# Heterogeneity in Mobility Behavior:

## Latent Classes from Long-Term Tracking Data

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# Outline

# Research Question

**How can we extract structurally distinct mobility patterns from rich long-term tracking data, and which socio-economic characteristics predict class membership?**

**The Challenge:**

- Daily mobility is noisy and variable
- Two "50 km/day travelers" can be fundamentally different
- Need to separate signal (structure) from noise

**Why It Matters**

- **Flexible users:** Respond to pricing, shift to off-peak
- **Constrained users:** Drive peaks, captive audience

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# Position in the Literature

**Mobility behavior is structured, but variable**

- Travel behavior is habitual, but not perfectly repetitive
- Multi-day patterns are difficult to compare
- Long-term data are needed to observe both regularity and variability

Examples: [Schlich and Axhausen, 2003], [Vij et al., 2013], [Walker and Li, 2007]

**Existing typologies only partially address this**

- Clustering identifies profiles, but usually fixes class membership
- Distance-based methods depend strongly on the chosen similarity measure

Examples: [Ben-Gal et al., 2019], [Tsoleridis et al., 2025]

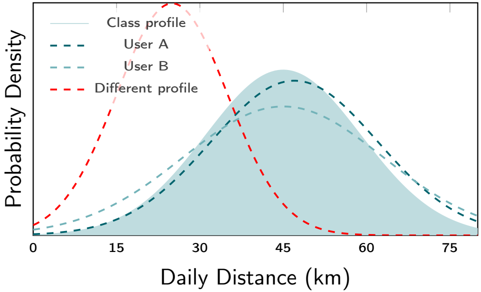
**Research gap:** A probabilistic framework is needed to identify mobility typologies while taking into account the data variability.

# The Methodological Challenge

**Tracking data contain several sources of variability that are difficult to separate.**

Observed variation may come from:

1. differences between mobility lifestyles,
2. persistent differences across individuals,
3. day-to-day fluctuations.




Same observed mobility range can mix within-class variation and overlap across classes.

# Outline

# Data: Continuous Mobility Panel

intervista

### Sample & Tracking

**2,011** respondents
**Oct–Dec 2024**
**96%** tracking completeness
Switzerland-wide CMP panel

### Who?

**50 / 50** women / men
**47 y.o.** median age
**69%** employed
**23%** with children

### Mobility Resources

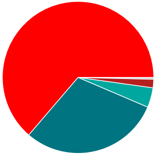
**66%** car available
**40%** Halbtax subscription
**7%** GA (annual pass)

Socio-demographic survey + Long-term daily mobility indicators from passive tracking data

# Key Mobility Metrics

intervista

## Modal Split (by distance)



- Private Vehicle (63.7%)
- Public Transport (29.9%)
- On Foot (4.2%)
- On Bicycle (1.8%)
- Other (0.4%)

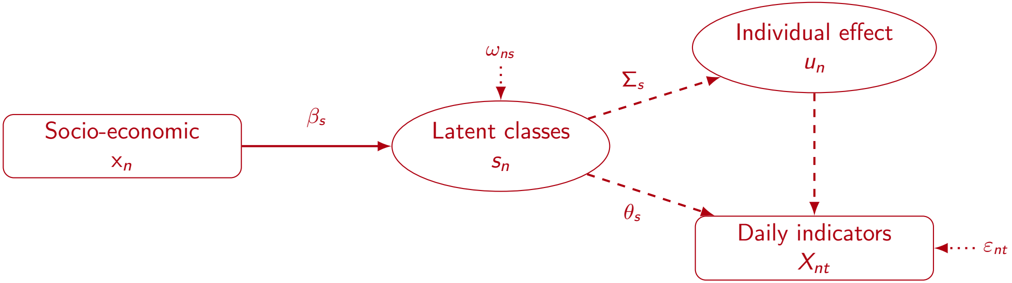
Note: Metrics computed excluding trips made outside Switzerland and by plane

## Trip & Distance Statistics

| Metric | Value |
|---|---|
| Total trips | 686,768 |
| Total legs | 1,156,045 |
| User-days | 154,279 |
| **Daily Distance** | |
| Median | 27.6 km |
| Mean | 52.1 km |
| 90th percentile | 131.2 km |
| **Trips per Day** | |
| Median | 4 |
| Mean | 4.5 |
| 90th percentile | 8 |

