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Beyond the Brand-Generic Divide: An Exploratory Factor Analysis of Determinants Underlying Low Generic Medicine Uptake in India

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Abstract

India is known as pharmacy of the world due to its manufacturing capacity of generic medicines as well as vaccines. India supplies about a fifth of the world's generic medicine exports by volume. Yet uptake of low-cost unbranded generics is low: branded generics made up about 87% (eighty-seven percent) of the Indian Pharmaceutical Market by value in 2023. Many researches have identified several barriers for usage but rarely focused on underlying latent core barriers.

Exploratory Factor Analysis (EFA) tool is used on Likert-scale attitude items from surveys of pharmacists (N = 78, 23 items) and the general public (N = 581, 18 items) in Telangana, India. Kaiser- Meyer-Olkin (KMO), Bartlett's test of sphericity, principal-axis factoring with varimax rotation, and Cronbach's α were used to establish factorability, recover latent structure, and verify internal consistency respectively.

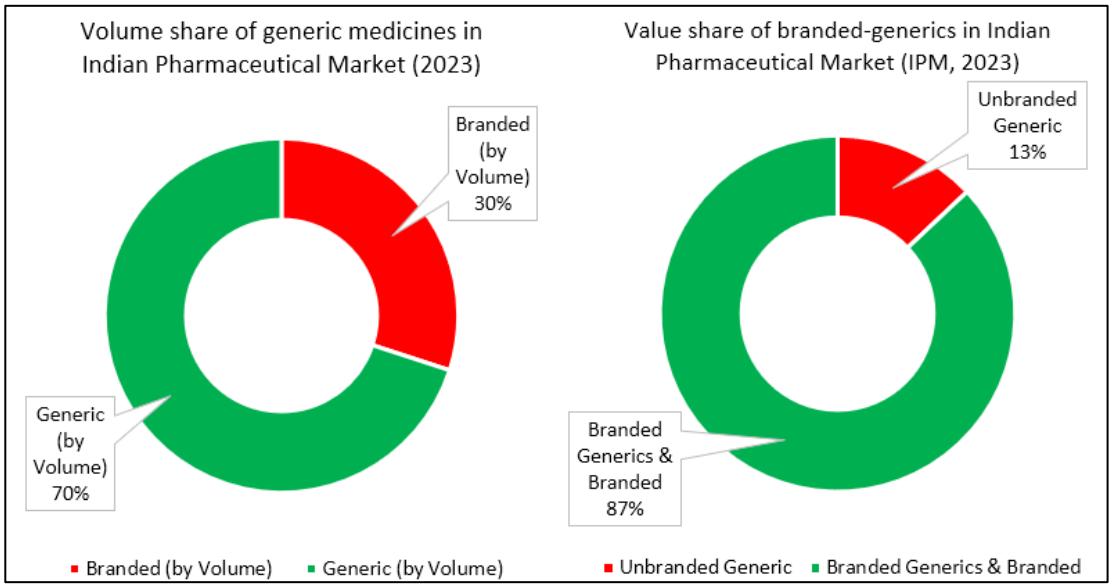
Both datasets independently supported a four-factor solution. Pharmacist factors: (F1) Trust in Generic Medicines and the Quality-Assurance System (α = 0.937, 10 items); (F2) Market and Demand-Side Resistance (α = 0.901, 6 items); (F3) Direct Clinical Confidence in Generic Pharmacology (α = 0.881, 3 items); (F4) Operational and Logistical Barriers (α = 0.839, 4 items). Public data showed a parallel four-factor structure with α values of 0.801, 0.782 for the two primary factors. The four- factor solution explained 74.80 per cent of variance in the pharmacist data and 51.89 per cent in the public data.

In this paper, Exploratory Factor Analysis (EFA) is utilized to analyze sixteen identified barriers to generic medicine usage, reducing them to four core latent constructs across both supply- and demand- side data. Methodologically, the paper argues for the routine integration of EFA in health-policy survey analysis, particularly when dealing with extensive barrier lists that lack dimensionality reduction. Finally, a Generic Medicine Uptake Index (GMUI) is empirically constructed and computed on a 0–100 scale as GMUI = 0.301·B_Doctors + 0.271·B_Pharmacists + 0.054·B_Public + 0.374·B_JAK, where block weights are derived from model-fit R2 values. These four latent factors ultimately serve as the pillars for policy formulation in a companion paper.

Keyword: Exploratory Factor Analysis, Generic medicines, Branded generics, Generic Medicine Uptake Index (GMUI), Composite index, Multi-stakeholder survey, India, Telangana

1. Introduction

India is the world's largest supplier of generic medicines by volume, providing about twenty per cent of global generic exports (IBEF, 2023). Yet domestic uptake of price-competitive unbranded generics is low. Generic medicines make up about seventy percent of the Indian pharmaceutical market by volume (IBEF, 2024). But the sales by value of branded generics which is pharmacologically identical to unbranded generics is about 87% of the Indian Pharmaceutical Market in 2023 (IQVIA via The Grey Swan, 2024). The branded generics are sold at premium. Generics are available to patients through five modes of distribution: branded generics in retail pharmacies, salt-name unbranded generics, state-corporation public hospital supplies, the Pradhan Mantri Bhartiya Janaushadhi Pariyojana (PMBJP, with 16,955 Kendras by October 2025; VSK Telangana, 2025), and online platforms. Figure 1 shows the paradox



Source: Author's compilation from IBEF (2024) and The Grey Swan / IQVIA industry analysis (2024).

