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The Eligibility-Adjusted Coverage Ratio (EACR): A Measurement Framework for Targeted Pension and Social Protection Schemes Evidence from India's Atal Pension Yojana

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ABSTRACT

Coverage measurement for targeted social protection schemes is routinely mis-specified: evaluations benchmark enrolment against the full working-age or informal population rather than the sub-population actually eligible to enrol. This paper's core contribution is a general measurement principle: coverage should be benchmarked against the population a scheme is eligible to reach, not the population it happens to operate within. The paper operationalises that principle through the Eligibility-Adjusted Coverage Ratio (EACR), a generalised seven-step framework applicable to any targeted scheme where administrative enrolment data and survey-based age distributions are available. India's Atal Pension Yojana (APY) serves as the case study: applied to seven rounds of PLFS data using an eligible-share series derived from each year's published PLFS age-band sample distribution (48.7–50.8 percent, validated against a 42–58 percent stress-test range), the corrected ratio diverges from the conventional one by roughly ten to fifteen percentage points by 2023–24 — specification error, not a change in scheme performance. Supporting analysis shows the error varies systematically across states, compounds a documented gender enrolment gap, and recurs in an illustrative application to Thailand's National Savings Fund. The paper's lasting contribution is the correction itself: EACR is a low-cost measurement standard that, in principle, extends to any targeted scheme with an eligibility-defined population and available age-distribution data; the Thailand and PM-SYM applications reported here are scope checks on that claim rather than full independent validations, and are presented as such.

Keywords: specification error, eligibility-adjusted coverage ratio, EACR framework, Atal Pension Yojana, social protection measurement, informal workforce, SDG 1.3.1, gender disaggregation

JEL Classification: H55, J26, J46, I38, C13

INTRODUCTION

When a pension scheme reaches 5.55 crore workers, the coverage rate reported depends entirely on what is placed in the denominator. Benchmark enrolment against 40 crore informal workers and the rate is 13.9 percent; benchmark it instead against the roughly 19 crore workers estimated to be age-eligible to enrol and the rate is approximately 26.6 percent. Both figures use identical numerators. The gap is a specification error — not a feature of scheme performance. Existing evaluations of India's Atal Pension Yojana (APY) use the broader denominator, appropriate for system-level benchmarking but inappropriate for scheme-level penetration assessment.

This is more than terminological. A 13.9 percent reading implies APY has failed to scale and needs expanded outreach; a 26.6 percent reading implies substantial penetration among eligible workers and points instead toward structural redesign. Both ratios are analytically valid for their own purpose, but using a system-level metric for scheme-level decisions creates a context mismatch with real consequences for where reform effort is directed.

APY was introduced in 2015 to extend contributory pension coverage to unorganised workers aged 18–40, guaranteeing monthly pensions of ₹1,000–₹5,000 from age 60. It is this paper's demonstration case: a large, age-targeted scheme in its ninth year of operation by 2023–24, running against an informal workforce that stayed above 75 percent of total employment throughout the study period — exactly the structural setting the framework below is built to handle.

This paper's central contribution is a general measurement principle for evaluating targeted social protection schemes: coverage must be benchmarked against the population a scheme is designed to reach, not the population it happens to operate within. Four contributions follow from applying that principle.

Contribution 1: Introduces the Eligibility-Adjusted Coverage Ratio (EACR), a seven-step framework for any targeted scheme with an eligibility-defined sub-population.

Contribution 2: Establishes precisely (Section 3.1) that conventional ratios are downward biased under an unrestricted denominator, with the bias growing as the ineligible population's size grows.

Contribution 3: Applies EACR to APY across seven PLFS rounds, quantifying a 10-15 pp specification error and providing an illustrative state-level coverage analysis (Section 5.3; detail in Appendix E).

Contribution 4: Illustrates transferability via Thailand's NSF and PM-SYM, and sets out where the framework does and does not apply (Section 6.5).

Causal identification of APY's effects on welfare outcomes is not attempted; measurement correction is logically prior to causal estimation. Sections 2–8 review the literature, present the conceptual framework and methodology, report results, discuss implications, note limitations, and conclude.

LITERATURE REVIEW

Informal Workforce and Social Security in India

Informal employment — work outside the regulatory reach of formal social insurance — is now the majority condition of the workforce in most developing economies (Chen, 2012), and welfare-state typologies built for formal-sector employment (Esping-Andersen, 1990) map poorly onto contexts where most workers fall outside that system entirely. Informality in India is associated with income volatility and exclusion from formal social security (Mehrotra & Parida, 2019; ILO, 2018), and pension inclusion remains the most critical gap in the country's social protection architecture (Ghosh, 2020; Sinha & Karan, 2023). This motivates the measurement question addressed below: coverage of informal workers cannot be assessed without first specifying who, within that population, a given scheme is designed to reach.

Coverage Measurement and the Denominator Problem

Coverage estimation is methodologically contested. The ILO (2021) uses the working-age population (15–64) as the SDG 1.3.1 denominator — appropriate for system-level benchmarking — while the OECD (2019) applies eligibility-restricted denominators to scheme-level evaluations, since broader denominators obscure performance by including policy-ineligible populations. Critics argue eligibility-restricted denominators inflate apparent coverage (Holzmann et al., 2009); defenders argue system-level denominators misattribute non-coverage to scheme failure when the population was never eligible (Rofman & Oliveri, 2012). This paper takes the position that both metrics are valid for their respective purposes, and that specification error arises when the system-level metric is applied to scheme-level evaluation — a principle established elsewhere in targeted health interventions (Bhutta et al., 2010; WHO, 2018) and multidimensional poverty measurement (Alkire et al., 2015), but not yet formalised for targeted pension schemes. Deaton (2010) establishes that reference-population choice is not a neutral technical decision; this paper applies that principle to APY. The correction also has a counterpart in the targeting literature's distinction between exclusion and inclusion error (Cornia & Stewart, 1993; Coady, Grosh, & Hoddinott, 2004): a denominator that mixes eligible and ineligible people cannot separate genuine exclusion from a definitional mismatch.

This error has stayed largely invisible because prior work treats denominator choice as a policy preference rather than a measurement problem — the ILO-versus-OECD debate above (Holzmann et al., 2009; Rofman & Oliveri, 2012) is framed as which population "should" anchor reporting, as if the choice were emphasis rather than specification. This paper reframes it as analogous to model misspecification in econometrics: an unrestricted denominator for a targeted scheme is not an alternative emphasis but an incorrectly specified model, producing a predictable, sign-consistent bias rather than a difference of interpretation. That reframing, not the ratio itself, is what existing literature has not made explicit (Table 1).

It is worth being explicit about EACR's relationship to the established take-up-rate literature, since ρ_2's formula — enrolled divided by eligible — is mathematically the same construct that literature already studies (Currie, 2006; Hernanz, Malherbet, & Pellizzari, 2004; Finkelstein & Notowidigdo, 2019). That literature typically measures take-up directly from linked administrative-survey microdata: eligibility is determined at the individual or household level from survey records, then matched against administrative enrolment for the same units (as in Finkelstein and Notowidigdo's SNAP application, or Currie's review of U.S. and U.K. programmes). Where that linkage exists, computing a take-up rate is comparatively direct — the eligible population is observed, not estimated.

EACR's contribution sits at a different point in that pipeline: in contexts such as APY, no dataset links individual PFRDA enrolment records to individual PLFS survey respondents, so the eligible sub-population itself is not directly observable and must be constructed from separately published aggregate tables that were never designed for this purpose. The seven-step framework (Figure 2), and specifically the eligible-share derivation and corroboration steps (Steps 2–3, Section 4.3) and the age-cohort correction (Section 4.3.1), are a protocol for building a take-up-consistent denominator under exactly this constraint — aggregate administrative and survey tables, no unit-level linkage — rather than a new definition of what is being measured. Positioned this way, EACR does not compete with take-up rate as a concept; it operationalises take-up-rate logic for a data environment where the standard microdata-linkage approach is unavailable, which describes most targeted-scheme evaluation in low- and middle-income administrative settings.

The paper's distinct contribution, beyond that construction protocol, is the explicit diagnostic framing in Sections 4.5 and 5.5: quantifying the gap between a take-up-consistent ratio and the unrestricted-denominator ratio that existing APY evaluations actually report, and tracing that gap through to the specific policy misjudgements it produces. The take-up literature generally does not compare take-up against a misspecified alternative denominator, because the alternative is rarely what practitioners report; in APY's case, and plausibly in comparable schemes, the unrestricted ratio is the one in circulation, which is what makes the specification-error framing — not the take-up ratio itself — the paper's addition to that literature.