# Outline

# Hierarchical Model Structure




**Three sources of variation:**

1. **Between-class** ($\theta_s$): Distinct mobility lifestyles
2. **Within-class** ($u_n$): Individual deviation within the class
3. **Daily** ($\varepsilon_{nt}$): Random fluctuations

**Result:**

- Interpretable classes
- Stable individual effects
- Uncertainty quantification
- Forecasting capability

# Estimation Strategy

**Joint posterior with all three levels.**
The model is estimated by sampling from the joint posterior distribution

$$p(s_n, u_n, \pi, \theta_s, \Sigma_s \mid X) \propto \underbrace{p(X \mid s_n, u_n, \theta_s, \sigma_s)}_{\text{likelihood}} \cdot \underbrace{p(u_n \mid s_n, \Sigma_s)}_{\text{random effects}} \cdot \underbrace{p(s_n \mid \pi_n)}_{\text{class membership}} \cdot p(\pi_n, \theta_s, \Sigma_s)$$

**Why Bayesian?**

- Handles latent classes naturally
- Incorporates expert prior knowledge
- Uncertainty quantification
- Handles hierarchical structure

**Current implementation:**

- Multiple chains with informative priors
- Class-specific prior distributions
- Monitor convergence (Rhat, trace plots)
- Cross-validation for class count

# Measurement Equation

Observed indicators

- For each individual $n$ and day $t$:

$$X_{nt} = (\text{homeonly}, \text{private\_veh}, \text{active\_PT}, \text{trips}, \text{daily\_dist})$$

- Latent class $s_n$ determines the distribution of each indicator
- Conditional independence given $s_n$ and $u_n$

| **Indicator** | **Type** | **Distribution** |
|---|---|---|
| Home-only day | Binary | Bernoulli($p_k^H$) |
| Private vehicle use | Binary | Bernoulli($p_k^V$) |
| Active/PT use | Binary | Bernoulli($p_k^{PT}$) |
| Daily trip frequency | Count | Poisson($\lambda_k$) |
| Daily distance | Continuous | $\mathcal{N}(\mu_k, \sigma_k^2)$ |

# Class Membership Model

- Each individual $n$ has observed characteristics $x_n$
- These predict the probability of belonging to each latent class

$$P(s_n = s \mid x_n) = \frac{\exp(\alpha_s + \beta_s^\top x_n)}{\sum_\ell \exp(\alpha_\ell + \beta_\ell^\top x_n)}.$$

- Multinomial logit specification

| **Variable** | **Type** | **Values/Range** |
|---|---|---|
| Education | Categorical | Low, Medium, High |
| Age | Continuous | Piecewise (15-83) |
| Car availability | Binary | Yes/No |
| PT subscription | Binary | Yes/No (for now) |
| Employment | Categorical | Student, Part-time, Full-time, Unemployed, Retired |

# Outline

# Results: Step-by-Step

**Our approach: iterative model building**

1. **Step 1:** Start simple → Can we identify classes at all?
2. **Step 2:** Diagnose the problem → Why is assignment uncertain?
3. **Step 3:** Add complexity → Individual random effects (under development)
4. **Step 4:** Characterize findings → What do the classes tell us?

