🧩 Problem Statement and Approach

Problem Statement

Aadhaar biometric updates are essential for maintaining accurate identity records and enabling access to a wide range of public and private services. Despite high overall Aadhaar coverage, certain population groups—particularly adults—may face **systemic exclusion** due to biometric failures, mobility constraints, uneven service availability, or digital access barriers.

Aggregate national indicators often obscure **localized disparities** in biometric update participation. Regions with low adult participation may experience reduced access to Aadhaar-enabled services, highlighting the need for granular, data-driven analysis to identify and address potential inclusion gaps.

This project seeks to identify **geographic and temporal patterns** in Aadhaar biometric update participation that may indicate exclusion risks, with a focus on adult populations (age 17+).

Analytical Approach

The analysis leverages Aadhaar biometric update data to assess participation patterns across **states, districts, and time**. Adult biometric updates are used as a proxy indicator for inclusion, as adults are more likely to encounter barriers related to mobility, authentication quality, and service accessibility.

Key elements of the approach include:

- Cleaning and standardizing geographic identifiers to ensure accurate aggregation
- Engineering participation metrics such as total updates and adult share percentages
- Aggregating data at the district and state levels to identify spatial disparities
- Conducting monthly trend analysis to assess stability and temporal variation
- Classifying districts into risk categories based on adult participation levels to support prioritization

The approach emphasizes **district-level analysis** to uncover localized exclusion risks that may be masked in higher-level summaries. Findings are translated into actionable insights through a simple risk classification framework, enabling targeted interventions and continuous system improvement.

📂 Datasets Used

The analysis uses the **Aadhaar Biometric Update dataset** provided by the Unique Identification Authority of India (UIDAI). The dataset records daily counts of biometric updates across India, disaggregated by geographic location and age group. Multiple biometric update CSV files covering different reporting periods were consolidated for analysis.

Each record represents biometric update activity for a specific date and location.

Key Columns Used

- `date`: Date of biometric update activity
- `state`: State or Union Territory
- `district`: District of the update location
- `pincode`: Postal code of the enrolment/update center
- `bio_age_5_17`: Biometric updates for individuals aged 5–17 years (child)
- `bio_age_17_`: Biometric updates for individuals aged 17 years and above (adults)

Derived Features

- `total_updates`: Total biometric updates per record
- `adult_share_pct`: Percentage share of adult biometric updates
- child_share_pct: Percentage share of child biometric updates
- `year_month`: Monthly time period derived from the date

The analysis focuses on **adult biometric update participation (age 17+)** as a proxy indicator for inclusion, with geographic aggregation at the district and state levels and temporal aggregation at the monthly level.

🛠️ Methodology

1. Dataset Selection

The analysis utilizes the **Aadhaar Biometric Update dataset** provided by UIDAI. The dataset contains daily records of biometric update counts disaggregated by geography and age groups. Adult biometric updates (age 17+) are treated as a proxy indicator for inclusion, as reduced adult participation may reflect access or usability challenges.

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2. Data Cleaning and Preprocessing

Several preprocessing steps were applied prior to analysis:

- **Date Processing:**
  The date column was converted to a standard datetime format, and monthly time periods were derived for trend analysis.
- **Text Standardization:**
  State names were normalized by converting text to lowercase, trimming whitespace, and mapping known spelling variations legacy or misspelled state names to standardized values. This prevented artificial duplication during aggregation.
- **Missing and Duplicate Checks:**
  The dataset was examined for missing values and duplicate records. No missing values were observed in key analytical columns.
- **Feature Engineering:**
  A total update count was computed as the sum of adult (17+) and child (5–17) biometric updates. Adult participation percentage was derived to enable comparative analysis across regions and time periods.

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3. Aggregation and Analysis

- **Geographic Aggregation:**
  Data was aggregated at the district and state levels to assess spatial disparities. District-level analysis was emphasized to uncover localized exclusion risks that may not be visible in state or national summaries.
- **Temporal Aggregation:**
  Monthly aggregation was applied to reduce daily volatility and reveal underlying participation trends over time.
- **Benchmarking:**
  A national average adult participation rate was calculated and used as a reference point to identify below-average regions.

