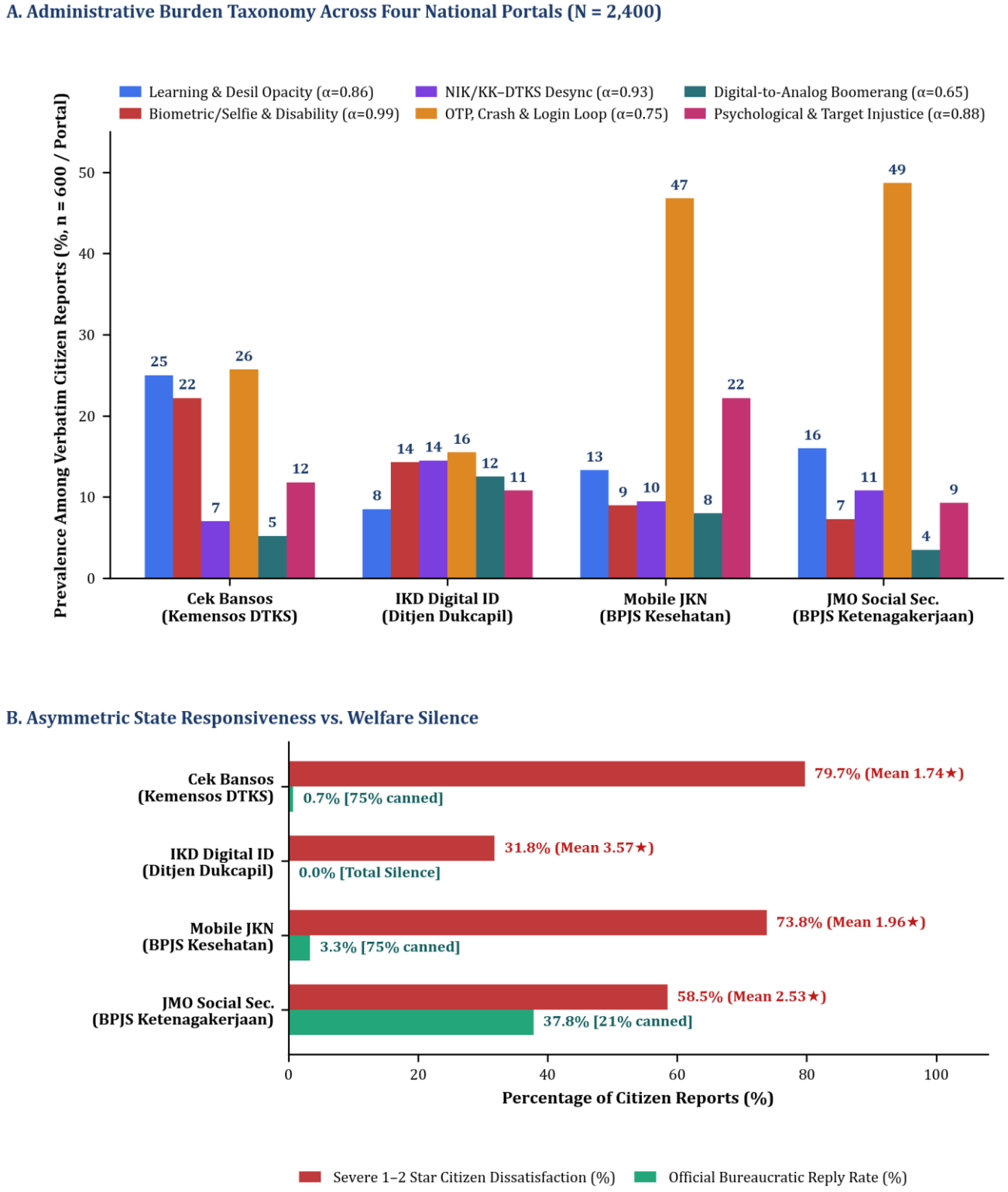


Figure 5. Portal-stratified administrative burden prevalence and institutional responsiveness contrast across N = 2,400 verbatim citizen reports. (A) Prevalence of six two-classifier validated burden domains (Krippendorff's α = 0.65–0.99) across Kemensos Cek Bansos, Dukcapil IKD, BPJS Kesehatan Mobile JKN, and BPJS Ketenagakerjaan JMO (n = 600 per portal). (B) Severe 1–2 star dissatisfaction juxtaposed against official bureaucratic helpdesk reply rates, revealing near-total silence and canned boilerplate deflection on poverty-targeted and civil-ID apps (0.0%–3.3%) versus active engagement on contributory JMO (37.8%).