# Step 1: Single-Layer Model Results

| Parameter | Est. | SE | t-stat | p-value |
|---|---|---|---|---|
| Home-only$_0$ | 0.0417 | 0.0203 | 2.05 | 0.0401 |
| Home-only$_1$ | 0.111 | 0.00824 | 13.5 | $< 0.001$ |
| Home-only$_2$ | 0.00172 | 0.000757 | 2.27 | 0.0229 |
| Home-only$_3$ | 0.001 | 0.0118 | 0.0851 | 0.932 |
| Home-only$_4$ | 0.001 | 0.0112 | 0.0895 | 0.929 |
| Home-only$_5$ | 0.001 | 0.0144 | 0.0694 | 0.945 |
| Private vehicle$_0$ | 0.001 | — | — | — |
| Private vehicle$_1$ | 0.995 | 0.00204 | 488 | $< 0.001$ |
| Private vehicle$_2$ | 0.983 | 0.00422 | 233 | $< 0.001$ |
| Private vehicle$_3$ | 0.001 | 0.0118 | 0.0851 | 0.932 |
| Private vehicle$_4$ | 0.001 | 0.0112 | 0.0896 | 0.929 |
| Private vehicle$_5$ | 0.791 | 0.0104 | 76.1 | $< 0.001$ |
| Active+PT$_0$ | 0.001 | — | — | — |
| Active+PT$_1$ | 0.001 | 0.0154 | 0.0649 | 0.948 |
| Active+PT$_2$ | 0.001 | 0.0144 | 0.0694 | 0.945 |
| Active+PT$_3$ | 0.998 | 0.00262 | 381 | $< 0.001$ |
| Active+PT$_4$ | 0.999 | 0.00744 | 134 | $< 0.001$ |
| Active+PT$_5$ | 0.164 | 0.0114 | 14.4 | $< 0.001$ |
| Trip rate$_0$ | 0.100 | 0.00802 | 12.5 | $< 0.001$ |
| Trip rate$_1$ | 4.41 | 0.0688 | 64.1 | $< 0.001$ |
| Trip rate$_2$ | 7.47 | 0.0400 | 187 | $< 0.001$ |
| Trip rate$_3$ | 7.09 | 0.0722 | 98.2 | $< 0.001$ |
| Trip rate$_4$ | 10.1 | 0.0521 | 194 | $< 0.001$ |
| Trip rate$_5$ | 10.8 | 0.0115 | 939 | $< 0.001$ |

| Parameter | Est. | SE | t-stat | p-value |
|---|---|---|---|---|
| Daily distance$_0$ | 0 | 0 | −0.0184 | 0.985 |
| Daily distance$_1$ | 5.08 | 0.0447 | 114 | $< 0.001$ |
| Daily distance$_2$ | 41.7 | 0.00238 | $1.75 \times 10^4$ | $< 0.001$ |
| Daily distance$_3$ | 15.7 | 0.00418 | $3.74 \times 10^3$ | $< 0.001$ |
| Daily distance$_4$ | 82.2 | 0.000992 | $8.28 \times 10^4$ | $< 0.001$ |
| Daily distance$_5$ | 175 | 0.000104 | $1.68 \times 10^6$ | $< 0.001$ |
| Daily dist (SD)$_0$ | 0 | 0 | 0.78 | 0.435 |
| Daily dist (SD)$_1$ | 3.48 | 0.0623 | 55.9 | $< 0.001$ |
| Daily dist (SD)$_2$ | 29.2 | 0.00118 | $2.47 \times 10^4$ | $< 0.001$ |
| Daily dist (SD)$_3$ | 8.78 | 0.00552 | $1.59 \times 10^3$ | $< 0.001$ |
| Daily dist (SD)$_4$ | 51.0 | 0.000631 | $8.09 \times 10^4$ | $< 0.001$ |
| Daily dist (SD)$_5$ | 109 | 0.000220 | $4.96 \times 10^5$ | $< 0.001$ |

# Step 1: Six Mobility Lifestyles

### Low-mobility

| Socio-econ | Indicators |
|---|---|
| ASC: 0 | Dist: |
| PT: 0 | 0 km |
| Car av.: 0 | Trips: 0.1 |
| | Home 1% |

### Short Car

| Socio-econ | Indicators |
|---|---|
| ASC: 0.19 | Dist: |
| PT: -0.44 | 20±19 km |
| Car av.: 0.50 | Trips: 3.4 |
| | Priv 99% |

### Long Car

| Socio-econ | Indicators |
|---|---|
| ASC: -1.70 | Dist: |
| PT: -0.68 | 51±56 km |
| Car av.: 1.12 | Trips: 8.8 |
| | Priv 99% |

### Short Multimodal

| Socio-econ | Indicators |
|---|---|
| ASC: 0.35 | Dist: |
| PT: 0.75 | 32±38 km |
| Car av.: -1.22 | Trips: 7.5 |
| | PT 99% |