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4. Risk Classification

To translate analytical results into actionable insights, districts were classified into three risk categories based on adult biometric update participation:

- **High Risk:** Adult participation below 30%
- **Medium Risk:** Adult participation between 30% and 50%
- **Low Risk:** Adult participation above 50%

This framework supports prioritization of regions that may require targeted outreach or alternative service delivery mechanisms.

📊 Data Analysis and Visualisation

Overview

The data analysis aims to uncover **geographic and temporal patterns** in Aadhaar biometric update participation, with a specific focus on adults (age 17+). Adult biometric updates are used as a proxy indicator to identify potential access barriers, as adults are more likely to face challenges related to biometric authentication quality, mobility constraints, or service availability.

The analysis combines **state-level benchmarking, district-level distribution analysis, and time-series trend examination** to ensure both breadth and depth of insights.

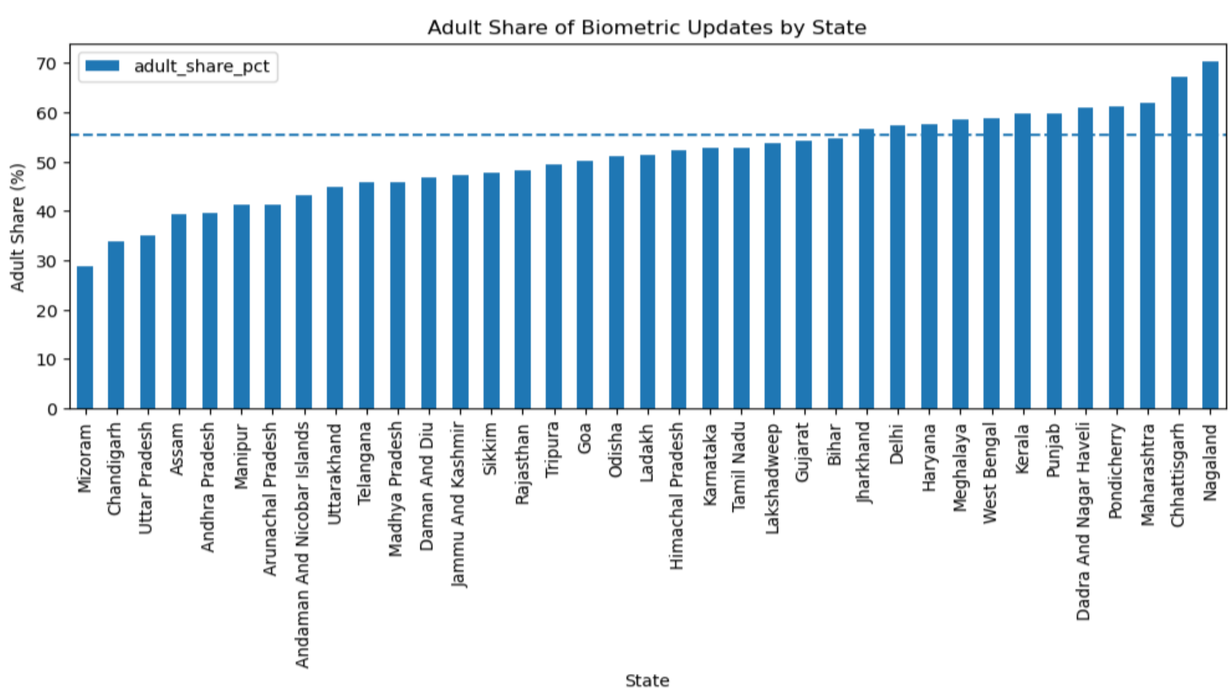
State-Level Analysis

State-wise aggregation of adult biometric update participation reveals **substantial inter-state variation**. Several states consistently fall below the national average adult participation rate, indicating uneven access to biometric update services across regions.

While some states demonstrate strong adult engagement, others exhibit persistently lower participation, suggesting differences in infrastructure availability, outreach effectiveness, or demographic and geographic constraints. Importantly, state-level averages alone are insufficient to identify exclusion risks, as they can mask significant disparities within states.