Fig 1: The Generic Paradox in the Indian Pharmaceutical Market

A substantial literature has examined barriers to generic uptake in India and comparable low- and middle-income contexts, identifying physician quality scepticism (Roy *et al*., 2012; Mohanty & Tripathy, 2017) [19, 17], pharmacist commission concerns (Kotwani *et al*., 2017) [16], patient stigma and brand loyalty (Babar & Awaisu, 2008) [2], supply-chain unreliability (CAG, 2019), regulatory fragmentation (Thakur *et al*., 2020) [23], packaging deficits (Bate *et al*., 2011), and the absence of point-of-care quality verification (WHO, 2017). Earlier researchers have enumerated fifteen to twenty distinct barriers. The cumulative effect is scattered interventions with little evidence about which lever moves the outcome. Traditional barrier-identification literature frequently emphasizes item-level frequencies, rank-orders, or bivariate correlations rather than formal dimensionality reduction. However, exploring whether these distinct barriers reflect broader latent constructs offers a more strategic approach; addressing an underlying disposition can resolve multiple related items at once, making intervention design highly efficient. Incorporating latent-variable analysis helps researchers distinguish core causal mechanisms from co-occurring correlates. Consequently, Exploratory Factor Analysis (EFA; Spearman, 1904; Cattell, 1966; Costello & Osborne, 2005) [20, 5, 7] offers a natural solution to address this analytical gap.

This paper makes three contributions. Empirically, EFA is applied on survey data of 78 pharmacists and 581 members of the general public in Telangana. EFA provides 16 barriers of usage and they reduce to four latent four factors in both supply- and demand-side data. Finally, Generic Medicine Uptake Index (GMUI) equation is developed with four major factors. The GMUI combines the regression-validated determinants of uptake across the four stakeholder blocks into a single 0–100 scale.

Further, Section 2 presents the conceptual framework for EFA in barrier research, Section 3 describes instruments, sampling, and analytical procedures, Section 4 presents EFA results, Section 5 interprets the four core factors, sketches the four-pillar policy direction, and develops the GMUI. Sections 6, 7, and 8 present limitations, cross-domain applicability, and conclusion in this paper.

2. Conceptual Framework

2.1 Factor analysis for barrier reduction

Survey research on generic medicine barriers often generates an overwhelming number of variables. The main analytical challenge is not that these individual survey items lack value, but that they frequently overlap. For instance, if a respondent expresses doubts about generic quality, effectiveness, and safety across three separate questions, they are likely not experiencing three distinct problems. Instead, these responses reflect a single, underlying attitude that influences all three items. Factor analysis formalizes this concept mathematically by defining each observed response (X) as a function of underlying factors (F), factor loadings (Λ), and unique error (ε): $X = \Lambda F + \varepsilon$

Through this model, Exploratory Factor Analysis (EFA) estimates the strengths of these connections and determines how many core factors are needed to explain the data's overall correlations. For policymakers, this provides a major practical benefit: a long, confusing list of barriers is condensed into a few clear, targeted areas for intervention.

2.2 Why EFA rather than adjacent techniques

Different statistical techniques have different purposes than Exploratory Factor Analysis (EFA):

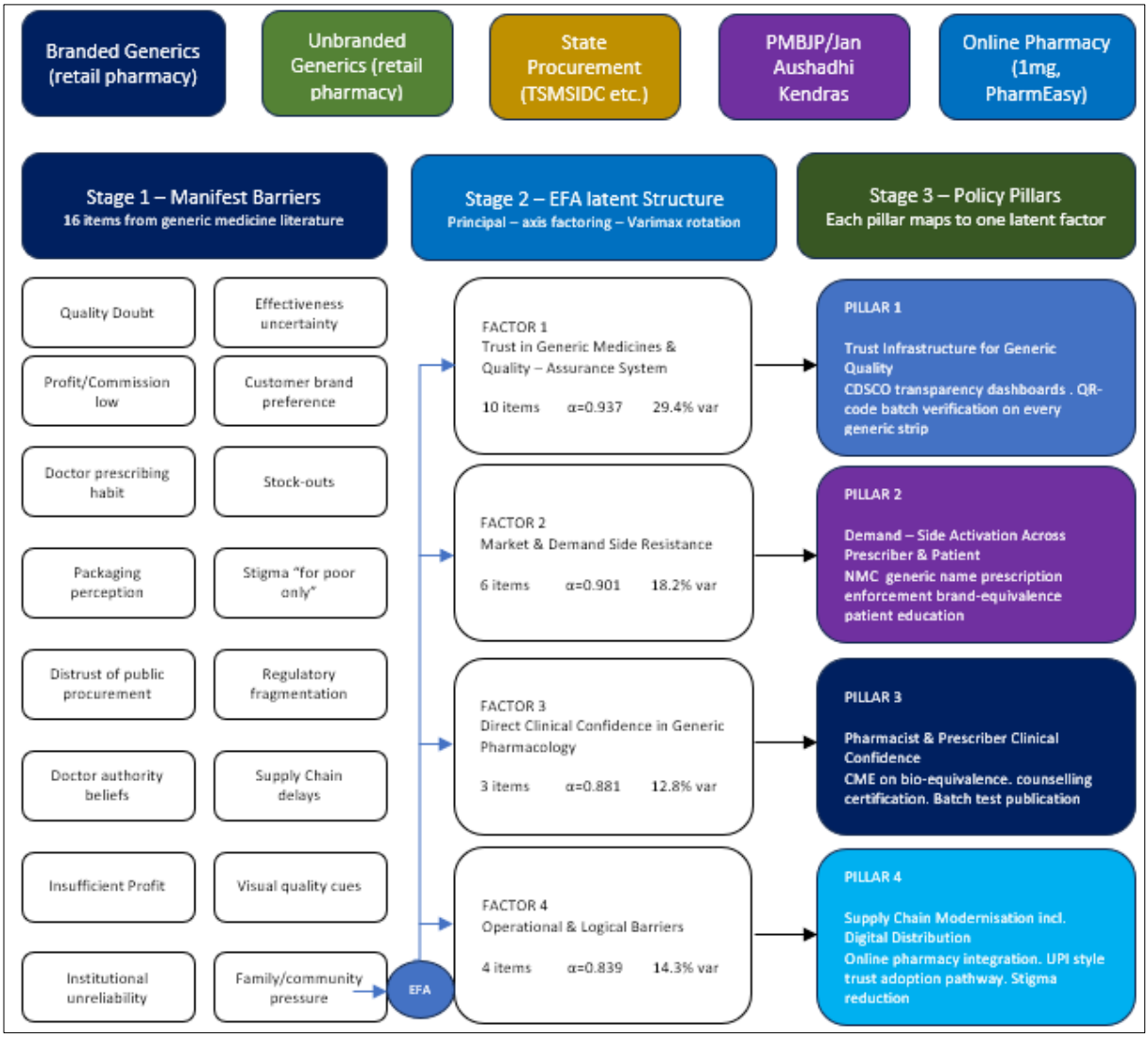
- **Principal Component Analysis (PCA)** simply reduces data by combining variables to explain maximum variance; it does not look for hidden, underlying themes (latent constructs).
- **Confirmatory Factor Analysis (CFA)** is used to test an already planned or expected structure against new data. It belongs *after* exploratory work, not before.
- **Multiple Factor Analysis (MFA, Escofier-Pagès)** is just a specialized version of PCA meant for data that is already organized into specific groups.
- **Multiple Linear Regression** needs a specific outcome variable to find out what predicts a certain result (Y), rather than finding the overall patterns that group the survey items together.