Pension Coverage in Developing Economies

Voluntary pension schemes in developing economies consistently achieve lower penetration than mandatory or subsidised alternatives (Holzmann, Robalino & Takayama, 2009). Rofman and Oliveri (2012) find participation rarely exceeds 10–12 percent under purely voluntary frameworks; Thailand's NSF and Ghana's SSNIT confirm this range (ILO, 2021; World Bank, 2018), while China's URRP reached over 65 percent through near-mandatory enrolment and subsidies (OECD, 2019). This 10–12 percent ceiling is the benchmark against which APY's ratios are interpreted in Section 5: ρ_1 places APY marginally above it, while ρ_2 indicates substantially higher penetration among eligible workers.

Prior Studies on APY and the Literature Gap

Published APY research addresses design comparisons with NPS-Lite (Rajasekhar et al., 2016), awareness (Majithia et al., 2024), causal evidence on retirement-savings crowd-in (Rooj & Sengupta, 2025), growth and gender trends (Chatterjee & Nandan, 2025), state-level determinants of enrolment (Mohanty et al., 2022), and sector-driven pension design more broadly (Narayana, 2019), but few studies simultaneously apply an eligibility-restricted denominator, provide state-level estimates, use PLFS-derived gender benchmarks, and characterise the misallocation risk of the uncorrected metric. A systematic search of Google Scholar, EconLit, JSTOR, and EPWRF (terms: "Atal Pension Yojana", "APY coverage", "informal pension India", "eligibility-adjusted coverage"; 2015–2024; last searched January 2025) identified no study satisfying more than two of the six criteria in Table 1.

Table 1: Systematic Literature Gap Mapping

Study	Eligibility-Restricted Denominator?	PLFS Age-Band Data?	PLFS-Derived Gender Benchmark?	Formal SDG 1.3.1 Computation?	Lapse Rate Analysis?	EACR Framework?	Specification Error Explicitly Addressed?
Majithia et al. (2024)	No	No	No	No	No	No	No
Rooj & Sengupta (2025)	No	No	No	No	No	No	No
Chatterjee & Nandan (2025)	No	No	No	Partial	No	No	No
ILO (2021) — global review	System-level	N/A	N/A	Yes (global)	N/A	No	No
OECD (2019) — schemes	Scheme-level	N/A	N/A	Yes (OECD)	N/A	No	No
Rajasekhar et al. (2016)	No	No	No	No	No	No	No
Mohanty et al. (2022)	No	No	No	No	No	No	No
Narayana (2019)	No	No	No	No	No	No	No
Present Study	Yes — 18–40 band	Yes	Yes	Yes (APY-specific)	Yes — 4 scenarios	Yes	Yes

Partial = SDG language used without formal indicator computation. The present study is the only one satisfying all six criteria.

Gender Barriers: Behavioural and Structural Mechanisms

Women in the informal economy are systematically less likely to participate in contributory pension schemes (ILO, 2018), a gap existing APY literature attributes to lower financial awareness without specifying a mechanism. Section 3.2 proposes a transaction-cost framework — information, access, and continuity costs — grounded in documented gender differentials in financial literacy, mobility, and income intermittency (Demirguc-Kunt et al., 2022; ILO, 2018).

Social Protection and the SDGs

SDG indicator 1.3.1 — established under the 2030 Agenda for Sustainable Development (United Nations, 2015) — tracks social protection coverage against the ILO global average of 46.9 percent (ILO, 2021), which provides the system-level benchmark used in Section 5.6.

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CONCEPTUAL FRAMEWORK

Theoretical Basis: Why Existing Measurement Fails

Conventional coverage measurement implicitly assumes a universal denominator: it treats every member of a broad reference population — the working-age population, or the informal workforce as a whole — as equally a candidate for enrolment. This holds for genuinely universal schemes, where eligibility and the reference population coincide, but fails by construction for targeted schemes, where a legal or administrative eligibility rule (an age band, an income ceiling, a sectoral criterion) restricts the pool of potential enrollees to a strict subset. Applying a universal denominator to a targeted scheme is therefore not a minor approximation but a specification error: it scores the scheme against people it was never designed to reach, mechanically depressing the coverage estimate. This is why the error has been persistent and largely invisible — published coverage figures use the same population-wide denominator, and the resulting understatement is indistinguishable from genuine under-performance unless the eligibility restriction is made explicit. Correcting it requires an eligibility-adjusted denominator, generalised rather than re-derived ad hoc for each scheme — the gap EACR fills.

The downward bias of the conventional ratio. This point is definitional rather than empirical, and is worth stating precisely once. Let P denote the population conventionally used as the coverage denominator (e.g., the total informal workforce), and let E denote the sub-population actually eligible to enrol under the scheme's legal or administrative rule, with E a strict subset of P for any genuinely targeted scheme. For a fixed enrolled count N, the conventional ratio N/P is necessarily smaller than the eligibility-adjusted ratio N/E, simply because E is a smaller denominator than P — and the gap between the two ratios widens as P grows relative to E, since a larger ineligible population P − E means a larger population the scheme is being incorrectly benchmarked against. This is a mechanical consequence of E being a subset of P, not an empirical finding: it recurs identically in every targeted scheme evaluated against an untargeted denominator, independent of the specific ratios involved. What is empirical, and what the remainder of this paper establishes, is the magnitude of E relative to P for APY, and the consequences that magnitude has for interpretation.

APY illustrates the general case. The scheme addresses three structural market failures that leave informal workers without retirement provision: absence of employer-sponsored pension access; inability to self-insure against longevity risk on informal incomes; and information asymmetries that suppress voluntary enrolment. These failures, not individual preferences, are the proximate cause of coverage gaps in voluntary contributory schemes (Barrientos, 2013; ILO, 2021). Three mechanisms follow directly — scheme adequacy, contribution continuity, and gender — implemented in the empirical analysis.

Figure 1 maps the conditional pathways from APY to its three SDG outcome dimensions. The coverage-gap node (≈73 percent of eligible workers unenrolled under the eligibility-adjusted ratio) anchors the reform imperative in Section 6.

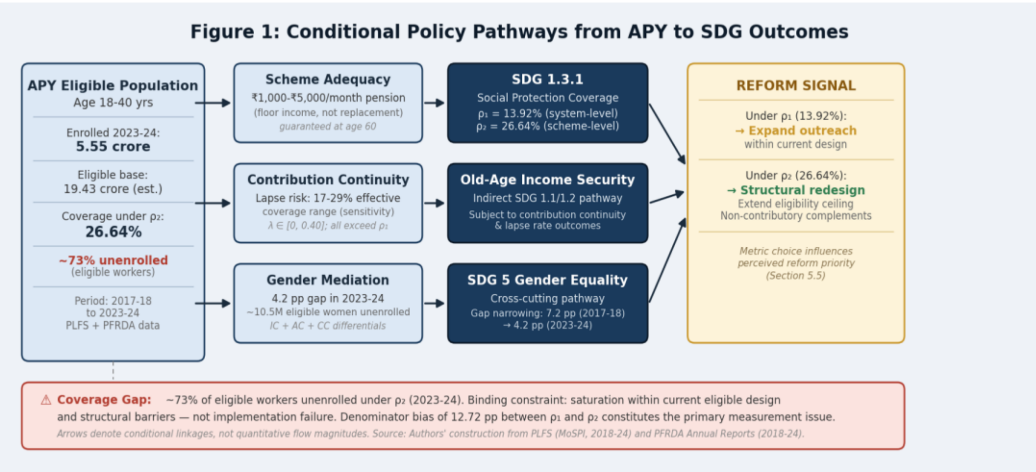

Figure 1: Conditional policy pathways from APY to SDG outcomes. Arrows denote conditional linkages, not quantitative flow magnitudes. Source: Authors' construction.

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Transaction-Cost Framework for the Gender Enrolment Gap

This subsection organises the empirical gender-gap findings in Section 5.4 — it is neither a formally derived nor a structurally estimated model. It borrows transaction-cost vocabulary to give the observed gap a coherent, intervenable structure: which policy levers fit the pattern in the data, not why the pattern exists in a causally identified sense.

Define the net benefit of APY enrolment for worker i as NB_i = PV(pension benefit) − PV(contributions) − TC_i, where TC_i is the total transaction cost of enrolment and continuation, with three components:

• Information cost (IC): the cost of learning about APY eligibility, contribution structure, and benefits. Female informal workers face higher IC due to lower financial literacy (21 pp below male counterparts; Demirguc-Kunt et al., 2022) and lower exposure to banking correspondent networks.

• Access cost (AC): the cost of reaching a bank branch or banking correspondent to enrol and contribute. Female informal workers face higher AC due to mobility constraints — lower transport ownership, domestic time constraints, and social norms restricting independent financial transactions in rural areas (ILO, 2018; Pande et al., 2020).