61]:
```
state_df.sort_values('adult_share_pct').plot(
    x='state', y='adult_share_pct',
    kind='bar', figsize=(12,4)
)

plt.axhline(national_adult_avg, linestyle='--')
plt.title("Adult Share of Biometric Updates by State")
plt.ylabel("Adult Share (%)")
plt.xlabel("State")
plt.show()
```



- State-wise bar chart of adult participation percentage, benchmarked against the national average.

District-Level Distribution Analysis

District-level analysis exposes **greater heterogeneity than state-level summaries**. The distribution of adult participation across districts spans a wide range, from near-zero values to almost complete adult dominance.

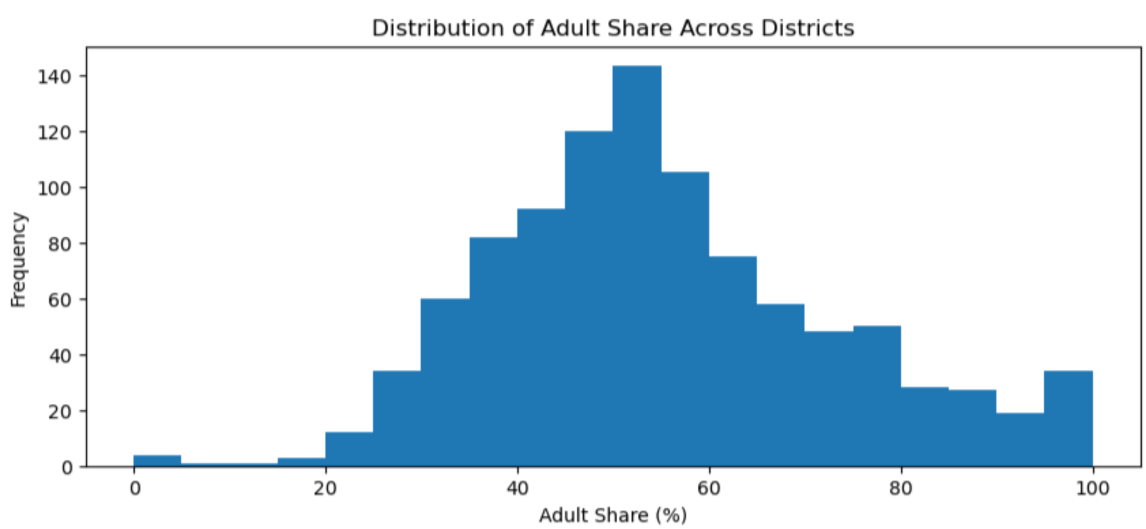
Most districts cluster within a moderate participation range, but a notable subset exhibits very low adult participation. These districts represent potential **high-risk zones for exclusion**, where adults may face disproportionate challenges in accessing biometric update services.

This finding underscores the importance of district-level monitoring, as reliance on higher-level averages may obscure localized service delivery gaps.

[60]:

	state	district	total_updates	adult_updates	child_updates	adult_share_pct	below_national_avg
556	Manipur	Pherzawl	2	0	2	0.000000	True
840	Uttar Pradesh	Auraiya *	1	0	1	0.000000	True
319	Jammu And Kashmir	Poonch	1	0	1	0.000000	True
985	West Bengal	South 24 pargana	1	0	1	0.000000	True
60	Arunachal Pradesh	Leparada	28	2	26	7.142857	True
64	Arunachal Pradesh	Lower Siang	367	52	315	14.168937	True
773	Tamil Nadu	Tirupathur	56	9	47	16.071429	True
10	Andhra Pradesh	Ananthapuramu	107310	18518	88792	17.256546	True
581	Mizoram	Mamit	10641	1870	8771	17.573536	True
826	Tripura	Gomati	14337	2870	11467	20.018135	True