### Long Multimodal

| Socio-econ | Indicators |
|---|---|
| ASC: -1.72 | Dist: |
| PT: 0.21 | 76±57 km |
| Car av.: -0.39 | Trips: 11.2 |
| | PT 100% |

### High-mobility

| Socio-econ | Indicators |
|---|---|
| ASC: -4.04 | Dist: |
| PT: -1.00 | 172±168 km |
| Car av.: -1.06 | Trips: 8.8 |
| | PT 75% |

# Step 2: The Overlapping Distributions Problem

**Challenge:** Within-class variance $\approxeq$ Between-class variance

**Implication for individual assignment:**

- Person with 5 km trip: Could belong to Low-mobility OR Short-distance Car
- Class membership probabilities become noisy
- Signal masked by noise

**Key insight:** Need to separate **individual persistence** from **daily noise**

# Why daily aggregation hides hybrid workers

**Expected finding:** Hybrid workers (flexible schedules, remote + occasional long trips)

**What we actually see:** "Local, short-range mobility" class

- Short radius of mobility
- Home-office workers do not dominate this class
  - They still have daily distances on average, maybe for errands, leisure, etc.

**The fundamental problem:**

- Daily mobility indicators miss the purpose of trips
- Without activity type, we see only aggregated distance, not flexibility patterns

# Step 3: Hierarchical Model with Individual Effects

| Class | Users | Class mean | Class SD | Mean $u_{n,d}$ | Credible nonzero |
|---|---|---|---|---|---|
| Low-mobility | 47 | 1.2 | 21.1 | $-18.4$ | 40% |
| Short-distance Car | 124 | 16.9 | 78.0 | $-17.8$ | 25% |
| Long-distance Car | 101 | 41.2 | 38.6 | $-14.1$ | 51% |
| Short-distance Multimodal | 83 | 23.5 | 64.2 | $-16.4$ | 36% |
| Long-distance Multimodal | 31 | 71.8 | 29.0 | $-28.7$ | 65% |
| High-mobility | 14 | 84.2 | 79.2 | 14.1 | 7% |
| All users | 400 | – | – | $-16.4$ | 38% |

Table: Class mean daily distance and individual deviations

- $u_{n,d}$ captures persistent individual deviation from the class mean daily distance
- Multimodal RC far shows the strongest within-class correction

Note: some variance parameters have weak convergence diagnostics and should be interpreted cautiously.

# Step 4: Diagnostic of the Hierarchical Model

**The hierarchical model reveals an identification challenge.**

## What the diagnostics show

- Distance means converge; variances do not
- Low ESS for variance and mode-use parameters
- Class membership needs stronger socio-economic characteristics

This suggests that the model identifies average class profiles more easily than the full decomposition of variability.

## Why sampling is hard

- Classes have overlapping daily profiles
- Binary indicators: limited individual information
- Distributions skewed and highly variable

Different chains explain observations via different effect combinations.

Daily aggregation cannot fully separate lifestyles, individual heterogeneity, and daily noise.

# Outline

# Key Takeaways

1. **Six distinct mobility classes**
   - Clear separation in mode choice and daily distances
2. **Individual random effects are as important as class means**
   - 38% credible individual deviations
   - Within-class SD often competes with between-class differences
3. **Daily aggregation masks activity purpose**
   - Cannot distinguish remote workers from local commuters
4. **Hierarchical decomposition works partially**
   - Reveals class means reliably
   - Needs richer socio-economic predictors

# Next Steps: Strategic Changes

**Class Membership Model enrichment:**

- Workplace locations (inferred from long visits)
- Household characteristics (size, children)
- Geographic context (urban density, transit access)

**Additional layer: Tour-level decomposition**

- **Decompose** days into tours (home-based sequences)
- **Classify** by duration: 8h+ (work), 2–8h (mixed), <2h (shopping)

# Thank You

## Questions?

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# Individual Level: Persistent Heterogeneity

**Individual random effects.** Each individual is associated with a single random-effect vector:

$$u_n \in \mathbb{R}^K.$$

**Class-dependent heterogeneity.** The distribution of individual deviations depends on the latent class:

$$u_n \mid s_n = s \sim \mathcal{N}(0, \Sigma_s).$$

**Role.** Individual random effects capture persistent deviations from class-level behavior and are shared across all days for individual $n$.