Figure 6. Determinants of collective civic endorsement and integrative process model of 'The Digital-to-Analog Boomerang.' (A) Multivariable Quasi-Poisson HC3 incidence rate ratios (IRR ± 95% robust CIs, log scale) predicting collective citizen endorsements (12,144 thumbs-up votes across N = 2,400 reports). (B) Critical Mixed-Methods synthesis illustrating how structural informality and low online digital-ID coverage interact with algorithmic registry/biometric gatekeeping to lead to forced offline queueing, paired with a four-pillar inclusive governance redesign protocol.

4. Discussion

4.1. Theorizing 'the Digital-to-Analog Boomerang' and regressive digital administrative burden

This study joins cross-national Findex/ID4D strata, a 10-year panel of all 514 Indonesian districts, and 2,400 verbatim citizen encounters. With that combination, it extends administrative burden and digital-governance theory past single-tier perceptual surveys.[6,9,55] Our central theoretical contribution is the identification and qualitative grounding of 'The Digital-to-Analog Boomerang.' Existing e-government scholarship mostly treats digital self-service portals and physical street-level counters as substitute service channels, and the debate is whether digitalization turns citizens into solitary 'accidental caseworkers'[3,11] or leaves them in 'administrative limbo'.[3,11] Our multi-tier

Indonesian evidence points to a harsher, sequential dynamic in Global South welfare states. Indigent and informal-sector citizens first spend scarce financial and cognitive resources. They buy mobile data. They photograph identity cards and dwellings, and they attempt biometric liveness checks. Then uncoordinated state databases reject their NIK/KK credentials, uploads crash midway, or PIN recovery is withheld, and claimants end up back at physical village (*desa/kelurahan*), subdistrict (*kecamatan*), Dukcapil, and *Dinas Sosial* counters. Digital efficiency does not replace analog red tape. Premature appification stacks digital learning and compliance costs on top of existing spatial travel costs.

This micro-mechanism offers a possible explanation for an apparent macroeconomic puzzle in our Tier 2 district panel. In 2017, Indonesia moved from universal/community in-kind *Raskin* rice to electronic card- and DTKS-gated BPNT/PKH transfers. Why did that shift leave linear TWFE poverty headcount near the statutory poverty line unchanged (β = −0.0317 pp, p = 0.558)? Yet in high-friction informal districts it was associated with a lower poorest-20% relative household expenditure ratio (−0.658 pp, p = 0.00072), wider intra-district Gini inequality (+0.0068, p = 9.05×10^{-5}), and a Doubly Robust +0.400 pp poverty-reduction slowdown (p = 0.0124). A possible answer lies in within-poor stratification.[6,59–61] Households clustered just below the poverty line in electrified, literate subdistricts had the civil documentation and nearby banking/agent access needed to turn electronic transfers into poverty exit. Ultra-poor bottom-quintile households fared differently. They are disproportionately concentrated in informal agriculture and petty trade (65.27% in *Kabupaten*), in unpaved dirt-road villages (14.04%), and in low-literacy pockets where adult illiteracy carries a +0.813 pp Q90 poverty penalty. They appear to have taken the full brunt of documentation mismatches, biometric lockouts, and travel boomerangs. They fell further behind median district living standards.

4.2. Bifurcated digital bureaucracy: contributory responsiveness versus residualist welfare silence

Tier 4 yields a second major institutional insight. State digital unresponsiveness is not a uniform byproduct of limited technological capacity across Indonesian bureaucracy. It reflects deep welfare-regime stratification.[17–19,30] All of these portals operate in the same national digital ecosystem and time window. BPJS Ketenagakerjaan's contributory worker portal (JMO) is financed through earmarked payroll contributions from formal enterprises and voluntary BPU worker premiums, and it replied to 37.8% of public citizen grievances within a median of 4.8 hours. Nearly four-fifths of those responses delivered substantive troubleshooting. The contrast is sharp. Kemensos's non-contributory poverty-relief app (Aplikasi Cek Bansos) replied to only 0.7% of grievances, with 75% canned boilerplate. BPJS Kesehatan's subsidized-heavy Mobile JKN replied to 3.3% (75% boilerplate). Dukcapil's mandatory civil-ID app (IKD) replied to 0.0%.