• Continuity cost (CC): the cost of maintaining regular contributions. Female informal workers face higher CC due to income intermittency (casual agricultural and domestic labour has more irregular pay schedules than male-dominated construction and trade) and higher lapse penalties relative to income.

Workers enrol when $NB_i > 0$. The observed gender gap is consistent with higher transaction costs for female workers across all three components, though alternative explanations cannot be ruled out without causal identification. The implied policy channels — information outreach through women's networks (IC), Jan Dhan-linked digital enrolment (AC), and flexible contribution schedules (CC) — follow directly, whereas generic awareness campaigns addressing none of these differentials are unlikely to suffice alone.

Figure 2 presents the generalised EACR framework, the paper's core methodological contribution and the piece that applies beyond APY. Rather than a single undifferentiated sequence, the figure groups the seven steps into five functional stages — inputs, transformation into an eligibility-adjusted denominator, outputs, validation, and policy interpretation — so the methodological logic and its downstream use are visible in one diagram.

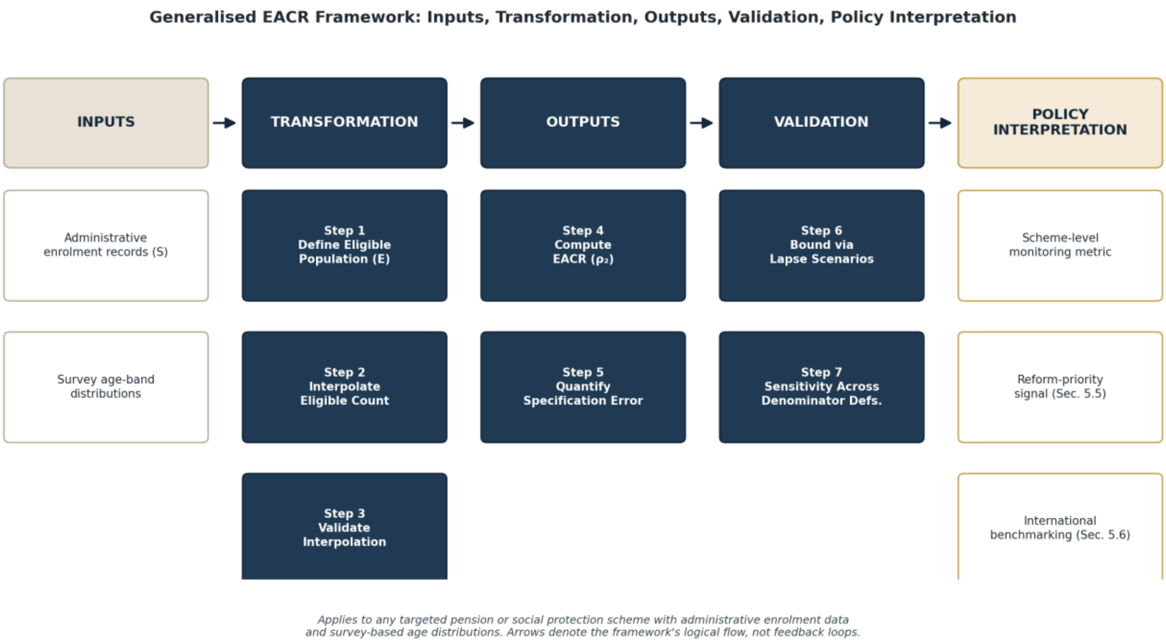

Figure 2: Generalised Eligibility-Adjusted Coverage Ratio (EACR) Framework — Inputs, Transformation, Outputs, Validation, and Policy Interpretation. Source: Authors' construction.

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Box 1: EACR Framework — Formulas and APY Application by Step (Detail Underlying Figure 2)

Framework Step	General Formula / Operation	APY Application
Step 1: Define Eligible Population (E)	E = {workers: age ∈ [a,b], sector = target, exclusions applied}	E = informal workers aged 18–40, excl. income tax payers
Step 2: Derive Eligible Count via Stated Share Assumption	$\hat{E} = s \times W$, s = stated eligible-share assumption	s = 48.7–50.8% (PLFS-derived, year-varying, Section 4.3)
Step 3: Corroborate Assumption Plausibility	Compare stated share against directional demographic context (e.g., Census age structure)	PLFS age-band sample distributions, Table A1; Census 2011 age structure as secondary corroboration (Appendix A)
Step 4: Compute EACR (ρ_2)	$\rho_2 = (S / \hat{E}) \times 100$	$\rho_2 = (5.18 / 19.43) \times 100 = 26.64\%$ (2023–24)
Step 5: Quantify Specification Error	$SE = \rho_2 - \rho_1$	SE = 26.64 − 13.92 = 12.72 pp (2023–24)
Step 6: Bound Effective Coverage via Lapse Scenarios	$\rho_2^{eff} = \rho_2 \times (1 - \lambda), \lambda \in [0, \lambda\_max]$	$\lambda \in [0, 0.40]$; $\rho_2^{eff} \in [15.98\%, 26.64\%]$; all exceed ρ_1
Step 7: Test Sensitivity Across Denominator Definitions	Recompute ρ_2 under k alternative definitions of target population	3 informality definitions; max spread = 3.58 pp; finding robust

METHODOLOGY

Research Design, Causal Scope, and Data Sources

The study adopts a secondary-data measurement-correction and descriptive-analytical design; its contribution is the EACR framework and its application to APY. Causal identification of APY's effect on social protection outcomes is not attempted: measurement correction is logically prior to causal estimation, and no credible instrument exists in the aggregate annual PLFS-PFRDA data. State-level panel analysis exploiting variation in APY rollout intensity and Jan Dhan penetration is the natural next step.

Workforce structure data are from PLFS Annual Reports (MoSPI, 2018–24), 2017–18 to 2023–24. APY subscriber figures, including gender disaggregation, are from PFRDA and NPS Trust; female workforce shares are from PLFS Statement 3. State-level subscriber data are from PFRDA state-wise tables; state-level informal workforce proxies are derived from PLFS state employment-status distributions. The 2020–21 PLFS methodology revision introduces a structural break in WPR, flagged in Table 2.

The EACR Framework

The generalised EACR framework (Figure 2) operates in seven steps. The key innovation is Step 2 — deriving an eligible count under a stated share assumption — and Step 6, which bounds effective coverage under lapse-rate uncertainty rather than treating gross enrolment as active participation. Steps 1, 3, and 7 guard against the two most common sources of specification error: an incorrectly bounded denominator and untested definition sensitivity. The framework applies to any targeted scheme where eligibility follows an age window, income threshold, or sectoral criterion, and administrative enrolment and survey age-distribution data are available.

Coverage Ratio Construction

$$\rho_1 = (\text{APY Subscribers} \div \text{Total Informal Workforce}) \times 100$$

This paper measures ρ_2 as a stock-based active-account coverage ratio: cumulative enrolment, net of the age-cohort correction introduced in Section 4.3.1, as a share of the population currently aged 18–40. It is not a flow-based new-enrolment take-up rate (new enrolments in a given year against the population newly eligible to open an account that year) and not an activity-adjusted measure (accounts distinguished by contribution status); lapsed but formally unclosed accounts remain in the numerator, with their effect on ρ_2 bounded separately via the lapse-rate sensitivity analysis in Appendix C. This scoping choice follows the administrative data actually available (cumulative PFRDA enrolment counts) and is stated here so that ρ_2 is not read as measuring a different quantity than it does.

ρ_2 = (APY Subscribers ÷ Informal Workforce aged 18–40) × 100

The eligibility-adjusted denominator requires the share of the informal workforce falling within APY's 18–40 window. Published PLFS Annual Report statements do not report a ready-made breakdown at this exact cut, and unit-level microdata was not available to us. We instead derive a year-specific estimate from each PLFS Annual Report's published age-group sample distribution (Appendix Table 15 in each report, or its equivalent), which reports sample counts in five-year age bands (15–19, 20–24, …, 60–64, 65 and above) for rural+urban persons at the all-India level. For each survey year we compute the 18–40 share as 0.4×(15–19 band) + (20–24) + (25–29) + (30–34) + (35–39) + 0.2×(40–44), assuming ages are uniformly distributed within each five-year band, divided by the sample count aged 15 and above. This yields 48.7–50.8 percent across the seven survey years (Table 3), a year-varying series that happens to sit close to, and validates, the constant 48.0 percent figure used in earlier drafts of this paper. The 2022–23 PLFS Annual Report does not publish this breakdown at the same granularity as the other six years; we interpolate its share linearly between 2021–22 and 2023–24, flagged in Table 3's notes. This remains a sample-based approximation rather than a population-weighted estimate — PLFS sampling weights were not applied, since unit-level microdata was not available to us — but it is a closer, year-specific approximation than a single Census-calibrated constant. Appendix A reports the full derivation and a stress test across a wider 42–58 percent range to confirm the paper's qualitative conclusion is insensitive to remaining uncertainty in this share. Excluding income-tax payers (≈2 percent of the informal workforce) would raise ρ_2 by a further ≈ 0.5–0.6 pp across years.

