APS TARC
Adult Protective Services Technical Assistance Resource Center
enhancing effectiveness of APS programs

Using AI to Predict Adult Maltreatment

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About the APS TARC

The mission of the APS TARC is to enhance the effectiveness of state APS programs by:

- Supporting federal, state, and local partners’ use of data and analytics,
- Applying research and evaluation to practice, and
- Encouraging the use of innovative practices and strategies.

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- All attendees will receive an automatically generated email approximately 24 hours after the webinar ends with a link to a certificate of attendance.

Quick Attendee Poll

Which of the following do you identify the most with?

- Adult Protective Services Professional
- Other Social Services Professional
- Medical Professional
- Legal Professional
- Other

Our Speakers

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Agenda

- ACL’s Vision
- Define predictive analytics and describe use cases
- Discuss possible applications for APS
- Describe research on risk and protective factors
- Explain processes to identify and assess data sources
- Predictive Modeling
- Findings
- Implications

ACL's Vision for Elder Justice

A comprehensive, multidisciplinary system
that effectively supports
older adults and adults with disabilities
so they can exercise their right
to live where they choose,
with the people they choose, and
fully participate in their communities
without threat of
abuse, neglect, or financial exploitation.

ACL

Predicting Risk of Adult Maltreatment (PRAM)

1

Objective 1: Learn from similar disciplines (e.g. child welfare and healthcare) about the use of predictive analytics.

2

Objective 2: Identify risk and protective factors associated with adult maltreatment.

3

Objective 3: Experiment with predictive analytics, specifically artificial intelligence/machine learning, to answer a research question about adult abuse, neglect, and exploitation.

Predicting Risk of Adult Maltreatment

- Background and Purpose
  - The Administration of Community Living (ACL) and Centers for Medicare and Medicaid Services (CMS) are interested in leveraging predictive analytic technologies and approaches to assist in the **prevention of abuse, neglect, and exploitation (ANE)** of older individuals and people with disabilities.
  - The purpose of this study is to assess opportunities for using predictive analytics to identify individuals who are at increased risk for abuse, neglect, and exploitation.

Definition of Terms

- Predictive Analytics: the branch of advanced analytics used to make predictions about unknown future events. Predictive analytics uses many techniques from data mining, statistics, modeling, machine learning, and artificial intelligence to analyze current data to make predictions about the future.

- Artificial Intelligence: the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. The term is frequently applied to the project of developing systems endowed with the intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize, or learn from past experience.

- Machine Learning (ML): discipline concerned with the implementation of computer software that can learn autonomously.

Examples of Predictive Analytics In Practice

Predictive Analytics in Child Welfare

- Common use cases:
  - to assist with decision making,
  - to reduce risk of reoccurrence,
  - to predict severe harm,
  - to identify locations with increased risk.

- Transparency in algorithm design is paramount to ensuring a sense of trust between the child welfare agency and the members of the public that they are serving.

Predictive Analytics in Healthcare

- Common use cases:
  - reduce readmission,
  - rare disease identification,
  - to improve resource allocation,
  - to predict medically underserved areas.

- While there are some post-implementation issues to consider, the successful use of predictive analytics integrates multiple sources of data to improve quality of care and reduction of healthcare costs.

Predictive Analytics in Criminology

- "Predictive Policing"
- Common use cases:
  - to tie perpetrators to multiple crimes they've committed,
  - to predict likely victims,
  - to improve resource allocation,
  - to assign police to high-crime areas when crime is likely to happen.

- Challenges:
  - More policing leads to more recorded crime
  - Accused of racial bias & racial profiling, especially when applied to individuals instead of locations

Predictive Analytics in Adult Maltreatment

- No study has employed a machine learning approach to predict adult maltreatment.
- No study has employed a geospatial approach to predict adult maltreatment.
- However, recently…
  - Tony Rosen and colleagues (2019): Can artificial intelligence help identify elder abuse and neglect?
  - Jason Burnett and colleagues (2020): Socioecological indicators of senior financial exploitation: an application of data science to 8,800 substantiated mistreatment cases.