EFA is the right choice when you want to uncover the hidden structure behind correlated survey questions without using a preconceived hypothesis. While psychologists traditionally

use EFA to build personality or behavioral scales, this paper adapts it for a slightly different purpose: condensing a long list of barriers to help design better policies. The standard data tests and quality checks (Kaiser-Meyer-Olkin adequacy, Bartlett's test, Kaiser-Guttman eigenvalue criterion, scree-plot inspection, and Cronbach's alpha) are detailed in Section 4.

2.3 The conceptual framework

Figure 2 illustrates the conceptual framework this research. The framework has three stages. In Stage 1, long list of qualified barriers is identified and then, EFA converges the long list of barriers into four core structural factors. In Stage 3, Generic Medicine Uptake Index (GMUI) equation is developed with four major factors.



Source: Author's analysis of pharmacist (N=78, 23 items) and public (N=494, 18 items) Survey data from Telangana, India, Cronbach's α values from Pharmacist EFA

Fig 2: Conceptual Framework — From Sixteen Manifest Barriers to Four Latent Factors to Four Policy Pillars. EFA-based reduction across the five-channel Indian generic medicine ecosystem Generic Medicine Reaches Indian Patients Through Five Channels

3. Methods

3.1 Study setting and population

Telangana state is chosen for the study, as the Telangana state is hub of pharmaceuticals manufacturing in the country and there is set ecosystem mirroring the country, where there exists many Jan Aushadhi Kendras across the state, India's second-largest organised pharmacy chain (MedPlus) headquartered in Hyderabad; TSMSIDC public procurement; and active online pharmacy platforms. Four stakeholder groups were surveyed: doctors, pharmacists, general public, and JAK operators.

3.2 Survey instruments

This paper focuses on the pharmacist and public surveys, which contained sufficient Likert-scale items for EFA. The questionnaire of the survey among the Public (Consumers), the Doctors (Prescribers), the Pharmacists and PMBJP outlets (Dispensers) is aimed to capture the barriers for usage of Generics, selling generics, clinical confidence in generic quality, trust in regulatory and procurement institutions and ethical motivation for promoting generics. The public survey tried to measure social stigma, quality concerns, doctor-authority beliefs, and trust in quality assurance.

3.3 Sampling and data collection

Pharmacists (N = 78) were drawn from urban, semi-urban, and rural retail-pharmacy locations in Telangana. General public respondents (N = 581) were drawn from Hyderabad and surrounding districts using stratified convenience sampling. Data were collected through structured face-to-face administration and online forms. Response completeness was high: 100 per cent (pharmacist) and 99.1

per cent (public). Complete-case analyses used 78 pharmacists and 494 public respondents.

3.4 Analytical procedure

Analysis proceeded in five steps. First, Likert items were coded numerically (Strongly Disagree = 1 through Strongly Agree = 5) and standardised. Second, the suitability of the data for factor analysis was assessed with the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity. Third, the number of factors to retain was determined by the Kaiser-Guttman criterion (eigenvalues > 1) supplemented by scree-plot inspection. Fourth, extraction used principal-axis factoring with varimax orthogonal rotation; items were assigned to factors on their highest absolute rotated loading, |loading| ≥ 0.40. Fifth, internal consistency was assessed with Cronbach's α; items loading negatively were reverse-coded prior to computation. Analyses were performed in Python 3.12 using numpy (NumPy: Handles large grids of numbers (like the matrix of survey responses), scipy (SciPy: Contains advanced tools for scientific computing used here to handle the linear algebra and matrix math required for Factor Analysis.), and a varimax (Varimax is a statistical method used to "rotate" the factors in Factor Analysis. Its goal is to clean up the results so that each survey question loads heavily onto *only one* factor, making the final data much easier to interpret.) implementation following Kaiser (1958).

4. Results

4.1 Sampling adequacy and factorability

Both datasets passed all conventional factorability tests (Table 1). Pharmacist data: KMO = 0.817 (meritorious, Kaiser-Hutcheson); minimum per-item KMO = 0.596 (Q23), above the 0.50 threshold; Bartlett $\chi^2 = 1683.45$ (df = 253, $p < 0.001$), strongly rejecting the identity-matrix null. Public data: KMO = 0.867; Bartlett $\chi^2 = 2398.31$ (df = 153, $p < 0.001$). The pharmacist sample-to-variable ratio of 3.39:1 is below the conventional 5:1 minimum and a note is presented in Section 6 regarding the study limitations.

