Leveraging Publicly Available SDOH Measures to Segment Members and Quantify Differences in Diabetic Medication Adherence: A Latent Profile Analysis

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Background

- Social determinants of health (SDOH) measures have become increasingly necessary to implement in both prediction of health outcomes as well as targeting of interventions to specific segments of the population to prevent nonadherence.
- Utilization of publicly sourced SDOH measures has become crucial, and thus an area of active research, as sourcing data directly at the member level is both costly and unstandardized.
- Latent profile analysis (LPA) is an unsupervised machine learning methodology that is able to identify subpopulations or groups with shared characteristics given a set of continuous variables. By employing LPA in this context, we can find groups of zip codes that have shared SDOH characteristics, which could help inform community-based interventions to improve health outcomes.

Objectives

To identify latent profiles of U.S. zip codes based on SDOH measures from American Community Survey (ACS) data, and to differentiate SDOH profiles by reporting medication adherence (MA) for patients with diabetes.

Methods

Sample

- Commercially insured sample of members continuously enrolled during the 2022 and 2023 calendar years (entire measurement period), and over the age of 18 at the start of 2022.
- Diabetic patients were identified using methodology consistent with Pharmacy Quality Alliance (PQA) specifications for calculating medication adherence – two or more diabetic pharmacy claims* on two or more different dates of service in each measurement window with the first diabetic medication being filled 91 days prior to the end of each measurement period.
- Sample demographics
  - Mean Age at beginning of study – 54.7
  - 46.25% Female (n = 8,506)
  - Mean Chronic Disease Score – 4.18 (2022), 4.24 (2023)

*Insulin was excluded from the PDC calculation and from diabetic medications used to identify members in the sample; however, using insulin did not rule anyone out of the study provided they met all the other criteria.

Outcomes

- The proportion of days covered (PDC) was calculated separately for each year to compare adherence from one year to the next. PDC was calculated as an all-class rate for diabetic medications excluding insulin, where overlapping fills were adjusted within generic ingredient, and fills that extended beyond the measurement period were right censored. Patients were considered adherent for a given year if PDC ≥ 0.80.[1]
- MA rates were for each latent profile for each year. Odds ratios with confidence intervals and the Wald test were used to compare adherence rates between profiles. Odds ratios were also calculated for adherence, year over year, within each latent profile.

Latent Profile Analysis

- Data from ACS[2] (2017-2021) was accessed from the Centers for Disease Control and Prevention.[3] ACS is an annually updated survey that provides SDOH data along with other demographic information that is vital for research efforts and directing resource utilization for federal funds.
- LPA was conducted using the tidyLPA[4] package in R for 31,923 zip codes using ACS data from 2017 to 2021.
- Nine variables were used to conduct the LPA (all have units of percentage).
  - Persons Living Below 150% of the Poverty Level
  - Crowding Among Housing Units
  - No Broadband Internet Subscription Among Households
  - Housing Cost Burden Among Households
  - Persons of Racial or Ethnic Minority Status
  - Single-Parent Households
  - Persons Age 65 Years or Older
  - No High School Diploma Among Adults Age 25 Years or Older
  - Unemployment Among People 16 Years and Older in the Labor Force
- A range of LPA hyperparameters were tested, including number of profiles and equal vs. unequal variances and covariances within classes.