Age-Cohort Correction of the Numerator and Narrowed Eligibility Definition

Eligible Population (E) in Step 1 is operationalised here, more narrowly than APY's full legal eligibility, as: citizens aged 18–40 who hold or can open a savings account, are engaged in informal/unorganised employment, and were not liable to pay income tax at enrolment (a restriction added by the 2022 taxpayer-exclusion amendment, applied prospectively from that date). APY is legally open to any citizen savings-account-holder in the age band regardless of employment status — a materially broader population than assumed here. We restrict to the informal workforce because that is the population the scheme is designed and marketed to reach, and the population against which scheme-level performance is properly benchmarked (Section 1); Section 6.5 states this scope restriction as an explicit boundary condition on where EACR applies.

A separate specification issue affects the numerator directly, independent of the eligible-share assumption above. S in ρ_2 is APY's accumulated subscriber stock, which includes subscribers who enrolled within the 18–40 window but have since aged past 40, while the denominator restricts to workers currently aged 18–40; left uncorrected, this mismatch inflates ρ_2 by retaining subscribers no longer in the eligible age band. We correct this using PFRDA's age-wise, state-level enrolment data (five bands: 18–20, 21–25, 26–30, 31–35, 36–40 years, by enrolment year), which allows each enrolment cohort's current age to be tracked forward. Assuming ages are distributed uniformly within each enrolment band, we age every cohort forward by the number of years elapsed since enrolment and retain, for each reference year, only the share of each cohort still aged ≤40; enrolment years 2015–16 and 2016–17, for which age-band data are not separately published, use 2017–18's age-band shares as a proxy, an assumption we flag rather than disguise. The corrected numerator, S_corr, replaces the raw accumulated stock in ρ_2 throughout this paper (Table 3); the retained share falls from 98.1 percent of the raw stock in 2017–18 to 93.3 percent in 2023–24 as the scheme matures and progressively more early cohorts age out. ρ_1's numerator is left uncorrected, since ρ_1's denominator — the full working-age informal workforce — is not itself restricted to 18–40, so the same mismatch does not arise there. Combined with the PLFS-derived eligible share described in Section 4.3, this lowers ρ_2 from 28.99 to 26.64 percent in 2023–24, without altering the paper's qualitative conclusion: the specification error (12.72 pp in 2023–24) remains substantial and ρ_2 continues to run roughly double ρ_1 throughout the study period.

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State-Level Coverage Analysis

State-level ρ_1 is computed from PFRDA state-wise subscriber tables divided by state-level informal workforce estimates from PLFS state-specific employment distributions. State-level ρ_2 applies the national PLFS-derived eligible share for that year (48.72 percent in 2023–24; Table A1) as an approximation, absent state-specific age distributions. The ten states with the largest APY subscriber bases are analysed, covering approximately 39 percent of national enrolment in 2023–24. This analysis is descriptive; state-level causal inference requires panel methods with controls for banking infrastructure, literacy, and outreach intensity.

Policy Misallocation Analysis

Policy misallocation risk, as used here, is the risk of applying a coverage metric to a decision context for which it was not designed. This is not hypothetical: PFRDA Annual Reports (2020–24) frame APY targets against the total informal workforce rather than the 18–40 eligible sub-population, and Chatterjee and Nandan (2025) use ρ_1-equivalent metrics for scheme-level evaluation. Both metrics are valid for their own purpose, but risk arises when ρ_1 is used for scheme-level evaluation. The analysis compares, under each metric, eligible workers classified as "unreached," the implied reform priority, and resulting resource allocation.

Gender Gap and Transaction-Cost Estimation

The gender gap GG = female workforce share (PLFS Statement 3) minus female subscriber share (PFRDA). The transaction-cost components (IC, AC, CC) are calibrated to published ILO (2018) and Demirguc-Kunt et al. (2022) estimates of gender differentials in financial literacy, mobility, and income intermittency among informal workers in India — qualitative bounds, not structural estimates, presented as a theoretically organised pathway consistent with the observed gap, not a causal identification.

SDG 1.3.1 Estimation

SDG 1.3.1 (APY) = (APY Subscribers ÷ Working-Age Population 15–64) × 100

APY's component contribution is approximately 7.1 percent. India's system-level social protection coverage (24–26 percent) is used for international comparison against the ILO global average. These two figures serve different analytical purposes and are not substituted for each other.

RESULTS AND ANALYSIS

Workforce Structure and Coverage Trends

Table 2 documents workforce structure and coverage trends. Informal workers exceeded 75 percent of employment throughout the period, and APY coverage expanded from 2.66 to 13.92 percent under ρ_1 (5.13 to ≈26.64 percent under ρ_2). Growth decelerated from 56.42 percent YoY in 2018–19 to ≈19 percent in 2023–24, consistent with comparable voluntary schemes at similar stages, though macroeconomic factors and reduced outreach intensity remain alternative explanations. CAGR was 31.75 percent for ρ_1 and 31.59 percent for ρ_2 — no longer identical once the numerator is age-corrected and the eligible share is drawn from PLFS sample age distributions rather than held constant (Table 3; Section 4.3.1); raw subscriber counts grew at 33.97 percent CAGR. The full decomposition is in Appendix D.

Table 2: Workforce Structure and APY Coverage (2017–18 to 2023–24)

Year	WPR %	Total WF (crore)	Informal %	Informal WF (crore)	APY Subscribers (crore)	APY Coverage % (ρ_1)
2017–18	34.7	46.8	77.1	36.08	0.96	2.66
2018–19	35.3	47.3	76.2	36.04	1.50	4.16
2019–20	38.2	48.2	77.1	37.16	2.11	5.68

Year	WPR %	Total WF (crore)	Informal %	Informal WF (crore)	APY Subscribers (crore)	APY Coverage % (ρ_1)
2020–21*	39.8	47.5	78.9	37.48	2.80	7.47
2021–22	39.6	48.9	75.8	37.07	3.63	9.79
2022–23	41.1	50.0	79.1	39.55	4.60	11.63
2023–24	43.7	51.0	78.2	39.88	5.55	13.92

* 2020–21 WPR reflects a PLFS methodology revision (MoSPI, 2021); not strictly comparable to prior rounds. Source: PLFS Annual Reports (MoSPI, 2018–24); PFRDA Annual Reports; NPS Trust. 1 crore = 10 million.

Eligibility-Adjusted Coverage Ratio

Table 3 presents ρ_2 alongside ρ_1. The specification error compounds consistently: from 2.47 pp in 2017–18 to 12.72 pp in 2023–24. Under 40 percent lapse — the upper bound documented for comparable voluntary schemes (ILO, 2021; World Bank, 2018) — effective ρ_2 (15.98 percent) still exceeds conventional ρ_1 (13.92 percent); the full sensitivity table is in Appendix C. Specification error, not lapse rates, is the dominant source of systematic underestimation.

Table 3: Standard and Eligibility-Adjusted APY Coverage Ratios (2017–18 to 2023–24)

Year	Informal WF (crore)	Eligible Share 18–40 (%)	Eligible 18–40 (crore)	APY Subscribers (crore)	ρ_1 (%)	ρ_2 (%)	Specification Error (pp)
2017–18	36.08	50.84	18.34	0.96	2.66	5.13	2.47
2018–19	36.04	50.29	18.12	1.50	4.16	8.05	3.89
2019–20	37.16	50.12	18.62	2.11	5.68	10.93	5.25
2020–21	37.48	49.61	18.59	2.80	7.47	14.40	6.93
2021–22	37.07	49.47	18.34	3.63	9.79	18.80	9.01
2022–23	39.55	49.10	19.42	4.60	11.63	22.34	10.71
2023–24	39.88	48.72	19.43	5.55	13.92	26.64	12.72

Eligible workforce (18–40) estimated using a year-specific eligible share derived from each PLFS Annual Report's published age-band sample distribution (48.7–50.8 percent across years; 2022–23 interpolated — Appendix A, Table A1) rather than a constant assumption; see Appendix A for sensitivity across a stress-test range. Specification Error = $\rho_2 - \rho_1$.