Top 10 Lowest Adult Participation Districts



- Histogram showing the distribution of adult participation percentages across districts.
- The figure illustrates the **distribution of adult biometric update participation (age 17+) across districts**. The x-axis represents the percentage share of adult updates, while the y-axis indicates the number of districts falling within each participation range.
- The distribution is **centered around the 40–60% range**, indicating that in most districts, adult biometric updates account for roughly half of total updates. This suggests moderate overall engagement by adult populations at the district level.
- However, the distribution also shows **long tails at both extremes**. A subset of districts records **very low adult participation**, including values approaching zero, which may signal significant access barriers, mobility limitations, or service delivery gaps for adult populations in these areas. These districts represent potential high-risk zones for exclusion.
- Conversely, another group of districts exhibits **very high adult participation**, approaching or reaching 100%. Such values may reflect districts with higher adult-driven update demand, localized service campaigns, or demographic compositions skewed toward adult populations.
- The wide spread of the distribution demonstrates that **district-level variation is substantially larger than state-level variation**. This finding reinforces the importance of granular geographic analysis, as state averages can conceal localized exclusion risks that are only visible at finer spatial resolutions.
- Overall, the distribution highlights the need for **targeted, district-specific interventions** rather than uniform state-level strategies, particularly for districts at the lower end of adult participation.

Temporal Trend Analysis

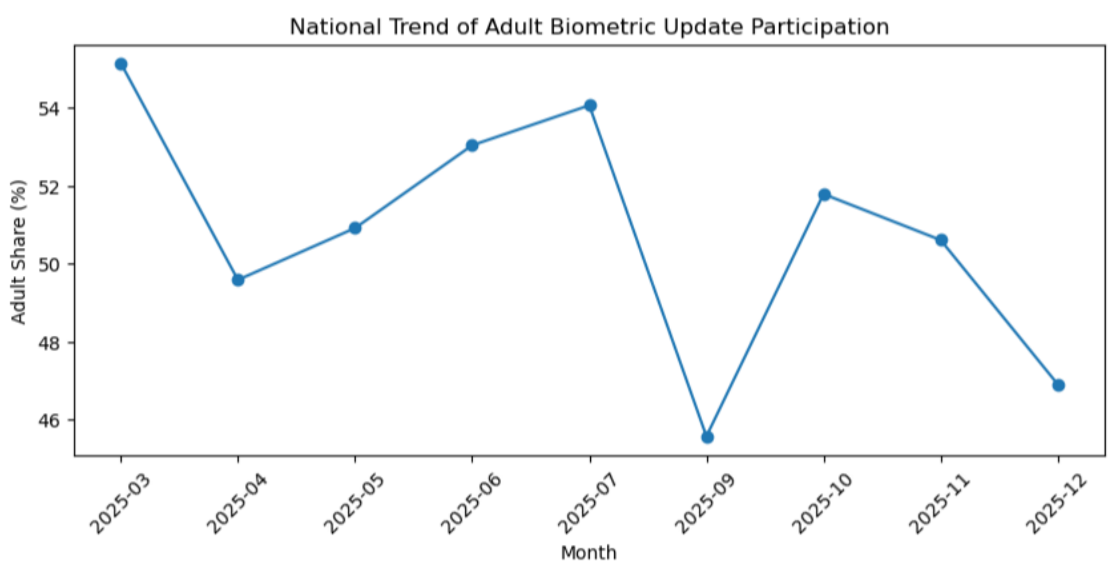
Daily data is usually noisy. So did Monthly aggregated which shows real trends.

Monthly aggregation of adult biometric update participation at the national level shows **relative stability over time**, with moderate fluctuations rather than sustained upward or downward trends. This suggests that participation patterns are influenced more by structural factors than by short-term disruptions.

A temporary peak observed during mid-2025 is followed by normalization in subsequent months. This pattern likely reflects **operational, compliance-driven, or seasonal factors**, rather than a lasting behavioral shift.