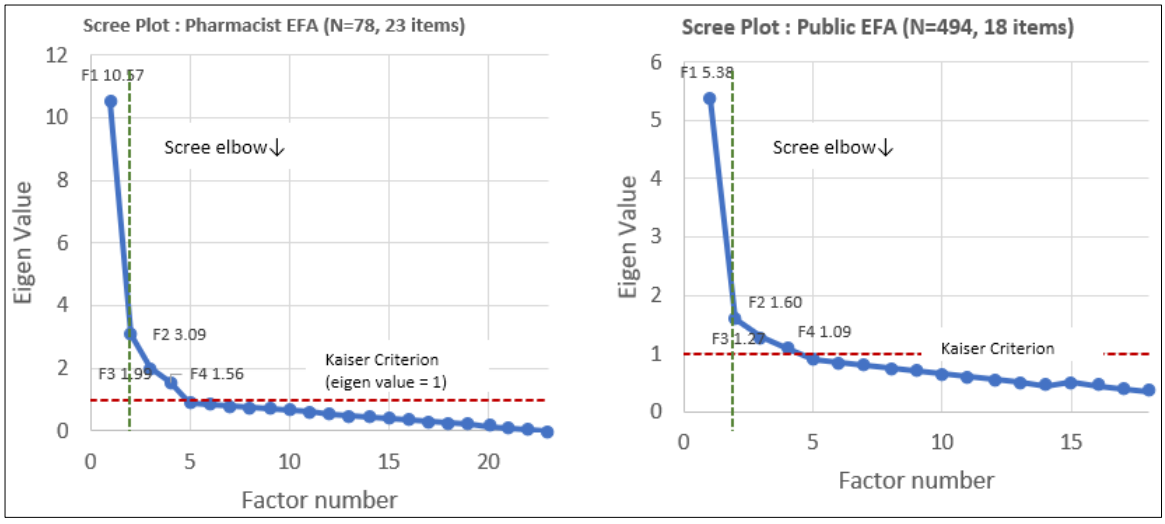
Table 1: Sampling adequacy and factorability diagnostics

Diagnostic	Pharmacists (N=78)	Public (N=494)	Threshold / Verdict
Sample size (N)	78	494	≥ 5 per item (≥ 10 ideal)
Number of items (p)	23	18	—
Sample-to-variable ratio	3.39 : 1	27.44 : 1	Pharm borderline; Pub strong
KMO overall	0.817	0.867	Both meritorious (> 0.80)
KMO minimum per item	0.596	0.55+	All > 0.50 retention threshold
Bartlett's χ^2	1683.45	2398.31	Both significant
Bartlett's df	253	153	—
Bartlett's p-value	< 0.001	< 0.001	p < 0.05 required — PASS

Source: Author's analysis of pharmacist and public survey data, Telangana, India

4.2 Determining the number of factors

The Kaiser-Guttman criterion determined the number of factors to retain. In the pharmacist data, the first four eigenvalues exceeded 1.0 (10.57, 3.09, 1.99, 1.56), while the fifth was 0.82. The same pattern emerged in the public data: first four eigenvalues 5.38, 1.60, 1.27, 1.09, with the fifth at 0.96. The scree plots (Figure 3) showed clear elbows at the fourth factor in both datasets. The four-factor solution explained 74.80 per cent of variance in the pharmacist data and 51.89 per cent in the public data.



Source: Author's analysis. The horizontal dashed line at eigenvalue = 1 indicates the Kaiser-Guttman retention criterion; the vertical dotted line marks the scree elbow.

Fig 3: Scree plots for Pharmacist EFA (left, N=78) and Public EFA (right, N=494).

4.3 Rotated factor loadings — Pharmacist data

The four-factor solution was extracted using principal-axis factoring with varimax orthogonal rotation. Figure 4 displays the rotated loadings for all 23 pharmacist items across the four retained factors. Items were assigned to factors by their highest absolute loading, with |loading| ≥ 0.40 as the retention threshold and |loading| ≥ 0.60 indicating strong primary loading. Communalities for all retained items exceeded 0.55, indicating that the four-factor solution adequately explained item variance.

Source: Author's analysis. Principal-axis factoring with varimax rotation; N=78. Cells with |loading| ≥ 0.40 are highlighted (green = positive, red = negative). Total variance explained = 74.80%.