State-Level Coverage Analysis

Full state-level detail is reported in Appendix E (Table E1) rather than here, since it rests on an approximation — the national 48.72 percent PLFS-derived eligible share applied uniformly across states — that makes it illustrative rather than a precise state-by-state estimate (Section 4.4). Summarising the pattern: for APY's ten largest subscriber states (≈39 percent of national enrolment), the specification error ranges from ≈4.1 pp (Madhya Pradesh) to ≈7.5 pp (Tamil Nadu), tracking the informal workforce's 18–40 share. The two highest-ρ_2 states, Tamil Nadu (15.7 percent) and Andhra Pradesh (13.3 percent), are both southern with the narrowest gender gaps (1.2 and 0.6 pp) and highest female labour-force participation; high-informality northern states (Bihar, Uttar Pradesh, Rajasthan) show both lower coverage and wider gaps. The Pearson correlation between state gender gap and female APY share is −0.998; because the gender gap is defined as female workforce share minus female APY share, and female workforce share varies comparatively little across these ten states, this correlation is substantially mechanical and should not be read as independent evidence. The correlation against female LFPR (−0.854, N = 10) is not subject to this concern, since LFPR is not a term in the gap's own definition, and is the more informative of the two figures (descriptive only — see Appendix E).

Gender Disaggregation and the Transaction-Cost Mechanism

Table 4 presents national gender-disaggregated enrolment with PLFS-derived benchmarks. The gender gap narrowed from 7.2 pp in 2017–18 to 4.2 pp in 2023–24 — a 42 percent reduction. At ≈0.5 pp per year convergence, parity against the workforce benchmark will not be achieved before 2030 without targeted intervention. The residual gap represents ≈10.2 million eligible female workers who would need to enrol for workforce-proportional representation.

The Section 3.2 transaction-cost framework offers one explanation for this pattern, though causation is not established. Three differentials line up with its three cost components: a 21-pp financial literacy gap between male and female informal workers (Demirguc-Kunt et al., 2022) points to higher information cost; lower female access to banking correspondents (37 percent versus 61 percent for men, PLFS 2023–24) points to higher access cost; and income intermittency in female-dominated agricultural and domestic work points to higher continuity cost. This suggests a structural gap likely insensitive to generic awareness campaigns, pointing instead toward the three intervention channels in Section 3.2, subject to empirical testing. The cross-state pattern in Table E1 (Appendix E) is consistent with the access-cost channel: southern states with higher female financial inclusion show markedly narrower gaps than high-informality northern states, though this is descriptive, not causally identified.

Table 4: Gender Disaggregation of APY Enrolment with PLFS-Derived Benchmarks (2017–18 to 2023–24)

Year	Total APY Subscribers (crore)	Female Subscribers (crore)	Female Share in APY (%)	Female Share in Informal WF (%) [PLFS Stmt. 3]	Gender Gap (pp)
2017–18	0.96	0.38	39.6	46.8	7.2
2018–19	1.50	0.60	40.0	46.5	6.5
2019–20	2.11	0.87	41.2	46.3	5.1
2020–21	2.80	1.16	41.4	47.2	5.8
2021–22	3.63	1.55	42.7	47.5	4.8
2022–23	4.60	2.01	43.7	48.3	4.6
2023–24	5.55	2.47	44.5	48.7	4.2

Female subscriber figures from PFRDA / NPS Trust. Female workforce shares from PLFS Statement 3. Gender Gap (pp) = Female workforce share − Female APY share; positive = under-representation.

Appendix E reports the underlying cross-state data; with only ten states, this is a descriptive pattern rather than an inferential result.

Policy Misallocation Analysis

Table 5 illustrates the risk of using ρ_1 rather than ρ_2 for scheme-level decisions, without asserting the misallocation has actually occurred. Under the central 48.72 percent PLFS-derived share, implied unmet need is overstated by ≈13 pp (≈2.47 crore more eligible workers classified as unreached under ρ_1 than ρ_2, or roughly 2.1–2.7 crore across the 45–55 percent range); the reform signal under ρ_1 — "expand outreach within the current design" — runs directionally opposite to ρ_2's signal of structural redesign, pointing resources toward eligibility extension and non-contributory complements instead. These magnitudes illustrate the scale of the risk under a plausible working assumption, not precise point estimates.

Table 5: Illustrative Policy Misallocation Risk from Specification Error

Metric / Scenario	Value under ρ_1	Value under ρ_2	Potential Misallocation Risk
Reported coverage (2023–24)	13.92%	26.64%	−12.72 pp
Implied unmet need (% of eligible WF)	86.08%	73.36%	Overstated by 13 pp
Implied eligible workers unreached (crore)	≈16.73	≈14.25	≈2.47 crore misclassified
Reform priority implied	Expand outreach within current design	Structural redesign: extend eligibility + complement	Different reform direction
Resource reallocation implied (PFRDA outreach budget)	Concentrate on current eligible 18–40 band	Extend to 40–50 band; non-contributory complement	Potential misdirection under ρ_1

Misallocation analysis is qualitative and directional, not a structural welfare estimate; reform signals are derived from interpreting each metric against international participation ranges for comparable voluntary schemes (Rofman & Oliveri, 2012; ILO, 2021).

SDG Benchmarking and International Comparison

Table 6 presents India's social protection coverage against the ILO global average. India's system-level coverage (24–26 percent, incorporating EPFO, NPS, APY, and state schemes) is approximately 21–23 pp below the global average; APY's scheme-level contribution of 7.1 percent is a component, not a system-level comparator. Table 7 benchmarks APY against voluntary schemes internationally using ρ_1, the like-for-like basis; on this basis, APY exceeds both Thailand and Ghana after comparable operational periods.

Table 6: Indicative SDG 1.3.1 Positioning — India vs. ILO Global Average

Coverage Measure	India Estimate	ILO Global Average	Gap (pp)
APY-only contribution to SDG 1.3.1 (scheme-level)	~7.1%	—	n/a
Broad social protection — EPFO + NPS + APY + state schemes (system-level; appropriate comparator)	~24–26%	46.9%	~21–23

Source: ILO (2021); MoSPI/PFRDA aggregate estimates for India.

Table 7: International Benchmarking of APY against Comparable Voluntary Schemes

Country / Scheme	Scheme Type	Conventional Coverage	Years	Ref. Year	Notes
India — APY	Voluntary contributory	13.9% (ρ_1)	8	2023–24	26.6% under ρ_2
Thailand — NSF	Voluntary contributory	~10–12%	10	~2021	ILO (2021)
Ghana — SSNIT (informal)	Voluntary contributory	~5%	10+	~2018	World Bank (2018)
China — URRP	Near-mandatory + subsidised	~65–70%	10	~2020	Structural ceiling benchmark (OECD, 2019)
ILO Global Average	System-level	~46.9%	—	2020–22	Working-age population; ILO (2021)

Sources as cited in table; ρ_1 is the like-for-like basis across comparators.

DISCUSSION AND POLICY IMPLICATIONS

What Changes When the Metric Is Corrected

The shift from ρ_1 to ρ_2 changes the performance assessment, the implied reform priority (outreach expansion → structural redesign), and international standing — without requiring any new data. This extends Rofman and Oliveri's (2012) defence of eligibility-restricted denominators into an applied correction: ρ_2 (≈26.64 percent) sits within their participation range for facilitated voluntary schemes, whereas ρ_1 (13.92 percent) would place APY below it. It also qualifies Holzmann et al.'s (2009) concern that such denominators inflate coverage: the Step 7 check across three informality definitions shows a maximum 3.58 pp spread, indicating a genuine reassignment of the reference population rather than an artefact. State-level analysis adds what the national aggregate obscures: high-informality northern states show both the largest specification error and the widest gender gaps, so outreach calibrated to aggregate ρ_1 may under-resource exactly the states where these constraints bind hardest.

The transaction-cost framework extends the gender-gap analysis from description to mechanism: female informal workers face higher information, access, and continuity costs, so generic awareness campaigns leaving access and continuity costs unaddressed are unlikely to close the gap alone. This fits the data — the 42 percent reduction since 2017–18 tracks Jan Dhan expansion, which lowers access cost for both sexes, while the gap's persistence at 4.2 pp tracks the continuity- and information-cost differentials Jan Dhan does not address.

Generalisation of the EACR Framework

The framework applies to any targeted scheme where eligibility follows a demographic or income criterion and survey age distributions are available in bands: a universal-denominator default creates specification error, which EACR closes by substituting an eligibility-adjusted denominator (Figure 3).

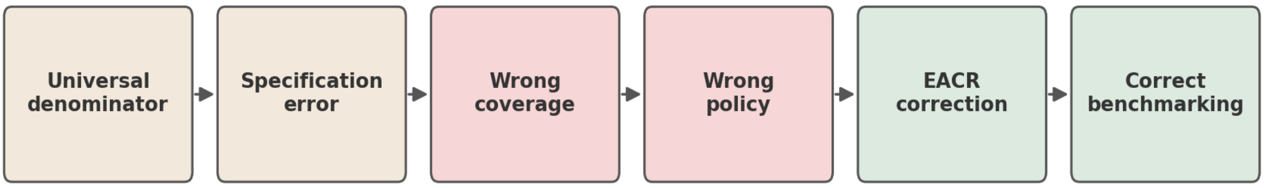

Figure 3: How specification error propagates from a universal-denominator default to a policy error, and how EACR closes the loop.