Possible Applications for APS

- How can predictive analytics be used for APS?
  - State- or county-level service planning
  - Targeted funding & hiring
  - Generate new questions about what leads to ANE
  - Guides new factors for preventive services to target
  - Suggests what groups of people might benefit most from prevention

Technical Expert Panel (TEP)

- The role of the TEP is to provide guidance and validation to the project.
- Participants included:
  - Federal Stakeholders
  - Federal Data Experts
  - State and local APS program administrators
  - Academics
  - Data scientists
  - Non-profit organizations

Research Question

What community (county) level characteristics predict adult maltreatment, neglect, and exploitation (ANE), and lead to Adult Protective Service system engagement and involvement?

Risk Factors

- 50+ different risk factors
- Inconsistency in the literature regarding terms
  - “abuse”, “maltreatment”, “mistreatment”
- Studies either focused on “maltreatment” in general (e.g. unspecified) or specific types of maltreatment
- There is some overlap and clear distinctions with regards to risk factors for different types of maltreatment
- There are several domains of risk

Most Frequently Cited Risk Factors

- Individual
  - **Low income**
  - **Social isolation**
  - Depression
  - Poor health
  - Need assistance with Activities of Daily Living (ADLs)
  - Marital status (separated or divorced)
  - Female
- Community context
  - Abuse Culture
  - Rural geography
- Caregiver
  - Caregiver (perceived) burden
  - Caregiver substance abuse
  - Caregiver mental illness (unspecified)
    - Depression
    - Anxiety
- Perpetrator
  - Dependency
  - Mental illness (unspecified)
  - Substance abuse

Protective Factors

- 15 potential protective factors
- There are no proven, 100% effective protective factors identified in the literature.
- Not necessarily characteristics associated with the individual or community, but societal interventions.
- Most frequently cited protective factors:
  - Social Support
  - Caregiver Interventions
  - Education about available services

Data

Data Sets

- Identified data sources including information on abuse, neglect, and exploitation as well as sources with risk factor information
- Developed a data set inventory
- Prioritizing data based on the following criteria:
  - County level data
  - Publicly available data
  - Population-wide or surveillance data
  - Data collected during a time period comparable to the time period of NAMRS

NAMRS

- **Key Data Source:** NAMRS (National Adult Maltreatment Reporting System)
- APS data from each state – some with more complete entries than others
- Restricted to states that submit *case component* data (33 states in FFY 2019)
  - Data on each report that is screened in and investigated by the agency
  - Information is specific to the investigation, including the clients, maltreatment, and perpetrators associated with the specific investigation.

Additional Data Sources

- American Community Survey (ACS)
- Area Health Resource Files (AHRF)
- County Health Rankings (CHR)
- Consumer Complaint Databases (CCD)
- IRS 990
- USDA Food Environment Atlas (USDA)

Development of the Algorithm

What do we want to predict or estimate?

Development Considerations

- Quality of data used to produce predictions
- Transparency of personnel who design the algorithm and who are responsible for using it
- Implicit or systemic bias in the data will be reflected in the predictions of the model

Implementation Considerations

- Accuracy of the results
- Training of staff who oversee using the predictive analytics algorithms
- Accounting for implicit or systemic bias in the data that may be reflected in the predictions of the model