# Likelihood with Individual Effects

**Parameters**

- $x_{nt}^{\text{dist}}$: Daily distance for individual $n$, day $t$
- $\mu_{s_n}$: Class mean distance
- $u_{n,\text{dist}}$: Individual deviation (constant across $t$)
- $\sigma_{s_n}$: Day-to-day noise (class-specific)
- $\tau_{s_n}$: Between-individual variance (class-specific)
- $s_n$: Latent class

**Measurement model:**

$$x_{nt}^{\text{dist}} \sim \text{TruncNormal}\left(\mu_{s_n} + u_{n,\text{dist}}, \sigma_{s_n}^2; 0\right)$$

**Random effect:**

$$u_{n,\text{dist}} \mid s_n \sim \mathcal{N}\left(0, \tau_{s_n}^2\right)$$

**Log-likelihood:**

$$\ell_n = \sum_{t=1}^{T_n} \log p(x_{nt}^{\text{dist}} \mid s_n, u_{n,\text{dist}}, \mu_{s_n}, \sigma_{s_n})$$

# Table 1: MLE Estimates (Single-Layer Model)

| Parameter | Estimate | Std. Err. | $t$-stat | $p$-value |
|---|---|---|---|---|
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# Table 2: Posterior Estimates (Hierarchical Bayesian Model)

| Parameter | Mean | SD | $\hat{R}$ | $ESS_{bulk}$ |
|---|---|---|---|---|
| Home-only$_0$ | 0.070 | 0.021 | 1.65 | 7.0 |
| Home-only$_1$ | 0.015 | 0.003 | 1.17 | 15.0 |
| Home-only$_2$ | 0.021 | 0.009 | 1.53 | 7.0 |
| Home-only$_3$ | 0.010 | 0.003 | 1.12 | 23.0 |
| Home-only$_4$ | 0.004 | 0.002 | 1.03 | 84.0 |
| Home-only$_5$ | 0.008 | 0.006 | 1.53 | 7.0 |
| Private vehicle$_0$ | 0.675 | 0.064 | 2.26 | 5.0 |
| Private vehicle$_1$ | 0.677 | 0.057 | 2.36 | 5.0 |
| Private vehicle$_2$ | 0.918 | 0.014 | 1.63 | 7.0 |
| Private vehicle$_3$ | 0.156 | 0.040 | 1.70 | 6.0 |
| Private vehicle$_4$ | 0.072 | 0.028 | 1.54 | 7.0 |
| Private vehicle$_5$ | 0.603 | 0.041 | 1.59 | 7.0 |
| Active+PT$_0$ | 0.308 | 0.062 | 2.36 | 5.0 |
| Active+PT$_1$ | 0.310 | 0.058 | 2.40 | 5.0 |
| Active+PT$_2$ | 0.074 | 0.013 | 1.59 | 7.0 |
| Active+PT$_3$ | 0.842 | 0.041 | 1.72 | 6.0 |
| Active+PT$_4$ | 0.926 | 0.029 | 1.55 | 7.0 |
| Active+PT$_5$ | 0.383 | 0.040 | 1.49 | 7.0 |
| Trip rate$_0$ | 6.681 | 0.474 | 1.62 | 7.0 |
| Trip rate$_1$ | 7.598 | 0.390 | 1.64 | 7.0 |
| Trip rate$_2$ | 7.008 | 0.309 | 1.34 | 10.0 |
| Trip rate$_3$ | 8.697 | 0.383 | 1.43 | 8.0 |
| Trip rate$_4$ | 8.899 | 0.646 | 1.26 | 12.0 |
| Trip rate$_5$ | 9.691 | 1.325 | 1.71 | 6.0 |