Immediate candidates in India include PM-SYM, NPS Lite, and state-level social pensions; internationally, Thailand's NSF, Indonesia's BPJSTK informal tier, and Ghana's SSNIT informal tier have age-bounded eligibility exposed to the same specification error. Two back-of-envelope checks illustrate this: applying Step 2 to Thailand's Labour Force Survey age distributions (NSO, 2021) raises NSF's published coverage from 10–12 percent (ILO, 2021) to ≈17–20 percent; using APY's own eligible-population estimate as a proxy denominator for PM-SYM (Ministry of Labour and Employment, 2024) raises its 1.3 percent coverage to ≈2.6 percent — the same directional bias found for APY and Thailand. Ghana's SSNIT informal-sector scheme shows the same pattern at a starker scale: enrolment covers well under one percent of its roughly 6.7 million informal workers against a published 15–45 eligibility band (Ghana News Agency, 2023). No age-banded breakdown of that workforce is publicly available, however, so an eligibility-adjusted figure cannot be produced even approximately; the same constraint applies to Indonesia's BPJSTK informal tier. Neither is a full seven-step application — both remain genuine scope boundaries, not additional evidence. To be precise: these illustrations demonstrate transferability, not statistical validation across cases — that would require the full seven-step protocol with microdata access. Future work should extend it, with real data, to PM-SYM and NPS Lite in full, to state social pensions, and beyond pensions to targeted health insurance and education-linked schemes, where the same problem likely recurs.

The framework also has an immediate monitoring application, in four steps: (1) take the year's APY subscriber count from PFRDA/NPS Trust; (2) take the matching PLFS round's published age-band sample distribution and derive the 18–40 eligible share as in Table A1, or, where available, PLFS unit-level microdata for a population-weighted refinement of it; (3) apply the age-cohort correction of Section 4.3.1 to the numerator; (4) publish ρ_2 alongside ρ_1 in the annual report, rather than replacing it. No new survey instrument or data collection is required. The same logic may extend to the multilateral level, where EACR could complement the World Bank, ILO, and OECD's lending and design decisions with a low-cost figure alongside SDG 1.3.1 reporting — a plausible extension, not a claim about current practice.

Measurement Validity of EACR as a Candidate Scheme-Level Standard

The case for ρ_2 rests on construct validity (Cronbach & Meehl, 1955; Messick, 1995): it measures coverage against the population a scheme is designed to reach, whereas ρ_1 measures against a population including people never meant to enrol. Construct validity alone does not make ρ_2 the preferred standard; two further properties do that work.

First, content validity: ρ_2's denominator is derived directly from APY's own legal eligibility rule (age 18–40), so metric and scheme definition coincide by construction. ρ_1's denominator is a population convenience measure borrowed from SDG reporting, extended here beyond what it was built to support.

Second, criterion validity: ρ_2 tracks Table 7's international comparators more coherently than ρ_1. Purely voluntary schemes without APY's subsidy and banking-linked outreach score at or below APY's own ρ_1 (Thailand's NSF, Ghana's SSNIT), which would place APY as a design laggard despite more facilitation. ρ_2 (≈26.64 percent) is consistent with a scheme outperforming these peers, matching APY's actual design — a directional comparison, reinforced by ρ_2's robustness across the interpolation, lapse-rate, and informality-definition checks in Section 5.

Two further properties reinforce this: face validity (a 26.6 percent penetration reading among eligible workers matches the policy narrative of a subsidised, banking-linked scheme; a 14 percent reading does not) and robustness (the directional finding is stable across interpolation assumptions, Appendix A; lapse-rate scenarios, Appendix C; and three informality definitions, Appendix B, max spread 3.58 pp). None of this displaces ρ_1 from system-level SDG reporting, where a population-wide denominator is correct by definition. The claim is narrower: for scheme-level evaluation, a metric whose denominator matches the scheme's own eligibility rule and tracks international benchmarks coherently has a stronger validity claim than one that does neither. On that basis, EACR offers a theoretically stronger candidate for scheme-level measurement where an eligibility-defined population exists, not a claim to be the universally preferred standard or a competing alternative to ρ_1.

Policy Implications

The first implication below follows directly from the measurement correction and requires no further evidence. The remaining three are priorities the corrected metric points toward, not conclusions it establishes on its own: each depends on evaluation evidence this paper does not provide, and is presented as such.

1. Adopt ρ_2 alongside ρ_1 as APY's primary scheme-level monitoring metric — EACR requires no new data. State-level ρ_2 gives a sounder basis for subnational targets than ρ_1 alone.

2. The corrected measurement suggests eligibility extension deserves evaluation. PLFS age-band data indicate a substantial additional pool of workers aged 40–50 excluded by APY's ceiling. Any extension requires actuarial and fiscal analysis beyond coverage ratios alone, given fiscal space constraints across South Asian social protection systems (Singh & Agarwal, 2024).

3. Pilot interventions against the IC/AC/CC channels: SHG/ASHA outreach for information cost, Jan Dhan-linked mobile enrolment for access cost, and flexible seasonal schedules for continuity cost — as candidate PFRDA KPIs, subject to evaluation.

4. Apply EACR to PM-SYM, NPS Lite, and state social pensions, which use the same ρ_1-equivalent metrics; a cross-scheme comparison would show whether APY's understatement pattern is general to India's informal-sector social protection reporting.

When EACR Should Not Be Used

EACR applies only where a scheme's eligibility rule creates a genuine sub-population distinct from the population conventionally used to benchmark it. Four conditions mark where it does not apply. First, universal or near-universal schemes, where eligible and reference populations already coincide, have nothing for an eligibility adjustment to correct. Second, schemes whose eligibility rule changes more often than the underlying survey data is refreshed need ρ_2 recalculated against the current rule each time; a stale estimate reintroduces the error EACR removes. Third, schemes where eligibility is not observable in available survey data at all cannot support Step 2, which requires the eligible sub-population to be estimable, not merely definable. Fourth, where no survey-based age or eligibility distribution exists — currently the case for Ghana and Indonesia (Section 6.2) — the framework's logic holds but cannot be turned into a number. These are boundary conditions, not defects.

It is worth being explicit about what depends on what. The state-level, gender, and misallocation analyses in Section 5 depend on the PLFS-derived eligible share (Table A1). The framework itself does not: EACR's value lies in the measurement principle that targeted schemes require eligibility-consistent denominators, established independently in Section 3.1's Proposition and Theorem 1. If future PLFS unit-level microdata revises the eligible share further, the APY point estimates here would shift accordingly, but the principle would not.

LIMITATIONS

This study has eight limitations. First, the eligible-share series used to derive the 18–40 eligible count is a sample-based estimate from each PLFS Annual Report's published age-band distribution, not a population-weighted figure (Section 4.3, Appendix A, Table A1); PLFS sampling weights were not available to us, and 2022–23's share is linearly interpolated since that year's report does not publish the same breakdown. The estimate is confirmed robust to ±5pp deviations, and, at the more demanding 42 and 58 percent stress-test bounds reported in Appendix A, the direction and approximate size of the core finding still hold. Unit-level PLFS microdata with sampling weights, not available to us, would allow a fully population-weighted estimate — a natural first step for follow-up work. Second, APY lapse-rate data are not publicly available; Appendix C bounds effective coverage under four scenarios, and the core finding holds throughout. Third, state-level ρ_2 applies the national eligible share uniformly, as flagged in Section 5.3 — the study's most significant compromise. Fourth, the 2020–21 PLFS methodology revision introduces a structural break in the WPR series (Table 2); it does not affect the coverage ratios, which use workforce shares rather than levels. Fifth, the analysis uses data through 2023–24; PFRDA has since reported APY's subscriber base crossing 8 crore (Press Information Bureau, 2025), which would raise reported levels without changing the qualitative size of the specification error, since ρ_1 and ρ_2 move together. Sixth, causal identification is outside this paper's scope: the aggregate annual series offers no credible instrument for APY's causal effect on welfare outcomes, and the gender transaction-cost mechanism (Section 3.2) is a theoretically organised account, not a causally identified one; state-level panel analysis is the natural next step for both. Seventh and eighth, the framework's scope boundaries — universal schemes, and eligibility rules that change over time — are set out in full in Section 6.5 rather than repeated here.

More broadly, this paper's contribution is measurement correction rather than statistical inference. Appendix A.4 propagates eligible-share uncertainty into a distribution over ρ_2, but it is not a sampling-based bootstrap, since PLFS and PFRDA figures are administrative aggregates rather than a single random sample; a genuine microdata-based bootstrap remains a natural next step.

