



Modeling Longitudinal Trajectories of Antiretroviral (ARV) Medication Adherence and Composite Medication Adherence for Non-HIV Chronic Conditions in People with HIV

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# Background

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- Medication adherence (MA) is often reported at the summary level over an aggregate period, which does not reflect the fluid, dynamic nature of medication-taking behavior over time.
- Condition-specific, summary MA measures do not represent the complexity medication-taking behavior from polypharmacy with chronic conditions.
- An alternative to traditional MA assessments is group-based trajectory modeling (GBTM), which has been used to characterize longitudinal medication adherence refill patterns (i.e., trajectories).<sup>1,2</sup>

# Objective

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- Although GBTM has been used to study MA in a variety of chronic conditions, a recent systematic review did not identify any published studies with application in people with HIV with multiple chronic conditions.<sup>2</sup>
- **Therefore**, we applied GBTM to monthly medication refill data to identify longitudinal trajectories of medication adherence behavior for antiretroviral (ARV) medications and non-ARV medications in people with HIV with one or more additional chronic conditions.

# Methods

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## Design:

- 37-month longitudinal retrospective observational cohort study between 9/2018 – 9/2021 (plus 6-month pre-observational period)
- 22,126 observation months

## Sample:

- 598 Adult people with HIV with type 2 diabetes, hypertension, and/or hypercholesterolemia
- Continuously enrolled in a US mid-Atlantic integrated health system.
- Actively dispensed qualifying medication for each diagnosis in both the pre-observational and observational periods
- Exclusions: Cumulative institutional stays exceeding seven days in the pre- and post-3/2020 observational periods; diagnosis of end stage renal disease pre-3/2020\*; death; or incomplete demographic information (n=2)

\*Note that 3 incident cases of ESRD were identified between 11/2020 and 3/2021 and were retained as their inclusion did not affect interpretation of the results.

# Methods

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## Measurements:

- Demographics
  - age, race/ethnicity, insurance type, comorbidities, COVID-19 interruption date
- Monthly proportion of days covered (PDC) was used to estimate both ARV medication adherence and non-ARV composite medication adherence (CMA)
  - non-ARV CMA included diabetes (T2DM), renin-angiotensin system antagonist (RASA), and statin medications during the observational period.
  - PDC is a consistent measure with CMS and health care quality organization standards.<sup>3-5</sup>
- Monthly continuous measure (i.e., proportion) of PDC ranging from zero (complete non-adherence) to 1 (complete adherence) was used

# Methods

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## Analyses:

- Univariate analyses used to describe the cohort characteristics.
- (Multi-trajectory) GBTM of ARV MA and CMA was used to identify dynamic MA trajectories over a 37-month observational period.<sup>6-10</sup>
- The optimal number of MA trajectories was selected using:
  - Bayesian Information Criterion (BIC)
  - Average posterior probabilities (APP) of trajectory membership  $>0.7$
  - Odds of correct classification (OCC)  $>5$
  - Interpretation of observed MA considering adequate thresholds (i.e.,  $PDC \geq 0.80$  for CMA,  $\geq 0.90$  for ARV medications).

# Results

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- A majority of the study cohort (n=598) was...
  - 51-64 years old (58%) and 65+ years old (19%)
  - Black (74%)
  - Male (69%)
  - Commercially insured (67%)
- In addition to HIV:
  - 62% of people with HIV had one of the 3 comorbidities
  - 30% had two comorbidities
  - 9% had three comorbidities
- Common non-ARV medication classes:
  - Statins (68%), RASA (55%), and T2DM (23%)
- Adequate medication adherence
  - **ARV  $\geq 90\%$ : 76% of observed months**
  - **non-ARV CMA  $\geq 80\%$ : 71% of observed months**

# Results

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- Trajectory Model Selection

| Trajectory Model Selection  |            |                |                |              |
|---|------------|----------------|----------------|--------------|
| Model   | n          | BIC            | AIC            | Entropy      |
| 3-Trajectory  | 598        | -31,669        | -31,634        | 0.962        |
| 4-Trajectory  | 598        | -30,919        | -30,873        | 0.974        |
| <b>5-Trajectory</b>   | <b>598</b> | <b>-30,234</b> | <b>-30,177</b> | <b>0.964</b> |
| BIC = Bayesian Information Criteria; AIC = Akaike Information Criterion |            |                |                |              |

- Compared to 3-trajectory and 4-trajectory solutions, the 5-trajectory taxonomy had the preferred BIC and AIC.
  - Smaller value closer to zero



# Results

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- 5-Trajectory Model Characteristics

| 5 Trajectory Model Characteristics                             |     |                                       |                                      |                   |
|--|-----|---------------------------------------|--------------------------------------|-------------------|
| Pattern  | n   | Average Posterior Probabilities (APP) | Odds of Correct Classification (OCC) | Total Probability |
| G1 - Inadequate, decreasing ARV MA and CMA                     | 68  | 0.99                                  | 946                                  | 0.114             |
| G2 - Inadequate, increasing ARV MA and decreasing CMA          | 66  | 0.98                                  | 360                                  | 0.109             |
| G3 - Inadequate, increasing ARV MA and CMA                     | 182 | 0.97                                  | 83                                   | 0.308             |
| G4 - Inadequate decreasing ARV MA and adequate, increasing CMA | 36  | ~1.0                                  | 37,283                               | 0.060             |
| G5 - Adequate, increasing ARV MA and CMA                       | 246 | 0.98                                  | 68                                   | 0.408             |

- The 5-trajectory taxonomy had average posterior probabilities  $\geq 0.97$  for all patterns, and odds of correct classification  $> 5$ .

# Results

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- 40.8% of the cohort consistently had adequate, increasing ARV MA and CMA (G5)
- 16.9% of the cohort had discordant adherence trajectories for ARV MA and CMA (G2 and G4)
- 42.2% of the cohort had consistent, but inadequate ARV MA and CMA adherence trajectories (G1 and G3)
  - One directional pattern was negative (G1) while the other was positive (G3)



# Limitations / Strengths

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- Observational design and small sample
- Analysis of historical (secondary) data
- Applying a surrogate measure of adherence
  - Actual adherence not measured
- No clinical outcome assessment
- Potential development of other conditions that may influence adherence
- CMA more accurately reflects the collective nature of non-ARV medication adherence in people with HIV and other chronic conditions.
- Study of CMA over an extended 37-month observation period reflects the chronicity of disease in people with HIV to realistically represent medication taking behavior.
- GBTM identifies dynamic patterns of medication adherence not previously done in older people with HIV with other chronic conditions.
- Muti-trajectory GBTM describes ARV MA and non-ARV CMA simultaneously.

# Conclusions

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- Varying patterns of ARV MA and non-ARV CMA suggests unique medication adherence needs.
  - Follow-up, in-depth qualitative inquiry is needed to fully understand
- GBTM can be used to identify people with HIV with specific MA needs and align them with tailored intervention strategies.
- Next steps include:
  - Evaluate the relationship between medication adherence trajectories and treatment outcomes.
  - Develop deeper understanding of the interplay among social determinants of health, social-behavioral, economic, health system, comorbidity-, therapy-, and other patient-related factors that shape these unique medication adherence trajectories through qualitative inquiry to inform optimal, tailored interventions.

# References

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# Questions?

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