Partners & Approach

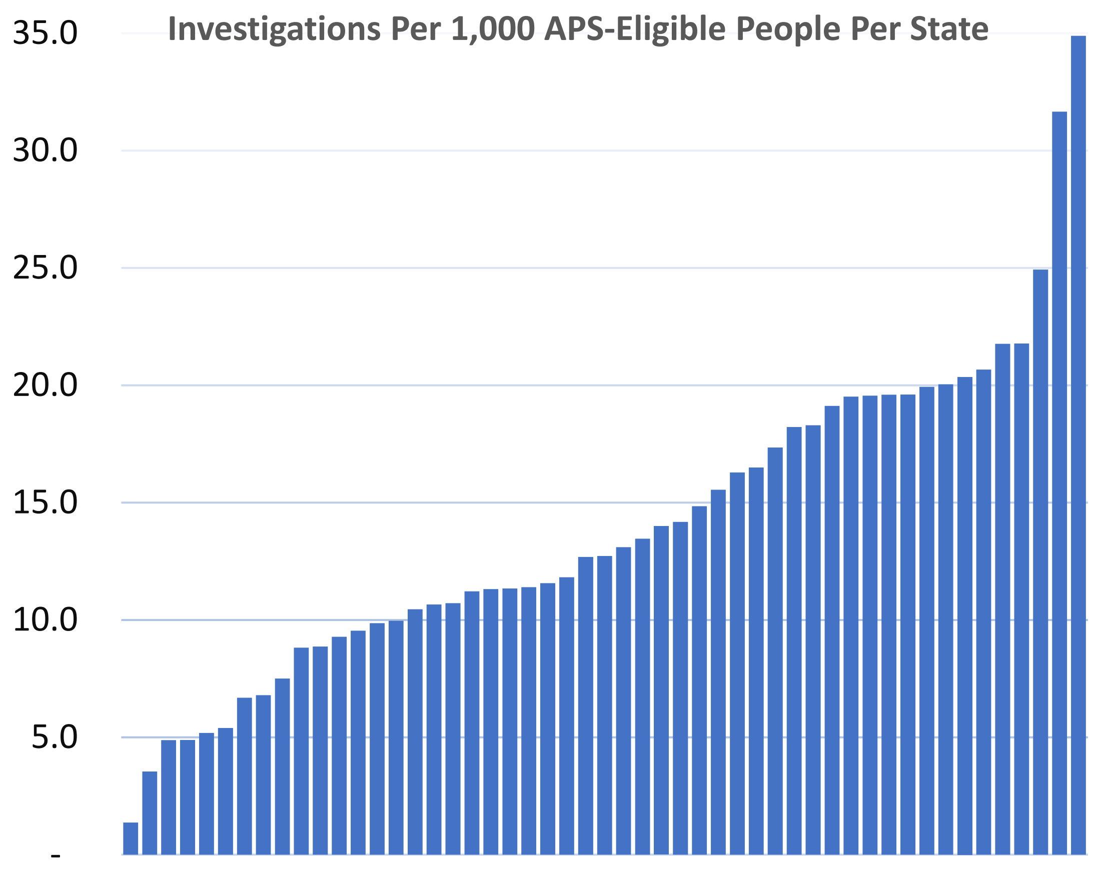
- BCT Partners
  - History of integrating social science with data science
  - Prioritize social justice and equity in their models
- Not just a black box
  - Common approach: maximize accuracy but can't tell you why
  - BCT's approach: target high accuracy, but explain the variables and factors that are most important