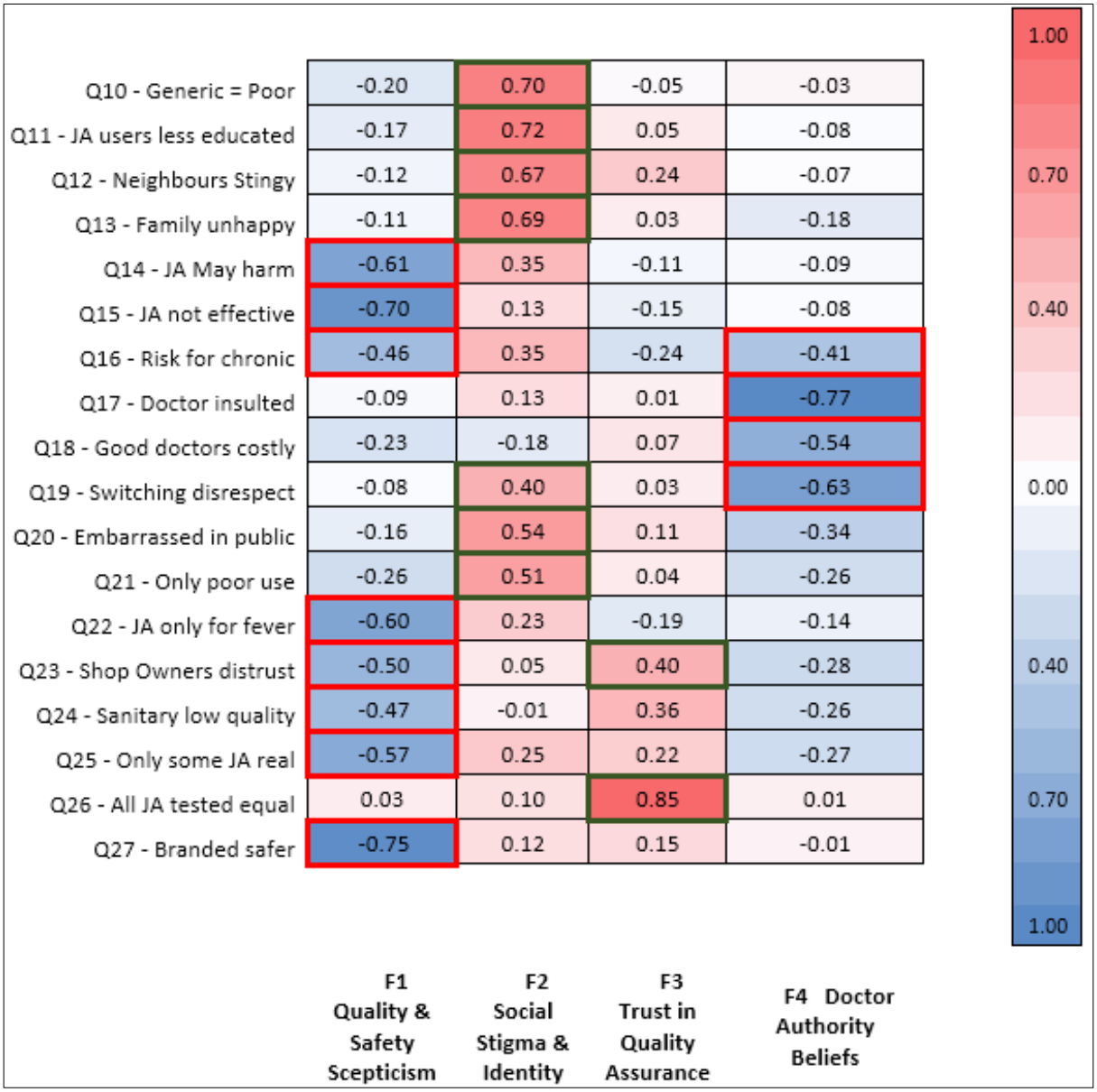
Fig 4: Rotated factor loadings matrix from the Pharmacist EFA.

4.4 Substantive interpretation of the pharmacist factors

The four pharmacist factors emerged with clear coherence and high internal consistency. Factor 1 — "Trust in Generic Medicines and the Quality-Assurance System" — comprised ten items on confidence in CDSCO regulatory strength (Q27, Q28), positive perception of the institutional ecosystem (Q29–Q31), willingness to use generics within one's own family (Q26), ethical motivation to promote generics (Q33, Q34), and reverse-coded institutional distrust (Q21); Cronbach's α = 0.937, excellent. The factor captures broad confidence in the regulatory-and-quality architecture that underwrites generics, not loyalty to any single channel. Factor 2 — "Market and Demand-Side Resistance" (α = 0.901, six items) — captured customer brand preference (Q15), branded prescribing (Q16), insufficient profit (Q22), commission concerns (Q14), perceived quality differences (Q20), and effectiveness uncertainty (Q13). Factor 3 — "Direct Clinical Confidence in Generic Pharmacology" (α = 0.881, three items) — comprised Q23–Q25 on generic quality, efficacy, and safety. Factor 4 — "Operational and Logistical Barriers" (α = 0.839, four items) — comprised stock-outs (Q17), packaging perception (Q18), "medicines for the poor" stigma (Q19), and quality doubt (Q12).

4.5 Public data factor structure

The public dataset replicated the four-factor structure (Figure 5). Factor 1 — "Quality and Safety Skepticism" (α = 0.801) — comprised eight items expressing doubt about generic quality and effectiveness. Factor 2 — "Social Stigma and Identity" (α = 0.782, six items) — measured poverty signalling, perceived lower education status, neighbour and family disapproval, and public embarrassment. Factor 3 isolated a single item (Q26: belief that all generic medicines are tested in the same laboratories) and is reported descriptively rather than as a validated scale. Factor 4 — "Doctor Authority Beliefs" (three items on physician-insult beliefs) — returned α = 0.472 and we flag as exploratory.



Source: Author's analysis. Principal-axis factoring with varimax rotation; N=494 complete cases. Total variance explained = 51.89%.

Fig 5: Rotated factor loadings matrix from the Public EFA

4.6 Internal consistency across both datasets

Cronbach's α values are summarised across all eight retained factors. All four pharmacist factors exceeded the 0.70 threshold, three exceeded 0.80, and one (F1) was classified as excellent (> 0.90). The two primary public factors (F1, F2) exceeded the 0.70 threshold. Convergence of acceptable-to-excellent internal consistency across primary factors in both datasets supports the interpretation of the recovered structure as capturing genuine latent constructs.

5. Discussion

5.1 From sixteen barriers to four latent factors

The main empirical finding is that the many reported barriers to generic medicine uptake reduce, under EFA, to four latent dimensions. This is a claim about the structure of pharmacist and public attitudes: the reported barriers are correlated in ways that imply fewer underlying constructs. The pharmacist factor structure is especially clear — four factors capture 74.80 per cent of variance in 23 attitude items, with Cronbach's α from 0.84 to 0.94. The public data show a parallel four-factor structure with weaker but consistent fit (52 per cent variance, α from 0.47 to 0.80). Recovering the same four-factor solution in two independently analysed datasets, using overlapping but distinct items, gives us more confidence that the structure reflects a real feature of the attitudes behind generic medicine uptake.

5.2 From four latent factors to four-pillar policy direction

Each of the four recovered latent factors maps onto a corresponding direction of policy intervention. Detailed development — comparative international evidence, the insurance lever, sequential lever activation, implementation pathways — is reserved for the companion policy paper. Here the four pillars are named briefly to show how the factor structure translates into intervention design.