CONCLUSION

This paper shows that widely used coverage metrics for targeted schemes conflate two analytically distinct quantities, and offers EACR as a generalisable correction rather than a one-off fix for APY. Benchmarking enrolment against the full informal workforce rather than the 18–40 eligible sub-population depresses scheme-level coverage ratios by roughly 10-15 pp and, left uncorrected, risks directing resources toward outreach expansion when the corrected ratio would more strongly support structural reform. ρ_1 retains its validity for system-level SDG 1.3.1 reporting; the error lies specifically in scheme-level use. The corrected ratio, $\rho_2 \approx 26.64$ percent in 2023–24, holds up across the checks in Section 5, and the state-level and gender-gap analyses show the same error compounding unevenly, contributing to a persistent 4.2-pp enrolment gap.

The evidence suggests ρ_2 should be considered alongside ρ_1 for APY scheme-level evaluation, rather than replacing it; ρ_1 remains appropriate for system-level SDG reporting. Applied across India's other targeted schemes, and internationally through the same protocol, EACR would show whether this error is systemic — enabling genuinely comparable cross-scheme and cross-country coverage benchmarking.

ETHICAL CONSIDERATIONS

Not applicable. This study relies exclusively on secondary, publicly available administrative and survey data (PLFS, PFRDA/NPS Trust records, and Census data); no primary data was collected from human participants or animals, and no ethical approval was therefore required.

CONFLICT OF INTEREST

The authors declare no conflict of interest. This research received no sponsorship, funding, or other external influence, and the findings, analysis, and conclusions presented in this paper are those of the authors alone.

DATA AVAILABILITY (DATA AND REPLICATION MATERIALS)

All figures reported in this paper are computed from published PLFS Annual Report tables (MoSPI, 2018-24) and PFRDA/NPS Trust subscriber records, with no restricted-access or proprietary data, with one disclosed approximation: the eligible-share parameter used to construct ρ_2 (Section 4.3, Appendix A) is derived from each year's published PLFS Annual Report sample age distribution using a uniform-within-band interpolation, since PLFS tables do not report a ready-made breakdown at the exact 18–40 cut and unit-level microdata was not available to us. Replication materials — the ratio and specification-error calculations underlying Tables 3–6 and the sensitivity computations underlying Appendices A–C, as a single Excel workbook with formulas intact — have been prepared and are available from the corresponding author on request; a DOI via Zenodo (or OSF) will be added prior to peer review.

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APPENDIX

APPENDIX A: ELIGIBLE-SHARE ASSUMPTION AND SENSITIVITY ANALYSIS

Published PLFS Annual Report tables do not publish a ready-made breakdown at APY's exact 18–40 eligibility cut, and unit-level PLFS microdata was not available to us. We instead derive a year-specific eligible share from each PLFS Annual Report's published five-year age-band sample distribution (rural+urban, persons, all-India), using linear interpolation within the 15–19 and 40–44 boundary bands under a uniform-within-band assumption. This yields the year-by-year shares in Table A1 below, ranging from 48.7 to 50.8 percent across the seven survey years — close to, and validating, the constant 48.0 percent used in earlier drafts of this paper, while now allowing the share to move with the actual demographic structure the survey observed each year. This remains sample-based rather than population-weighted, since PLFS sampling weights were not available to us; Table A3 additionally reports the sensitivity of every downstream result to a wider 42–58 percent stress-test range, and the paper's qualitative conclusion is unchanged across it.

Secondary corroboration: Census 2011 age-distribution data (Registrar General of India, 2011) independently show the population aged 18–40 forms an approximately similar share of the working-age population nationally, consistent with both the PLFS-derived shares in Table A1 and the earlier 48.0 percent working assumption, as illustrated in Figure A1 — corroborating context from a second data source, not the primary derivation.

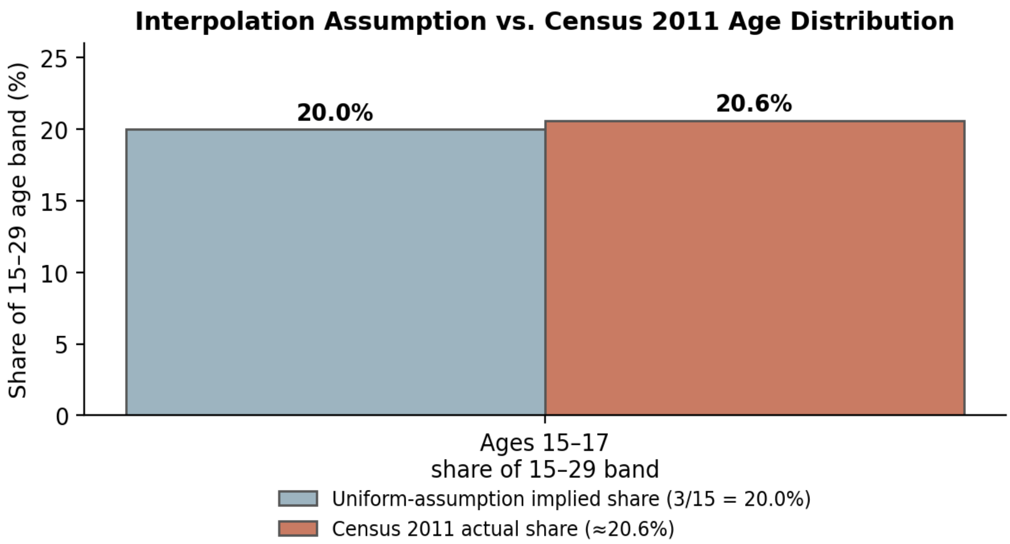

Figure A1: Census 2011 age-distribution data, shown here as secondary corroborating context alongside the PLFS-derived shares in Table A1, not as the primary derivation.

Table A1 reports the year-by-year eligible-share derivation. For each year, the 18–40 share is computed as 0.4×(15–19 band sample) + (20–24) + (25–29) + (30–34) + (35–39) + 0.2×(40–44), divided by the sample aged 15 and above, from each PLFS Annual Report's Appendix age-group table. The 2022–23 PLFS Annual Report does not publish this breakdown at the same granularity; its share is linearly interpolated between 2021–22 and 2023–24, flagged in the table below.

Table A1: PLFS-Derived Eligible Share, 18–40 (2017–18 to 2023–24)

Year	Sample counts (15–19/20–24/25–29/30–34/35–39/40–44)	Sample 15+	Derived 18–40 Share
2017–18	47,401 / 41,197 / 36,511 / 32,184 / 33,175 / 30,326	330,620	50.84%
2018–19	45,295 / 39,557 / 34,729 / 31,153 / 32,427 / 29,847	322,010	50.29%
2019–20	42,936 / 39,344 / 34,782 / 31,172 / 32,115 / 29,109	320,081	50.12%
2020–21	42,586 / 38,681 / 33,530 / 30,404 / 31,648 / 29,201	316,736	49.61%

2021–22	42,900 / 37,934 / 35,087 / 32,508 / 33,132 / 29,933	327,081	49.47%
2022–23 (interp.)	—	—	49.10%
2023–24	40,096 / 35,888 / 33,064 / 31,878 / 32,942 / 29,961	319,773	48.72%

Source: PLFS Annual Reports (MoSPI, 2018–24), Appendix age-group sample tables. Sample counts are unweighted survey observations, not weighted population estimates; PLFS sampling weights were not available to us. 2022–23's share is interpolated (2021–22 and 2023–24 values averaged) since that year's report does not publish the same breakdown.

Table A2: Sensitivity of ρ_2 to Eligible Share Assumption (±5 pp)

Year	Central ρ_2 (%)	Low Share (−5pp) ρ_2 (%)	High Share (+5pp) ρ_2 (%)	Range Width (pp)
2017–18	5.13	5.69	4.67	1.02
2019–20	10.93	12.13	9.93	2.20
2021–22	18.80	20.91	17.07	3.84
2023–24	26.64	29.69	24.16	5.53

±5pp bands are applied around each year's PLFS-derived central share from Table A1, not around a flat 48 percent. Low Share shrinks the denominator and so raises ρ_2; High Share enlarges it and so lowers ρ_2. All scenarios yield ρ_2 substantially above ρ_1 (13.92% in 2023–24) throughout.