[64]:
```
monthly_df = df.groupby('year_month').agg(
    total_updates=('total_updates', 'sum'),
    adult_updates=('bio_age_17_', 'sum'),
    child_updates=('bio_age_5_17', 'sum')
).reset_index()

monthly_df['adult_share_pct'] = (
    monthly_df['adult_updates'] / monthly_df['total_updates']
) * 100
```



- National monthly time-series line chart of adult participation

- The figure presents the **monthly national trend in adult biometric update participation (age 17+)** over the observed period. The x-axis represents time in months, while the y-axis shows the adult share as a percentage of total biometric updates.
- Overall, adult participation remains **relatively stable**, fluctuating within a moderate range rather than exhibiting sustained upward or downward trends. This stability suggests that adult biometric update behavior is influenced more by **structural factors**, such as service availability and routine update requirements, than by short-term disruptions.
- A noticeable **dip is observed around September 2025**, followed by a recovery in subsequent months. This temporary decline may reflect operational factors such as reduced service availability, seasonal mobility, or administrative slowdowns rather than a persistent reduction in adult engagement.
- The absence of sharp or prolonged declines indicates that, at the national level, there is no evidence of widespread systemic exclusion emerging abruptly during the period. However, the modest month-to-month variation highlights the importance of continuous monitoring to detect early signals of access constraints.
- Given the limited temporal coverage of the dataset, the observed pattern should be interpreted as **indicative rather than conclusive**. Longer time series data would enable more robust assessment of seasonality and long-term trends.

Analysis of Low-Performing States

A focused analysis of selected low-performing states reveals **distinct temporal dynamics**. Some states experience sharp short-term declines followed by rapid recovery, indicating temporary operational or reporting disruptions. Others display consistently lower participation across months, pointing to **persistent structural barriers** such as geographic dispersion, population scale, or limited service accessibility.

This differentiation highlights the need for **state-specific diagnostic approaches**, rather than uniform intervention strategies.

Month

[67]:
```
low_states = (
    state_df.sort_values('adult_share_pct')
    .head(3)['state']
    .tolist()
)

low_states
```

[67]:
```
['Mizoram', 'Chandigarh', 'Uttar Pradesh']
```

This states and ut has the lowest participation in adult biometric updates

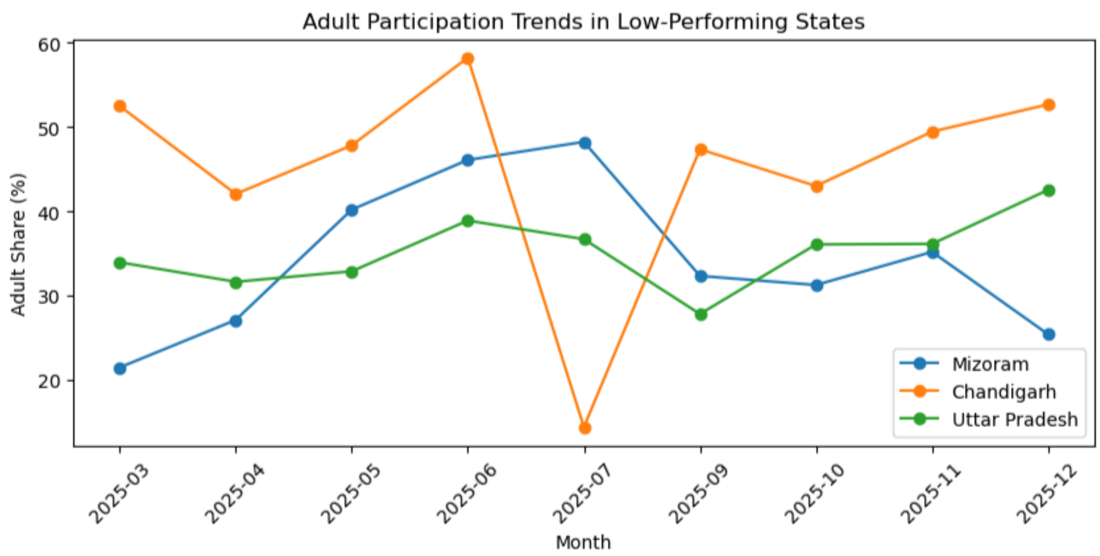
[68]:
```
state_month_df = df.groupby(
    ['state', 'year_month']
).agg(
    total_updates=('total_updates', 'sum'),
    adult_updates=('bio_age_17_', 'sum')
).reset_index()

state_month_df['adult_share_pct'] = (
    state_month_df['adult_updates'] /
    state_month_df['total_updates']
) * 100
```