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Figure 1

Map of underserved and advantaged zip codes in the United States

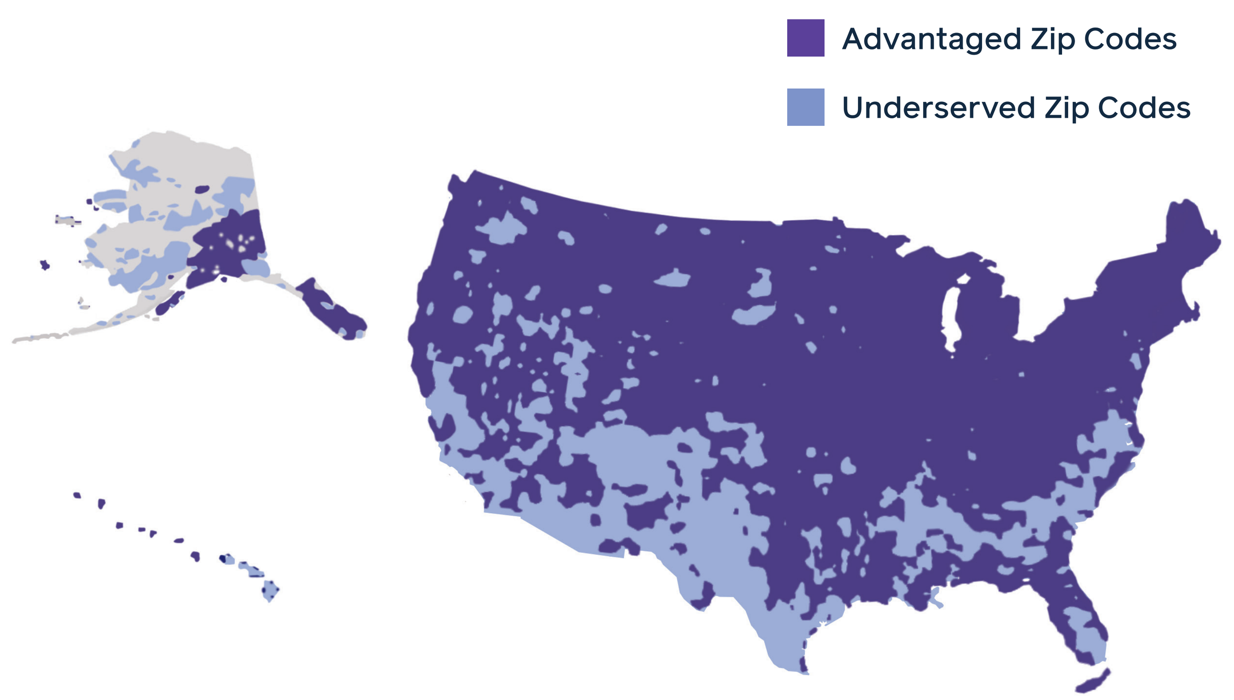


Figure 2

Averaged SDOH metrics in underserved and advantaged zip code

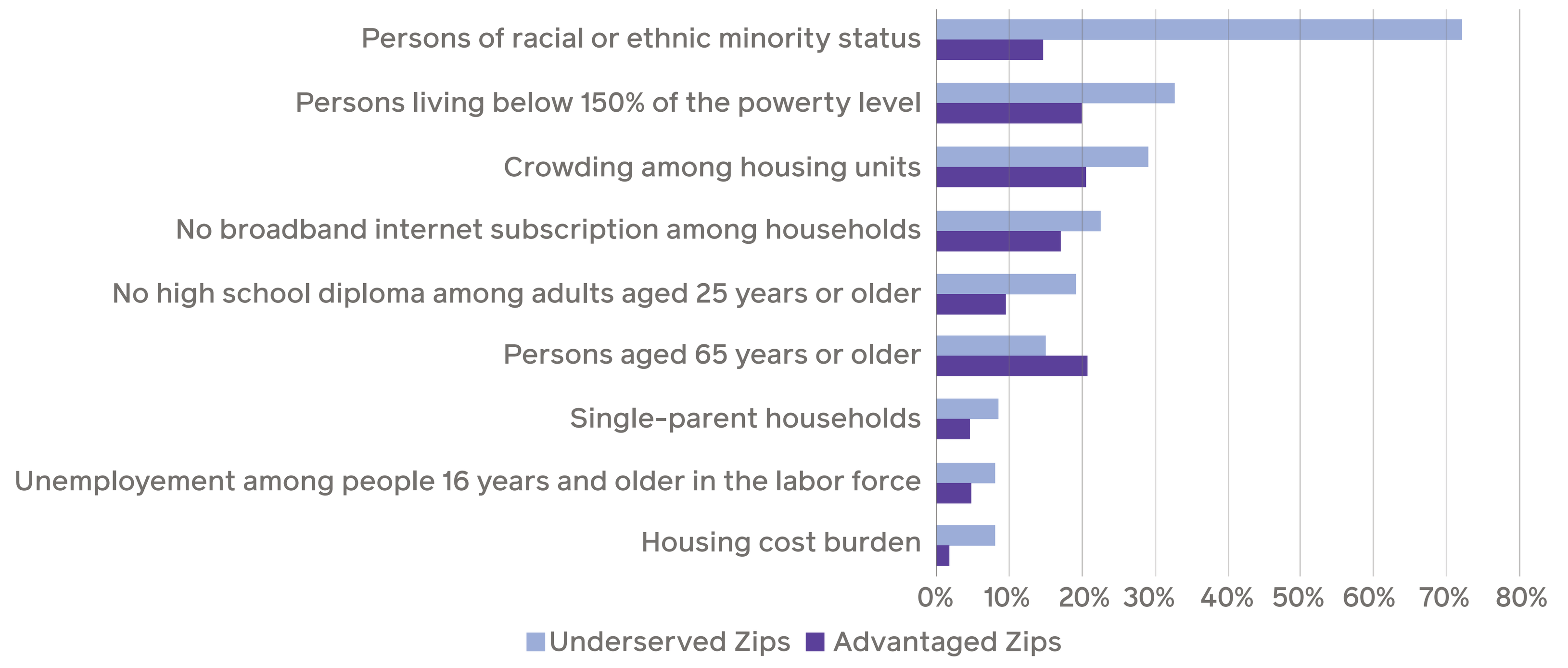
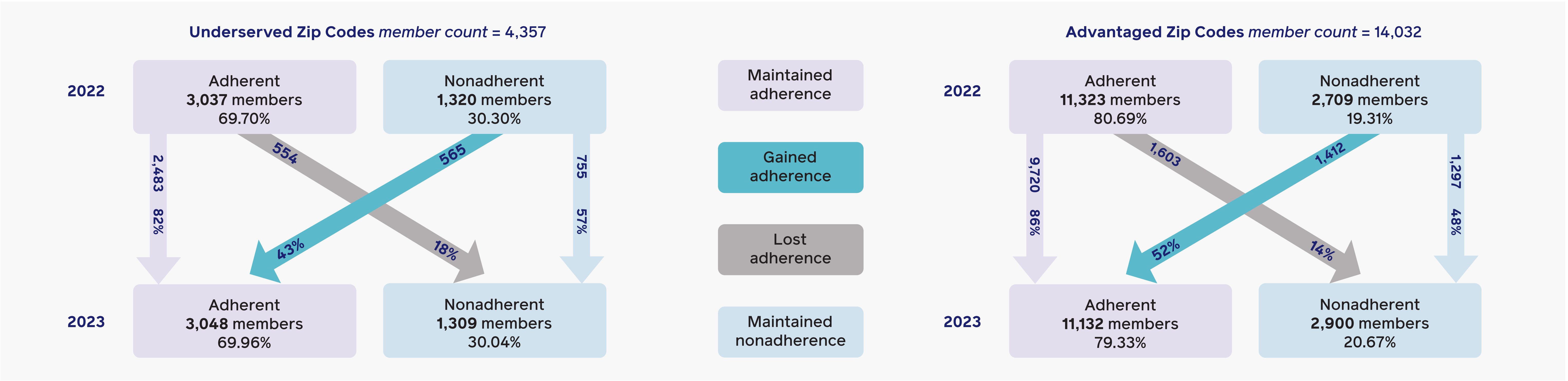