Pillar 1 — Trust infrastructure for generic medicine quality — addresses Factor 1 (Trust in Generic Medicines and the Quality-Assurance System; α = 0.937, 10 items), the strongest pharmacist factor. The policy direction is to extend the institutions that make the equivalence claim credible: regulatory transparency, public batch-test publication, and quality certification visible to consumers. Pillar 2 — Demand-side activation across prescriber and patient — addresses Factor 2 (Market and Demand-Side Resistance; α

= 0.901, 6 items), operating on enforcement of prescribing rules, patient education, and brand-equivalence labelling. Pillar 3 — Pharmacist and prescriber clinical confidence — addresses Factor 3 (Direct Clinical Confidence in Generic Pharmacology; α = 0.881, 3 items), building confidence through continuing education on bioequivalence, dashboards for pharmacists, and substitution-counselling certification. Pillar 4 — Supply chain modernisation and digital distribution — addresses Factor 4 (Operational and Logistical Barriers; α = 0.839, 4 items), combining physical supply discipline (stock-out elimination, packaging standardisation) with online-pharmacy integration.

The four pillars together operate across the multiple channels through which generic medicines reach Indian patients — branded generics, unbranded generics, state procurement, PMBJP, and online pharmacy. Their detailed development is the subject of the companion policy paper, for which the four-factor structure recovered here provides the empirical foundation.

5.3 The Generic Medicine Uptake Index (GMUI): operationalising the empirical findings

A policy framework that cannot be measured cannot be administered. To turn the empirical findings into a practical tool, we propose the Generic Medicine Uptake Index (GMUI). The GMUI combines the significant predictors of uptake from four block-level regressions (doctors, pharmacists, public, and JAK operators) into a single 0–100 scale. It follows the tradition of composite indices such as the Human Development Index and the Multidimensional Poverty Index. The GMUI is not a factor-analytic latent construct. It is an explicit weighted sum of regression-validated determinants, designed for periodic measurement, inter-state comparison, and intervention evaluation.

Construction of the GMUI

Construction follows four steps. First, for each stakeholder block, a multiple linear regression was estimated with the block-specific outcome as dependent variable and theoretically motivated predictors from the questionnaire. Second, only predictors achieving significance at α = 0.05 were retained. Third, each retained predictor was normalised to a 0–100 scale so blocks can be combined. Fourth, each block contributes to the composite weighted by its adjusted R^2, so that better-fitting models carry proportionately greater weight.

Formally, the GMUI is defined as:3

$$GMUI = \sum_{k=1}^{K} w_k B_k$$

Where

$$w_k = \frac{\text{Adj. } R_k^2}{\sum_{j=1}^{K} \text{Adj. } R_j^2}$$

$$GMUI = \sum_{k=1}^{K} \left(\frac{\text{Adj. } R_k^2}{\sum_{j=1}^{K} \text{Adj. } R_j^2} \right) B_k$$

where k indexes the four stakeholder blocks, w_k is the model-fit weight of block k normalised across all four blocks, and B_k is the block-level composite computed as the weighted sum of the standardised significant predictors in that block, with signs respecting the direction of the regression coefficient. Each B_k is itself normalised to the 0–100 scale so that the overall GMUI ranges from 0 (critical friction across all stakeholder blocks) to 100 (healthy uptake equilibrium).

Table 2: Block-level weights and significant predictors used in GMUI construction

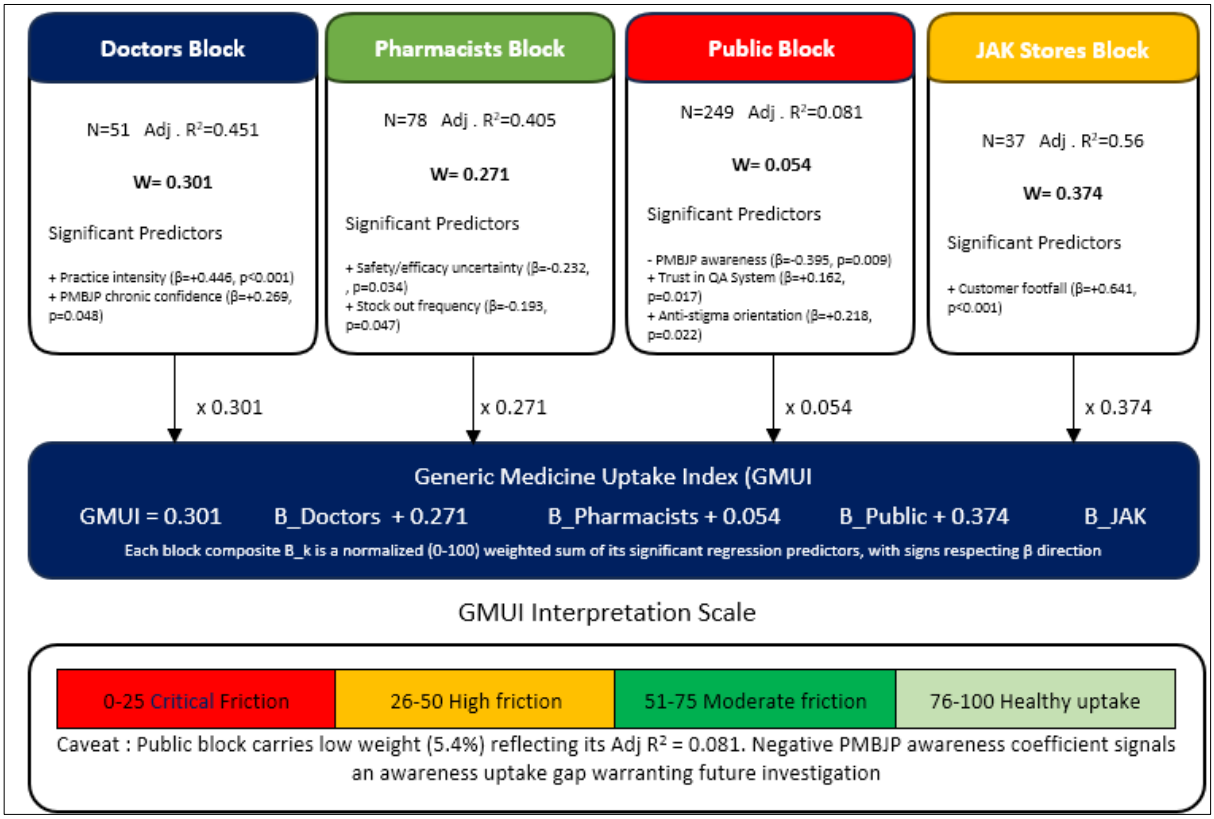
Stakeholder Block	Sample (n)	Adj. R^2	Model-fit weight w_k	Significant predictors
Doctors	51	0.451	0.301	Practice intensity (+); PMBJP chronic confidence (+)
Pharmacists	78	0.405	0.271	Safety/efficacy uncertainty (−); Stock-out frequency (−)
Public	249	0.081	0.054	PMBJP awareness (−)†; Trust in QA (+); Anti-stigma (+)
JAK Stores	37	0.560	0.374	Customer footfall (+, β* = 0.641)
TOTAL	415	Σ adj. R^2 = 1.497	Σ w_k = 1.000	—