- Other firms as peer reviewers:
  - Microsoft

What Level Do We Look At?

- Individuals?
  - *Yes, but not yet*
- Geographic areas?
  - State?
    - *Not granular enough; not enough states for meaningful models*
  - County?
    - *Feasible and interesting*
  - Census tract?
    - *Not available in NAMRS*

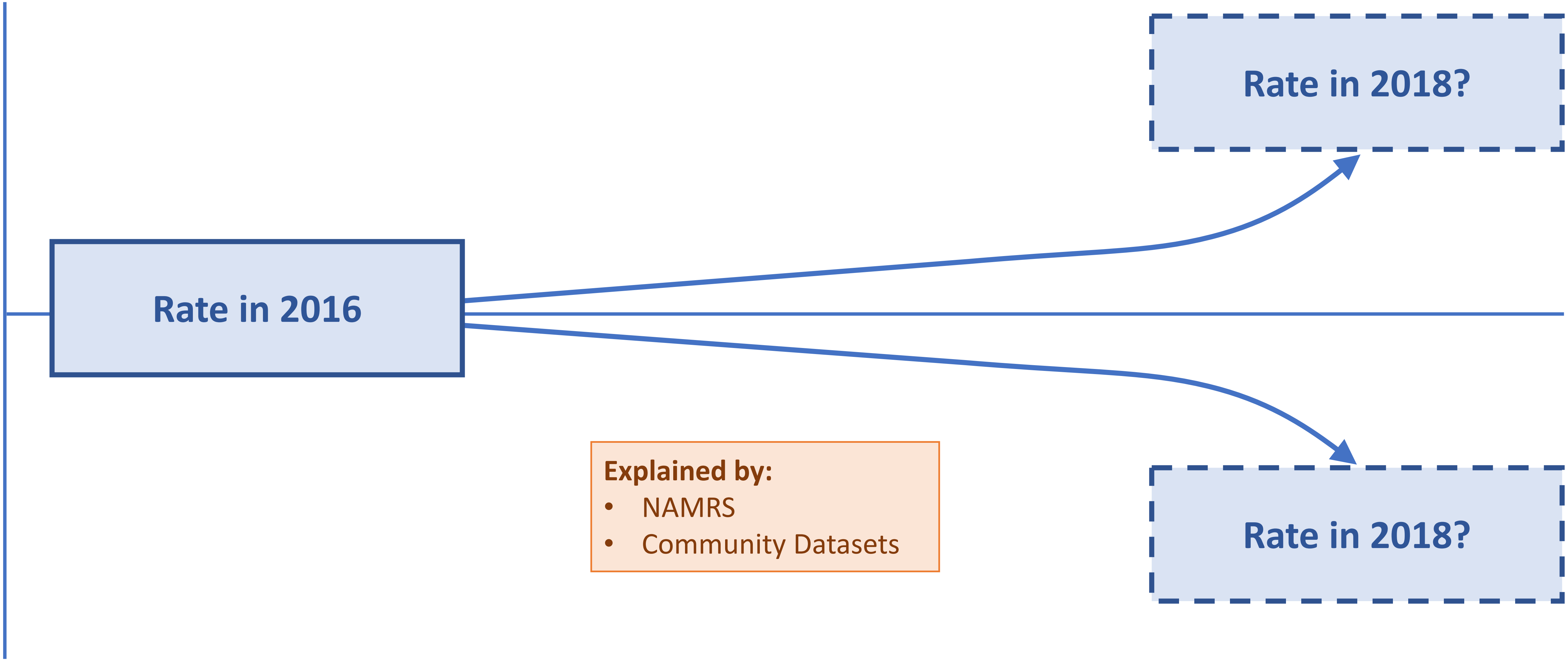
What Metric Do We Predict?