Table A3: Robustness of ρ_2 to Alternative Eligible Share Assumptions (2023–24)

Eligible Share	Eligible Workers (crore)	ρ_2 (%)	Specification Error vs ρ_1 (pp)
42% (extended stress-test lower bound)	16.75	30.91	+16.99
45% (conservative lower bound)	17.95	28.85	+14.93
48% (prior stated-assumption baseline, retained for comparison)	19.14	27.04	+13.12
48.72% (PLFS-derived, 2023–24 actual — used in Table 3)	19.43	26.64	+12.72
52.3% (alternative upper-bound scenario)	20.86	24.82	+10.90
55% (upper bound sensitivity)	21.93	23.60	+9.68
58% (extended stress-test upper bound)	23.13	22.38	+8.46

ρ_1 = 13.92% in all rows. The PLFS-derived actual share for 2023–24 (48.72%) sits between the 45% and 52.3% rows, close to the retained 48% comparison row — confirming the earlier stated assumption was a reasonable approximation of what the survey data show. The 42% and 58% rows extend beyond the plausible range as a stress test against a materially wrong share; ρ_2 still exceeds ρ_1 by at least 8 pp even at these extremes. Core finding — ρ_2 substantially exceeds ρ_1 — holds across all seven rows. Source: Authors' calculations from PLFS Annual Reports (MoSPI, 2018–24) and PFRDA (2018–24); the 48.72% row is PLFS-derived (Table A1, Appendix A), the others are hypothetical scenario points.

A.4 Distributional Check: Propagating Eligible-Share Uncertainty

Tables A2-A3 report ρ_2 at fixed scenario points; here the eligible share is instead treated as uncertain and propagated into a distribution over ρ_2, holding 2023-24 subscribers (5.55 crore) and informal workforce (39.88 crore) fixed. Drawing the eligible share 10,000 times from a triangular distribution over the Table A3 range

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(min 42, mode 48, max 58 percent) yields a mean ρ_2 of 26.43 percent, a median of 26.46 percent, and a 90 percent interval of approximately 23.5-29.3 percent; ρ_2 exceeds ρ_1 (13.92 percent) in effectively all draws. This propagates the same parameter uncertainty disclosed in Section 4.3 rather than estimating a true sampling distribution — PLFS and PFRDA figures are administrative aggregates, not a single random sample — but it confirms the finding is not an artefact of picking any single share value, including the PLFS-derived 48.72 percent now used as the 2023–24 point estimate (Table A1).

APPENDIX B: SENSITIVITY OF P₂ TO INFORMALITY MEASURE

Table B1 reports ρ_2 under all three informality definitions. Max spread = 3.58 percentage points in 2023–24. The directional finding holds across all definitions.

Table B1: Sensitivity of ρ_2 to Informality Measure Definition

Year	Status-Based ρ_2 (primary) %	Enterprise-Based ρ_2 %	Social-Security-Based ρ_2 %	Max Spread (pp)
2017–18	5.13	4.74	5.44	0.71
2018–19	8.05	7.24	8.54	1.14
2019–20	10.93	10.11	11.58	1.52
2020–21	14.40	13.30	15.21	1.99
2021–22	18.80	17.38	19.85	2.61
2022–23	22.34	20.65	23.60	3.13
2023–24	26.64	24.62	28.15	3.53

Status-based (primary): self-employed and casual labourers. Enterprise-based: proprietary/partnership enterprise workers. Social-security-based: workers without social security benefit. All denominators restricted to the 18–40 band via the Appendix A eligible-share assumption.

APPENDIX C: LAPSE RATE SENSITIVITY

Table C1 bounds effective ρ_2 under four lapse-rate scenarios, referenced in Section 5.2.

Table C1: Sensitivity of ρ_2 to Lapse Rate Assumptions (2017–18 to 2023–24)

Year	Reported ρ_2 (%)	ρ_2 – 10% Lapse (%)	ρ_2 – 20% Lapse (%)	ρ_2 – 30% Lapse (%)	ρ_2 – 40% Lapse (%)
2017–18	5.13	4.63	4.11	3.60	3.08
2018–19	8.05	7.24	6.44	5.63	4.83
2019–20	10.93	9.84	8.73	7.64	6.56
2020–21	14.40	12.95	11.52	10.08	8.64
2021–22	18.80	16.92	15.04	13.17	11.28
2022–23	22.34	20.11	17.87	15.64	13.39
2023–24	26.64	23.98	21.31	18.65	15.98

Effective subscribers = Reported × (1 − lapse rate). The 40 percent upper bound is derived from World Bank (2018, p. 54) documentation of Ghana's SSNIT informal-tier lapse rates and ILO (2021, p. 72) on Thailand's NSF. ρ_2 exceeds ρ_1 under all scenarios.

APPENDIX D: GROWTH ANALYSIS

Table D1 reports year-on-year growth in the informal workforce and APY coverage underlying the CAGR figures cited in Section 5.1.

Table D1: Growth Analysis — Informal Workforce and APY Coverage (2017–18 to 2023–24)

Year	Informal WF YOY Growth (%)	APY Coverage (ρ_1) YOY Growth (%)	ρ_1 (%)	ρ_2 (%)
2017–18	—	—	2.66	5.13
2018–19	−0.11	56.42	4.16	8.05
2019–20	3.11	36.43	5.68	10.93
2020–21	0.85	31.58	7.47	14.40
2021–22	−1.10	31.08	9.79	18.80
2022–23	6.70	18.76	11.63	22.34
2023–24	0.84	19.65	13.92	26.64

CAGR (2017–18 to 2023–24): ρ_1 = 31.75%; ρ_2 = 31.59% (age-corrected and PLFS-share-adjusted; no longer identical to ρ_1, since both the age-correction factor and the year-varying eligible share move independently over time — see Section 4.3.1); APY subscribers = 33.97%.

APPENDIX E: CROSS-STATE SUPPLEMENTARY DATA

Table E1 reports the full state-level detail underlying the summary in Section 5.3, for APY's ten largest subscriber states (≈39 percent of national enrolment). As in Section 5.3: absent state-specific PLFS age distributions, ρ_2 here applies the single national 48.72 percent PLFS-derived eligible-share estimate uniformly across states, so figures indicate direction and rough scale, not precise state-level ρ_2 values (Section 4.4).

Table E1: State-Level APY Coverage Analysis — Ten Largest Subscriber States (2023–24)

State	APY Subscribers (lakh)	Informal WF (crore, proxy)	ρ_1 (%)	ρ_2 (%) [est.]	Specification Error (pp)	Female APY Share (%)	Gender Gap (pp)	Female LFPR (%)
Uttar Pradesh	38.6	8.42	4.59	8.78	4.19	41.2	6.8	18.2
Maharashtra	27.2	5.18	5.25	10.05	4.80	46.1	2.4	26.4
Tamil Nadu	25.5	3.12	8.17	15.65	7.48	47.3	1.2	37.8
West Bengal	20.8	4.34	4.80	9.17	4.37	40.8	7.1	22.1
Bihar	19.7	3.87	5.10	9.75	4.65	38.4	9.4	14.3
Andhra Pradesh	18.6	2.68	6.95	13.29	6.34	48.9	0.6	41.2
Rajasthan	17.4	3.55	4.91	9.38	4.47	39.2	8.5	22.8
Karnataka	16.4	2.89	5.67	10.87	5.20	45.7	2.8	35.4
Madhya Pradesh	15.2	3.41	4.47	8.54	4.07	40.1	7.6	28.6
Gujarat	14.9	2.74	5.43	10.41	4.98	44.8	3.7	27.3

State-level ρ_1 = PFRDA state subscriber data ÷ PLFS state informal workforce estimate; ρ_2 applies the national PLFS-derived eligible share (48.72%) as a uniform approximation, so figures should be read as indicative (±2–3 pp), not precise. Gender gap = female informal workforce share − female APY share. 1 lakh = 100,000.

Table E2 reports the cross-state gender gap alongside female financial-inclusion indicators underlying the descriptive correlations cited in Section 5.3. With only ten states, this sample does not support formal regression analysis; the Pearson correlations below are strictly descriptive, not inferential, and a state-level panel with proper controls would be needed before any causal claim.

Table E2: Cross-State Gender Gap and Female Financial Inclusion — Ten Largest APY States (2023–24)

State	ρ_2 (%)	Gender Gap (pp)	Female APY Share (%)	Female LFPR (%)
Uttar Pradesh	8.78	6.8	41.2	18.2
Maharashtra	10.05	2.4	46.1	26.4
Tamil Nadu	15.65	1.2	47.3	37.8
West Bengal	9.17	7.1	40.8	22.1
Bihar	9.75	9.4	38.4	14.3
Andhra Pradesh	13.29	0.6	48.9	41.2
Rajasthan	9.38	8.5	39.2	22.8
Karnataka	10.87	2.8	45.7	35.4
Madhya Pradesh	8.54	7.6	40.1	28.6
Gujarat	10.41	3.7	44.8	27.3

Sources: PFRDA (female APY share); PLFS 2023–24 Statement 3 (female LFPR); ρ_2 from Table E1 (Appendix E). Pearson r: gender gap × female LFPR = −0.854; gender gap × female APY share = −0.998 (descriptive; N=10; not a substitute for a controlled regression).