Source: Author's regression analyses on the four-stakeholder primary survey (Telangana, India). Signs in parentheses indicate the direction of the standardised β coefficient. † See methodological notes for discussion of the negative PMBJP-awareness coefficient.

Substituting the model-fit weights into the general form gives the operational equation for the Telangana baseline GMUI:

$$GMUI = 0.301B_{\text{Doctors}} + 0.271B_{\text{Pharmacists}} + 0.054B_{\text{Public}} + 0.374B_{\text{JAK}}$$

Figure 6 displays the GMUI architecture visually, showing how significant predictors at each stakeholder block flow through model-fit weights into the composite index, together with the four-band interpretation scale (0–25 critical friction; 26–50 high friction; 51–75 moderate friction; 76–100 healthy uptake).



Source: Author's construction from the four-stakeholder regression results. Weights are normalised model-fit weights computed as w_k = adj. R^2_k / Σ adj. R^2_j across the four blocks.

Fig 6: Generic Medicine Uptake Index (GMUI) — Architecture and Weights

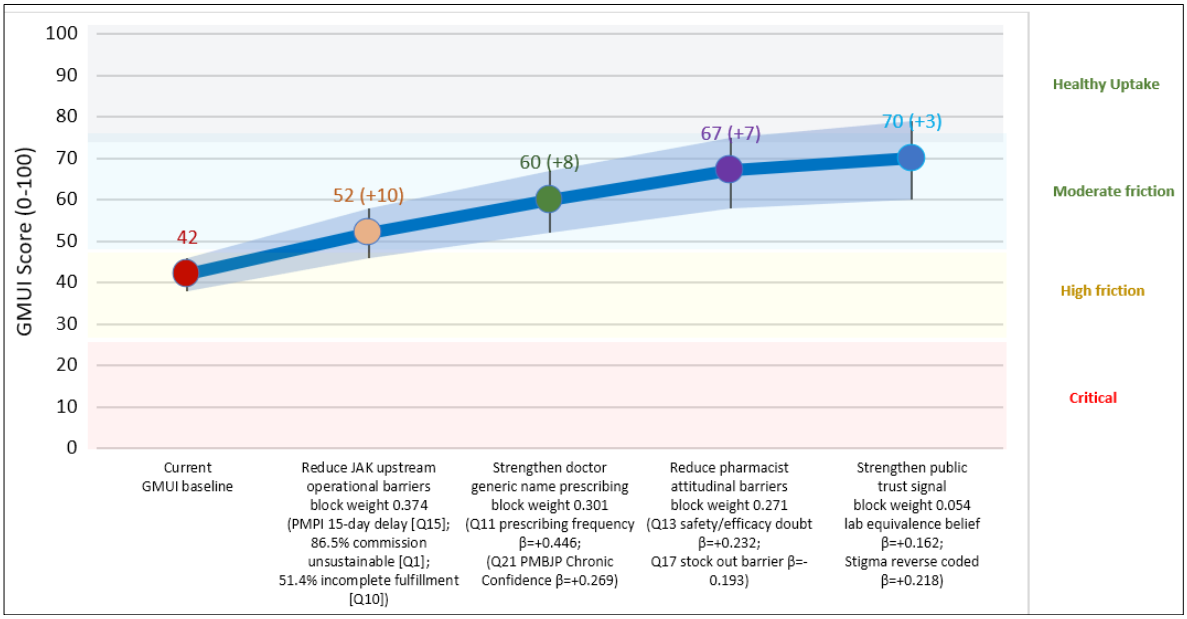
Methodological notes

Three methodological notes accompany the GMUI. First, the Public block carries a model-fit weight of just 5.4 per cent reflecting its low adjusted R^2 (0.081); it is retained for representational coverage of the demand-side voice, though its construct strength is statistically modest. Second, the negative coefficient on PMBJP awareness in the public regression ($\beta = -0.395$, $p = 0.009$) is counter-intuitive; the likeliest explanation is a selection effect — respondents aware of PMBJP are disproportionately drawn from groups exposed to negative information about generic quality — rather than a causal claim that awareness reduces uptake. The sign is preserved in the composite to maintain fidelity to the data and flagged as a target for purpose-designed future investigation. Third, the GMUI aggregates statistically significant determinants identified within the survey instruments used; it is not a measure of every plausible institutional factor influencing generic uptake.