- Rate of APS engagement (“Per Capita ANE”)
  - Varies considerably between jurisdictions
  - Challenging to predict actual rate
  - May vary considerably based on local policies, procedures, & practices
- More straightforward to predict change over time
  - “Growth Rate in ANE”
  - Average annual growth from 2016 to 2018



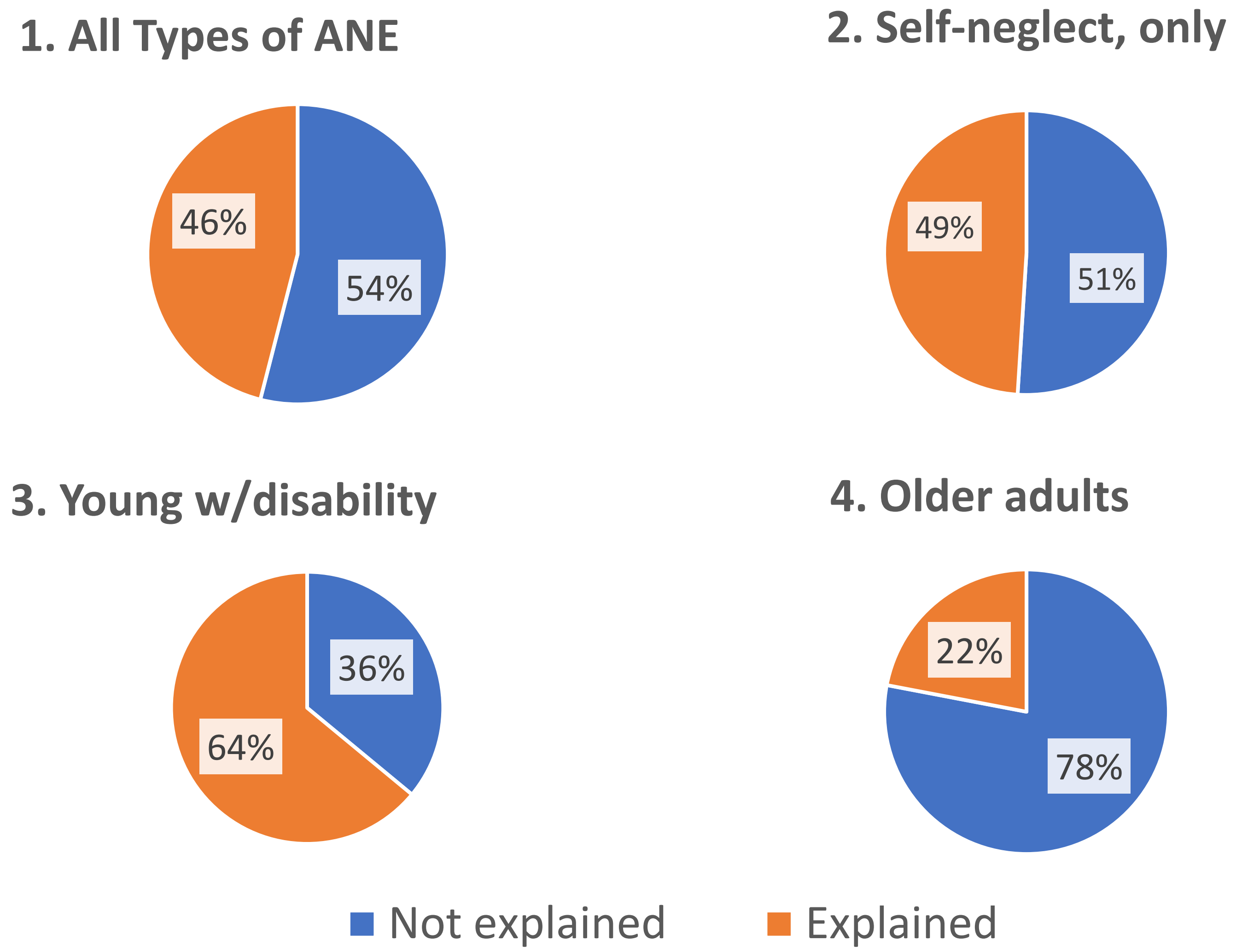
Source: NAMRS Agency Component and US Census