# Table 2: Posterior Estimates (Hierarchical Bayesian Model)

| Parameter | Mean | SD | $\hat{R}$ | ESS$_{bulk}$ |
|---|---|---|---|---|
| Daily distance$_0$ | 1.200 | 0.953 | 1.05 | 71.0 |
| Daily distance$_1$ | 16.880 | 1.049 | 1.08 | 34.0 |
| Daily distance$_2$ | 41.243 | 2.012 | 1.16 | 17.0 |
| Daily distance$_3$ | 23.527 | 1.145 | 1.18 | 15.0 |
| Daily distance$_4$ | 71.779 | 1.930 | 1.06 | 45.0 |
| Daily distance$_5$ | 84.244 | 7.208 | 1.81 | 6.0 |
| Daily distance (SD)$_0$ | 21.112 | 2.216 | 2.28 | 5.0 |
| Daily distance (SD)$_1$ | 78.024 | 8.518 | 2.14 | 5.0 |
| Daily distance (SD)$_2$ | 38.597 | 4.118 | 2.52 | 5.0 |
| Daily distance (SD)$_3$ | 64.201 | 22.811 | 2.14 | 5.0 |
| Daily distance (SD)$_4$ | 28.998 | 28.863 | 1.55 | 7.0 |
| Daily distance (SD)$_5$ | 79.190 | 48.334 | 2.30 | 5.0 |

# Table 3: Multinomial Logit Coefficients

| Class | Covariate | Mean | SD | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|
| Short-dist car | Education | 0.030 | 0.293 | −0.544 | 0.604 |
| | Age | −0.221 | 0.225 | −0.663 | 0.220 |
| | Car availability | 0.766 | 0.392 | −0.002 | 1.535 |
| | Transit subscription | 0.854 | 0.359 | 0.151 | 1.557 |
| | Job: other | 0.078 | 0.547 | −0.995 | 1.152 |
| | Job: retired | 0.867 | 0.514 | −0.141 | 1.874 |
| | Job: student | −0.603 | 0.559 | −1.699 | 0.492 |
| Long-dist car | Education | 0.134 | 0.211 | −0.279 | 0.546 |
| | Age | 0.028 | 0.239 | −0.440 | 0.496 |
| | Car availability | 1.557 | 0.464 | 0.647 | 2.466 |
| | Transit subscription | −0.854 | 0.364 | −1.568 | −0.140 |
| | Job: other | −0.499 | 0.559 | −1.595 | 0.598 |
| | Job: retired | −0.586 | 0.597 | −1.755 | 0.583 |
| | Job: student | 0.081 | 0.658 | −1.208 | 1.371 |
| Short-dist modal | Education | −0.194 | 0.270 | −0.723 | 0.335 |
| | Age | 0.095 | 0.249 | −0.393 | 0.583 |
| | Car availability | −0.978 | 0.388 | −1.738 | −0.217 |
| | Transit subscription | 0.523 | 0.504 | −0.466 | 1.512 |
| | Job: other | 0.033 | 0.538 | −1.022 | 1.088 |
| | Job: retired | −0.350 | 0.690 | −1.702 | 1.003 |
| | Job: student | 0.476 | 0.614 | −0.727 | 1.679 |

# Table 3: Multinomial Logit Coefficients

| Class | Covariate | Mean | SD | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|
| Long-dist PT | Education | −0.170 | 0.268 | −0.695 | 0.355 |
| | Age | −0.127 | 0.285 | −0.686 | 0.431 |
| | Car availability | −0.951 | 0.445 | −1.823 | −0.079 |
| | Transit subscription | 0.351 | 0.607 | −0.838 | 1.541 |
| | Job: other | −0.282 | 0.669 | −1.593 | 1.028 |
| | Job: retired | −0.382 | 0.781 | −1.912 | 1.149 |
| | Job: student | −0.062 | 0.710 | −1.453 | 1.329 |
| High-mobility | Education | 0.020 | 0.466 | −0.895 | 0.934 |
| | Age | −0.274 | 0.324 | −0.909 | 0.361 |
| | Car availability | 0.658 | 0.573 | −0.465 | 1.780 |
| | Transit subscription | −0.108 | 0.573 | −1.232 | 1.016 |
| | Job: other | −0.897 | 0.800 | −2.465 | 0.671 |
| | Job: retired | −0.714 | 0.822 | −2.324 | 0.897 |
| | Job: student | 0.044 | 0.698 | −1.325 | 1.412 |

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