Interpretive implications of the block structure

The GMUI block structure, read alongside the underlying regressions, points to a further finding. In the Public block, two positive predictors emerge: belief in laboratory-testing equivalence (Q26, $\beta = +0.162$, $p = 0.017$) and reverse-coded stigma orientation (composite of Q10, Q20, Q21, $\beta = +0.218$, $p = 0.022$). Read against the descriptive baseline in the companion paper — 84 per cent of surveyed physicians prescribe generic names frequently or always (Doctor Q11) — the pattern suggests something clear. The Indian population is willing to accept generics when given quality-assurance signals in stigma-free settings. The main within-block drivers of outcomes lie in operational and institutional dimensions, not in consumer resistance. In the Doctor block, the strongest predictor is generic-name prescribing frequency (Q11, $\beta = +0.446$, $p < 0.001$), supported by PMBJP chronic-disease confidence (Q21, $\beta = +0.269$, $p = 0.048$). In the Pharmacist block, both significant predictors are negative: safety/efficacy doubt as a selling barrier (Q13, $\beta = -0.232$, $p = 0.034$) and stock-out frequency (Q17, $\beta = -0.193$, $p = 0.047$). In the JAK block, the policy-relevant findings lie upstream in the descriptive items: a 15-day average PMBI supply delay (Q15), 86.5 per cent of operators reporting commissions unsustainable (Q18), 51.4 per cent reporting incomplete prescription fulfilment (Q10), and 62.2 per cent reporting the current model long-term unviable (Q23). Across all four blocks, the pattern of significant predictors and upstream operational findings points to operational and institutional barriers — not consumer unwillingness — as the main drivers of observed uptake.

The directional policy implication is conservative but clear. The JAK block (weight 0.374) responds to interventions reducing PMBI supply delays and restoring commission viability. The Doctor block (weight 0.301) responds to strengthening generic-name prescribing enforcement — anchored in the strongest coefficient in the doctor regression (Q11, $\beta = +0.446$). The Pharmacist block (weight 0.271) responds to coordinated PMBI supply discipline reducing stock-out reluctance (Q17) and visible quality-assurance signalling reducing safety/efficacy doubt (Q13). The Public block (weight 0.054) responds to quality-assurance signals reinforcing the positive coefficients on Q26 and reverse-coded stigma. Two upstream interventions — PMBI supply-chain modernisation and NMC generic-name prescribing enforcement — together address the JAK and Doctor blocks (67.5 per cent of composite weight). Figure 7 sketches an illustrative counterfactual trajectory under sequential barrier reduction.



Source: Author's analysis. Each step references the specific questionnaire items it acts upon (item numbers in brackets); sequencing follows GMUI block weights (largest leverage first). For the JAK block, the step is anchored in the descriptive upstream barriers documented by the JAK questionnaire (Q10, Q15, Q18, Q23) rather than on the customer-count regression coefficient. Numerical estimates are illustrative and directional, not forecasts.

Fig 7: Counterfactual GMUI trajectory under sequential reduction of barriers identified by the four-stakeholder regression analysis.

5.4 Methodological reflection on EFA for barrier reduction in policy research

The analytical approach demonstrated here — applying EFA to barrier inventories to recover latent factor structure, and then constructing a regression-based composite index that converts the recovered structure into a measurable instrument — has, to our knowledge, not been systematically applied to generic medicine policy research in India. The literature has documented many individual barriers and tested their bivariate associations, but has rarely investigated the dimensional structure underlying them, and has not previously constructed a composite uptake index of the type developed here. The methodological contribution is twofold. First, the many barriers in a complex multi-stakeholder ecosystem is reducible to a parsimonious four-factor structure convergently recovered in both supply- and demand-side data. Second, the recovered structure, combined with stakeholder-block regression, can be turned into a measurable tool into a composite instrument with explicit model-fit weighting — moving the analysis from descriptive barrier identification to measurement usable for administration. The same pathway should apply to other survey-based health-policy contexts where barrier inventories have multiplied without dimensional analysis; Section 7 develops this point.

6. Limitations

The researcher notes seven limitations. First, the pharmacist sample-to-variable ratio of 3.39:1 is below the conventional 5:1 minimum (Hair *et al*., 2019) [9]. The meritorious KMO (0.817) partly offsets this, but the solution should be treated as exploratory pending replication. Second, Factor 4 in the public data returned α = 0.472, below the 0.70 threshold. We flag it as exploratory; it needs additional items or a more heterogeneous sample. Single-item Factor 3 is similarly underspecified and reported descriptively. Third, the analysis is cross-sectional, so we cannot infer how attitudes change over time. Fourth, the survey was conducted in Telangana only. The factor structure may not generalise to other Indian states. Fifth, we rely on self-reported attitudes, which may not match actual behaviour. Sixth, the GMUI aggregates regression-validated determinants from the present instrument. It is not a complete measure of every institutional factor. Seventh, the instruments captured attitudes within the existing institutional architecture, not perspectives on the architecture itself. Institutional levers known to influence uptake elsewhere — pharmacy substitution authority, insurance formulary defaults, prescriber-marketing restraint — are addressed in the companion policy paper.

7. Conclusion

This paper applied EFA to survey data from pharmacists and the general public in Telangana, India. We asked whether the many barriers to generic medicine uptake reported in the literature reflect a smaller number of latent constructs. Three principal findings emerge. First, the many reported barriers reduce statistically to four latent factors in both supply- and demand-side data: Trust in Generic Medicines and the Quality-Assurance System, Market and Demand-Side Resistance, Direct Clinical Confidence in Generic Pharmacology, and Operational and Logistical Barriers. Second, the four-factor structure shows acceptable to excellent internal consistency, with Cronbach's α from 0.78 to 0.94 for the validated scales. Third, the structure can be turned — through block-level regression with model-fit weighting — into a composite policy tool, the GMUI, computed as GMUI = 0.301·B_Doctors + 0.271·B_Pharmacists + 0.054·B_Public + 0.374·B_JAK on a 0–100 scale.

The methodological contribution is the demonstration that EFA, adapted from its classical psychometric use of scale development to the policy-research task of barrier reduction, can productively recover the latent dimensional structure of survey-derived barrier inventories, and that the recovered structure can be turned into a measurable tool as a measurable composite index. The four-pillar policy direction sketched in Section 5.2 is developed in detail in the companion policy paper.

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