Approach to Estimating Growth

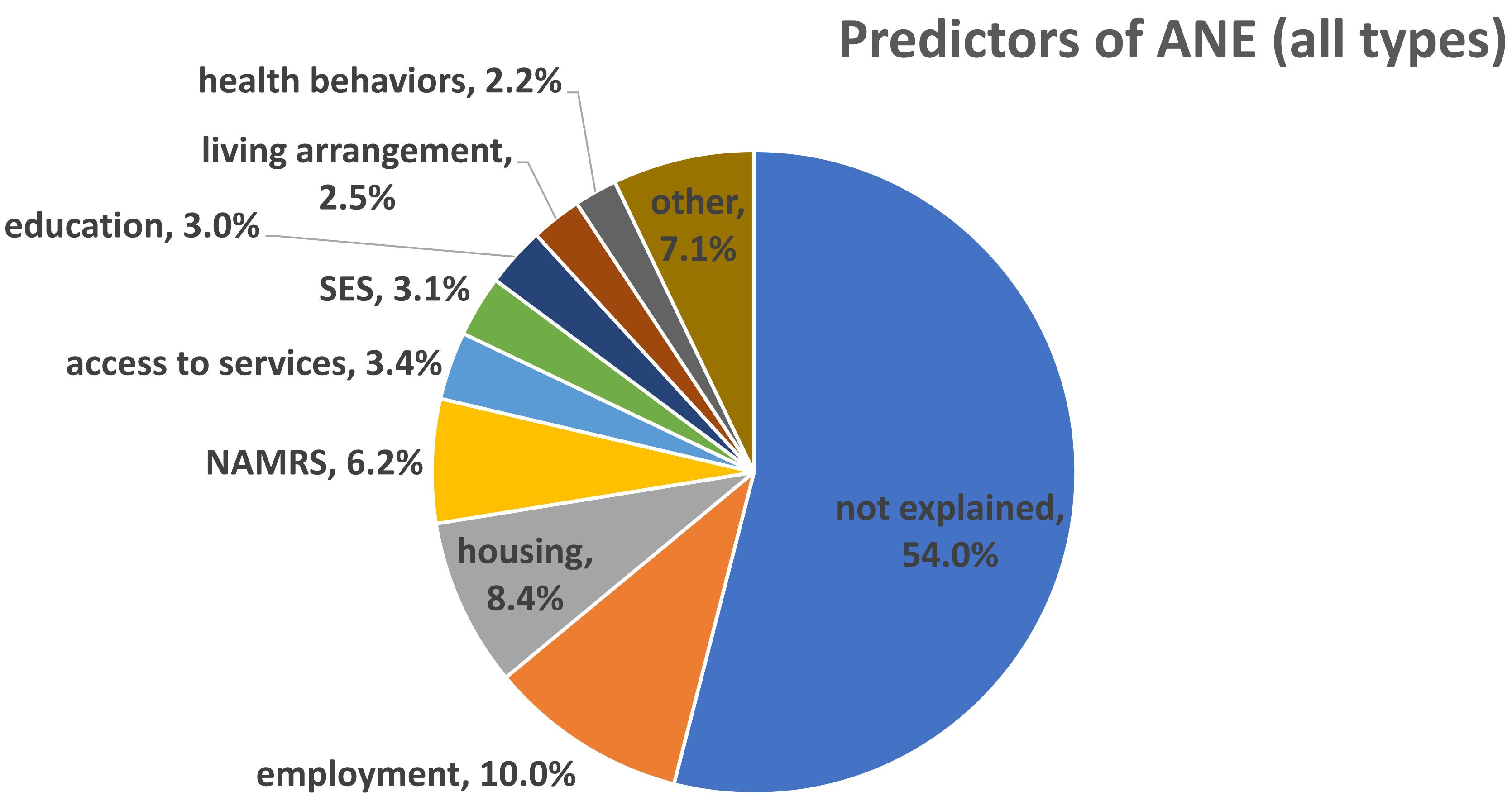


Findings

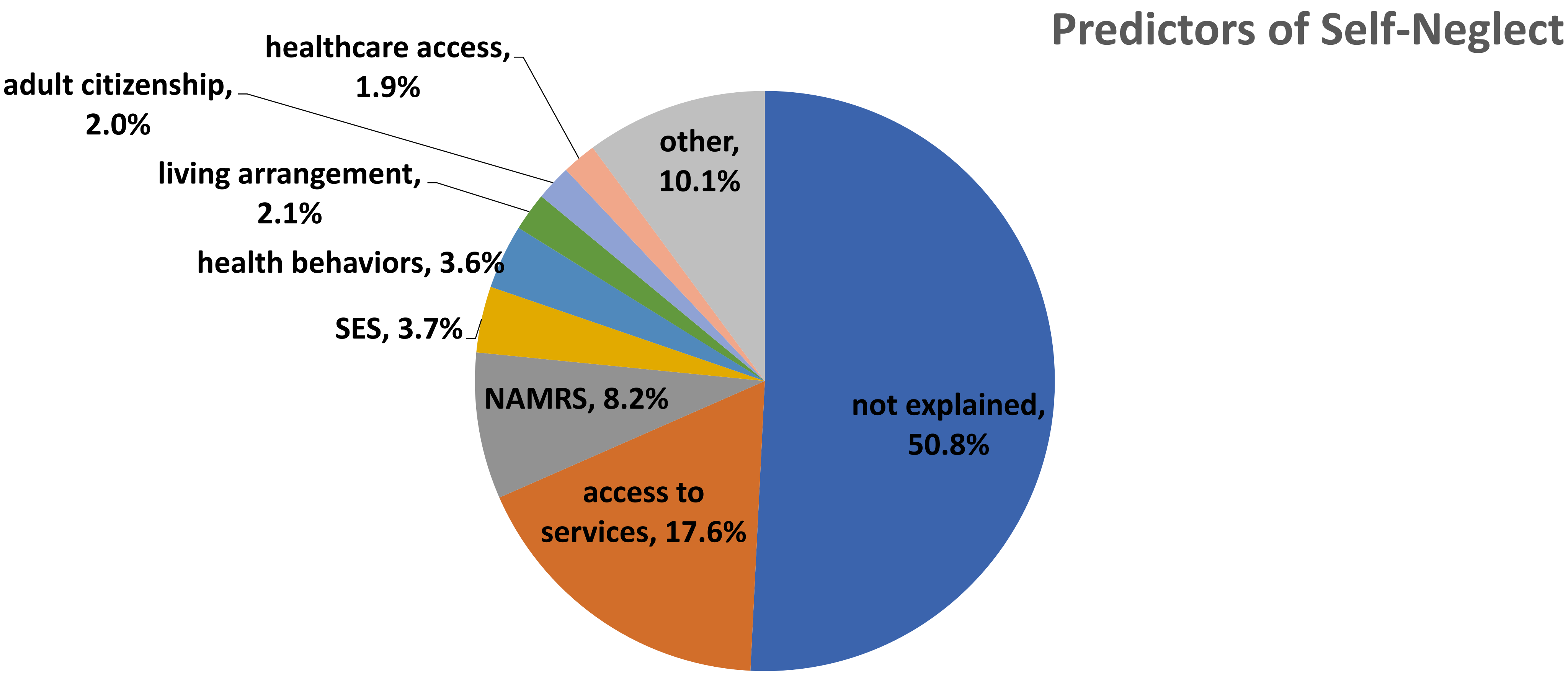