We term this responsiveness gap (more than 50-fold between JMO and Cek Bansos) 'Bifurcated Digital Bureaucracy.' In contributory corporatist social insurance tiers, beneficiaries are institutionally framed as rights-bearing premium contributors. Their digital retention directly sustains fund liquidity, so the institution has a reason to staff customer care and resolve tickets quickly.[8,62] Poverty-targeted residualist social assistance tiers differ. Indigent claimants there have no market exit options. Institutionalized bargaining power is absent too. Suppose an algorithmic DTKS proxy-means model misclassifies a poor informal household into Deciles 6–10, or PBI health coverage is frozen, and responsive digital grievance redress is absent. In such cases software bugs and database desynchronization can become silent administrative rationing.[10,15,16,18]

4.3. Vernacular algorithmic agency and critical mixed-methods reflexivity

Our Critical Mixed-Methods integration also speaks to digital-sociology and methodological debates on how marginalized citizens contest opaque platform architectures.[31,42,63] Purely quantitative sentiment or star-rating analyses of e-government portals routinely read 5-star ratings as citizen satisfaction and 1-star ratings as complaints. Suppose we had relied on star ratings alone, without qualitative narrative integration. Dukcapil's IKD (mean 3.57 stars) would then have looked largely trouble-free. The negative multivariable Quasi-Poisson coefficient of 1–2 star ratings on community thumbs-up endorsements (IRR = 0.475, p = 0.0428) would have seemed counterintuitive. Joint-Display inspection (Table 7) showed something else. Indonesian claimants actively practice '5-star visibility hacking.' They assign maximum stars to urgent accounts of app crashes and login loops, explicitly 'so that people and officials will see this.' They also use community thumbs-up votes (12,144 collective endorsements) as a horizontal solidarity ledger that validates shared bureaucratic suffering.[13,31]

On the methodological side, critical mixed-methods scholarship stresses reflexivity about power in research design.[41,42] In this study, cross-strand friction exposed a power asymmetry in the measurement instrument itself, the star rating. Qualitative quotes that only illustrate regression slopes would fall short of that. Friction is the point.

4.4. Policy implications: a four-pillar protocol for inclusive digital welfare governance

Digital welfare transformation should not deepen informal-sector and rural marginalization. Preventing that does not mean abandoning digital public infrastructure. It means re-engineering administrative law and software design so that synchronization burdens move off vulnerable citizens and back onto the state (Figure 6B). First, Indonesia's Electronic-Based Government System framework (*Sistem Pemerintahan Berbasis Elektronik* [SPBE]) and Ministry of Social Affairs regulations should codify a statutory 'No-Wrong-Door Offline and Assisted-Digital Parity Mandate.' Smartphone apps such as Cek Bansos, IKD, and Mobile JKN must strictly serve as optional convenience channels. They must not act as mandatory gatekeepers. Funded mobile village outreach facilitators (*pendamping PKH* / *Puskesos*) should back this up. These facilitators would be empowered to complete end-to-end enrollment in unpaved and low-connectivity *Kabupaten*, so claimants need not travel to subdistrict capitals.[64,65]

Second, inter-agency database mismatches ('*NIK/KK tidak padan Dukcapil*') must be resolved. Automated server-side Application Programming Interface (API) reconciliation protocols between Kemendagri Dukcapil, Kemensos DTKS, and BPJS Kesehatan/Ketenagakerjaan should do the work. Benefit suspension must not occur while civil-record updates are pending.[15,20] Third, mandatory biometric facial liveness (FRISTA / KTP-selfie) and complex password resets must come with statutory

non-biometric fallback verification, such as community health-worker attestation or offline smartcard PINs, and mandatory Web Content Accessibility Guidelines (WCAG 2.1 Level AA) screen-reader compliance is also needed, so that blind, disabled, and frail elderly citizens are never locked out of constitutional social rights. Fourth, algorithmic transparency and accountable grievance SLAs are essential. DTKS decile notices in Cek Bansos should display human-readable asset/welfare criteria, alongside an offline-accessible appeal track that is independent of village-elite veto. Non-contributory portals need parity: they should be bound by audited 72-hour substantive helpdesk response SLAs that match contributory JMO standards.[66]