[69]:
```
plt.figure(figsize=(10,4))

for st in low_states:
    subset = state_month_df[state_month_df['state'] == st]
    plt.plot(
        subset['year_month'].astype(str),
        subset['adult_share_pct'],
        marker='o',
        label=st
    )

plt.legend()
plt.xticks(rotation=45)
plt.title("Adult Participation Trends in Low-Performing States")
plt.ylabel("Adult Share (%)")
plt.xlabel("Month")
plt.show()
```



- Comparative monthly trend line charts for selected low-performing states.
- The figure illustrates **monthly trends in adult biometric update participation** for selected states identified as low-performing based on their overall adult participation levels. The comparison highlights how exclusion risks can evolve differently across regions, even within a common low-performance category.
- Mizoram exhibits **high variability** over the observed period, with adult participation increasing steadily until mid-year, followed by a decline toward the end of the period. Such volatility may indicate sensitivity to short-term operational or accessibility factors, suggesting that service availability or outreach efforts are inconsistent over time.
- Chandigarh demonstrates the **most pronounced fluctuation**, including a sharp decline in July 2025, followed by a rapid recovery in subsequent months. This pattern suggests that the dip is likely driven by **temporary reporting or operational disruptions** rather than sustained exclusion. The swift rebound indicates underlying capacity for effective service delivery once constraints are resolved.
- Uttar Pradesh shows a **comparatively stable but consistently lower trajectory**, with adult participation remaining within a narrow range. This pattern may reflect **persistent structural barriers**, such as population scale, geographic spread, or demand–supply imbalances, rather than episodic disruptions.
- The contrasting trajectories emphasize that **low adult participation does not arise from a single underlying cause**. Some regions experience short-term shocks with quick recovery, while others face sustained challenges requiring long-term, systemic interventions.
- Overall, this analysis underscores the importance of **state-specific diagnostic approaches**, combining temporal monitoring with local context, to design effective and proportionate inclusion strategies.

🔍 Key Insights

1. Geographic disparities are the dominant pattern in adult biometric update participation.
2. District-level variation is significantly greater than state-level variation, revealing localized exclusion risks.
3. Adult participation patterns are largely stable over time, indicating persistent rather than episodic barriers.
4. Low-performing regions exhibit heterogeneous dynamics, requiring differentiated responses.
5. Robust preprocessing and data standardization are essential for reliable analysis.

⚠️ Limitations

- The analysis uses biometric update counts as a proxy for exclusion and does not directly observe authentication failure events.
- The dataset lacks socio-economic, disability, and infrastructure variables that may explain observed disparities.
- Temporal coverage is limited, restricting long-term trend and seasonality analysis.
- Variations in reporting volume across regions may influence observed participation percentages despite data quality safeguards.

🛠️ Recomendations

1. **Strengthen District-Level Monitoring:**
   Institutionalize district-level indicators to detect localized exclusion risks early.
2. **Adopt Risk-Based Prioritisation:**
   Use adult participation thresholds to identify high-risk districts for targeted outreach, mobile enrolment units, or alternative service delivery.
3. **Differentiate Interventions:**
   Address short-term operational disruptions differently from persistent structural barriers.
4. **Enhance Data Integration:**
   Combine biometric update data with service access, infrastructure, and socio-economic datasets to improve causal understanding.
5. **Extend Temporal Tracking:**
   Longer time-series monitoring can support early warning systems and performance evaluation.

☑ Conclusion

This analysis demonstrates that Aadhaar biometric update data can be effectively leveraged to identify **geographic and temporal patterns of potential exclusion**. By combining state benchmarking, district-level distribution analysis, and temporal trend assessment, the study highlights localized risks that are often hidden in aggregate indicators.

The findings support a **data-driven, targeted approach** to improving inclusion, emphasizing the need for granular monitoring, differentiated interventions, and continuous system improvement. With expanded data integration and longer temporal coverage, this analytical framework can serve as a scalable tool to support inclusive Aadhaar service delivery.