Figure 3

Transitions between adherence and nonadherence from 2022 to 2023 in underserved and advantaged zip codes.



Results

Latent Profile Analysis (Figures 1 & 2)

- A two-profile model requiring equal variances and covariances within classes was determined to be most appropriate for this analysis based on BIC, parsimony, and entropy of resulting latent classes.[5]
- Based on profile characteristics, LPA results revealed two types of zip codes: underserved zip (UZ) codes (16.6%) and advantage zip (AZ) codes (83.5%).
- UZs had more severe metrics across most SDOH measures included in the LPA – in particular, UZs averaged 12.5% higher prevalence of persons living below 150% of the poverty line, and 9.7% higher rates of persons without a high school diploma.

Diabetic Medication Adherence (Figure 3)

- 18,389 members met study inclusion criteria.
  - 4,357 (23.7%) members were identified as residing in UZs.
  - 14,032 (76.3%) members were identified as residing in AZs.
- Diabetic medication adherence (MA) was significantly lower for members in UZs compared to those in AZs.
  - Adherence was 11% lower in 2022 (OR = 0.55, p<0.001).
  - Adherence was 9% lower in 2023 (OR = 0.60, p<0.001).
- 82% of members in UZs that were adherent in 2022 maintained MA in 2023 compared to 86% of members in AZs, suggesting that it is less likely for members to maintain MA in UZs.

Conclusion

- Using zip code aggregated SDOH metrics, we identified latent profiles of underserved communities where diabetic medication adherence was significantly lower than other areas.
- This segmentation could help direct interventions specific to individual community needs as well as encourage increased efforts where they are needed most to address these health care disparities at a community level for underserved populations. For example, members in UZs are significantly less likely to have broadband internet, so interventions or reminders requiring internet access such as email may not be the most efficient means of communication for members in these areas.

Limitations

- This analysis used zip code level SDOH measures for the latent profile analysis – as more publicly available data becomes available at various granularities; further efforts should be made to see if other groupings or variables are useful in identifying patterns of inequality in health outcomes.
- This analysis focused solely on medication adherence for diabetes, and results may not generalize to other disease states – future efforts should examine health outcomes for other chronic conditions.
- The sample for this study was derived from a commercially insured population, and results may not generalize to government populations.

References

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