4.5. Methodological strengths, limitations, and future research directions

Several methodological limitations need transparent discussion. First, our Tier 2 INDO-DAPOER panel captures virtually the entire universe of 514 Indonesian districts over a decade (2011–2020), and it pairs district-clustered TWFE DiD with Doubly Robust AIPW (post-weighting max |SMD| = 0.083) and E-value / Cinelli–Hazlett sensitivity bounds. Even so, district-level aggregates cannot track intra-household consumption shifts. Neither can they follow individual claimants. Transitions across formal and informal jobs stay hidden. Future research should link administrative DTKS longitudinal micro-records directly to multi-wave household panels such as SUSENAS or IFLS, where restricted data-use agreements permit. Second, in Tier 1, stratified unbanked documentation-barrier modules (fin11c.7) in the World Bank Global Findex are fielded only in economies with sizable unbanked populations (N = 22 LMICs in the harmonized multivariable specification). This limits finite-sample bootstrap precision, despite strong HC3 regression significance ($p = 0.010$). Third, our Critical Mixed-Methods reflexivity audit stressed that Tier 3 public app-store reviews carry digital-access survivorship bias. Completely offline, illiterate, or device-less citizens cannot post reviews directly unless younger relatives assist them. Our 60.0% administrative burden prevalence therefore represents a conservative lower bound on real-world exclusion in remote archipelagic regencies. Finally, five burden domains reached high reliability between the two classifiers (Krippendorff's $\alpha = 0.754–0.991$). Vernacular diversity in naming local offices yielded $\alpha = 0.646$ on the Digital-to-Analog Boomerang indicator. That motivates future multi-site in-person ethnography at village *Puskesos* and subdistrict Dukcapil counters. Fifth, the district estimates relate a baseline structural index to post-2017 trajectories, so they should be read as associations rather than causal effects of electronic gatekeeping. Sixth, the app reviews (2021–2026) cannot be geolocated or matched in time to the 2011–2020 district panel, so the integration of the tiers is thematic. Seventh, both classifiers are rule-based and were not validated against human coding, and the corpus mixes high-endorsement and recent reviews, so the prevalence figures describe this sample.

5. Conclusion

Three bodies of evidence were triangulated. One was macro-comparative: World Bank Global Findex and ID4D indicators for 157 sovereign economies. Another was longitudinal. It used difference-in-differences and unconditional quantile econometrics across all 514 Indonesian regencies and cities (2011–2020), and the last was a computational-qualitative analysis of 2,400 verbatim citizen encounters on four national social-protection and civil-identity applications. The findings are consistent with unbuffered algorithmic welfare gatekeeping redistributing regressive administrative burdens onto informal-sector, low-literacy, disabled, elderly, and rural populations. Indonesia moved to electronic card- and registry-gated transfers in 2017. Afterward, districts with high informal employment and analog–digital infrastructure deficits were associated with a 0.658 pp lower bottom-quintile relative household expenditure ratio, a +0.0068-point rise in intra-district Gini inequality, and a Doubly Robust +0.400 pp slowdown in poverty reduction. The upper tail stands out. Adult illiteracy's unconditional poverty penalty was more than 16 times larger in extreme-poverty regencies (+0.813 pp at Q90) than at Q10. At the street level, opaque DTKS decile scoring, NIK–registry desynchronization, and biometric and screen-reader failures meet 96.7%–100.0% helpdesk silence on poverty-targeted portals. The citizen reports point to a 'Digital-to-Analog Boomerang'. It pushes indigent citizens back into costly physical queueing. Equitable digital transformation in the Global South needs e-governance anchored in statutory offline parity, server-side civil-registry reconciliation, accessible non-biometric fallbacks, and enforceable bureaucratic accountability.

Acknowledgments

The authors acknowledge the open-data teams of the World Bank Development Data Group (Global Findex, ID4D, ASPIRE, and INDO-DAPOER), Statistics Indonesia (*Badan Pusat Statistik* [BPS]), the International Labour Organization, and the Indonesian citizens whose public feedback made empirical evaluation of digital public service delivery possible.

6. Declarations

Statement on the Use of Artificial Intelligence

None. The authors declare that no generative artificial intelligence tools were used in the design, analysis, or writing of this manuscript.

Author Contribution Statement

Conceptualization: APP. Methodology: APP. Software: APP. Validation: AS, AH. Formal analysis: APP. Investigation: APP. Data curation: APP. Writing – original draft: APP. Writing – review & editing: APP, AS, AH. Visualization: APP. Supervision: APP. Project administration: APP.

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest / Competing Interests

The authors declare no competing interests.

Data Availability Statement

All research data are available from corresponding author on reasonable academic request.

Ethics Approval and Consent to Participate

This study analyzed exclusively publicly archived aggregate macroeconomic and subnational statistics (World Bank Global Findex, ID4D, ASPIRE, WDI, and INDO-DAPOER) and publicly posted, de-identified software platform feedback records from which personal display names were stripped before analysis. In accordance with international ethical guidelines for secondary analysis of public archives and non-interventional digital-trace social research, ethical committee of Enigma Institute, Indonesia approved this research protocol (approval number 2026/922).

Consent for Publication

Not applicable. All verbatim citizen excerpts derive from public software feedback feeds and are referenced solely through non-identifying UUID keys, without personal names or contact identifiers.

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