Model Findings



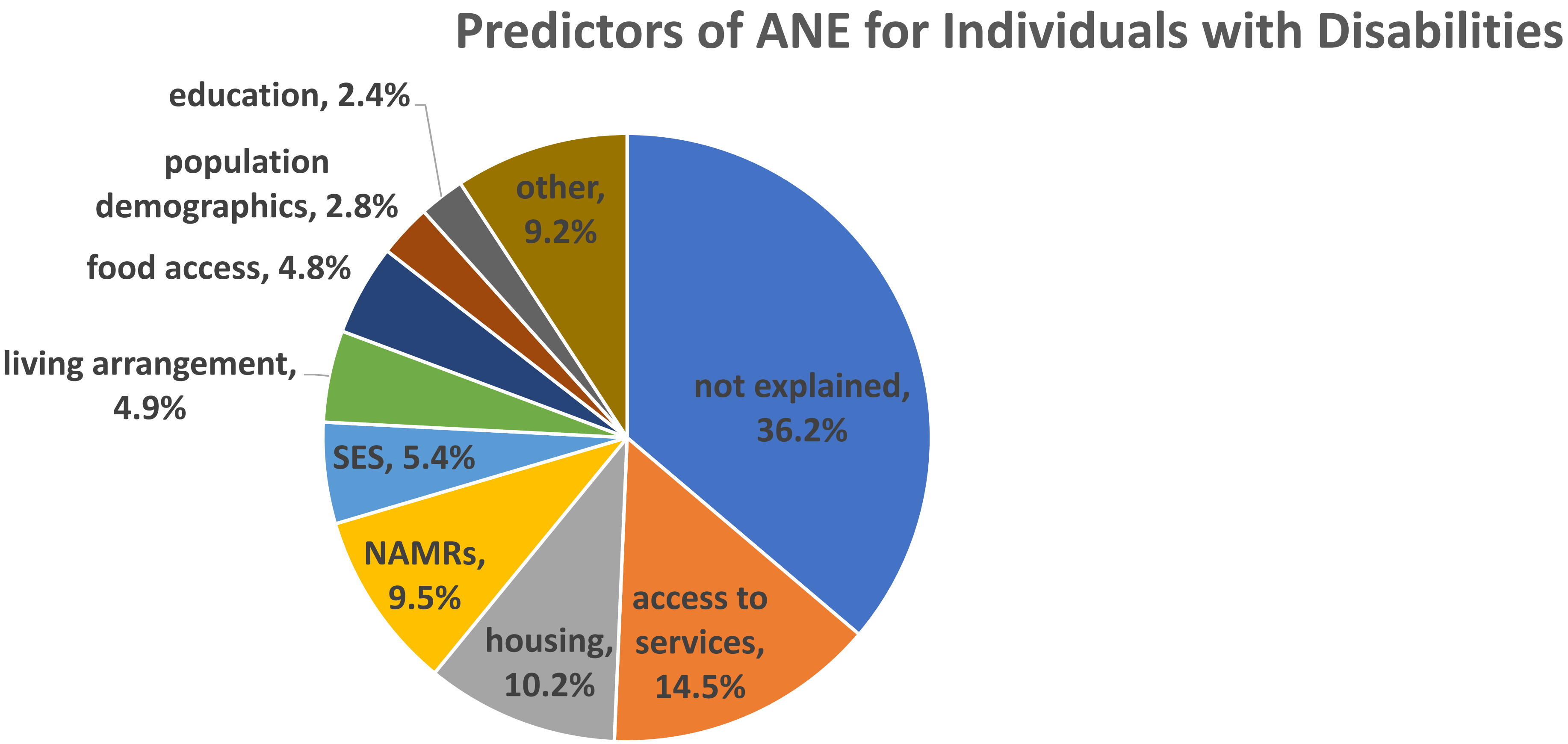
Model Target: Any type of ANE



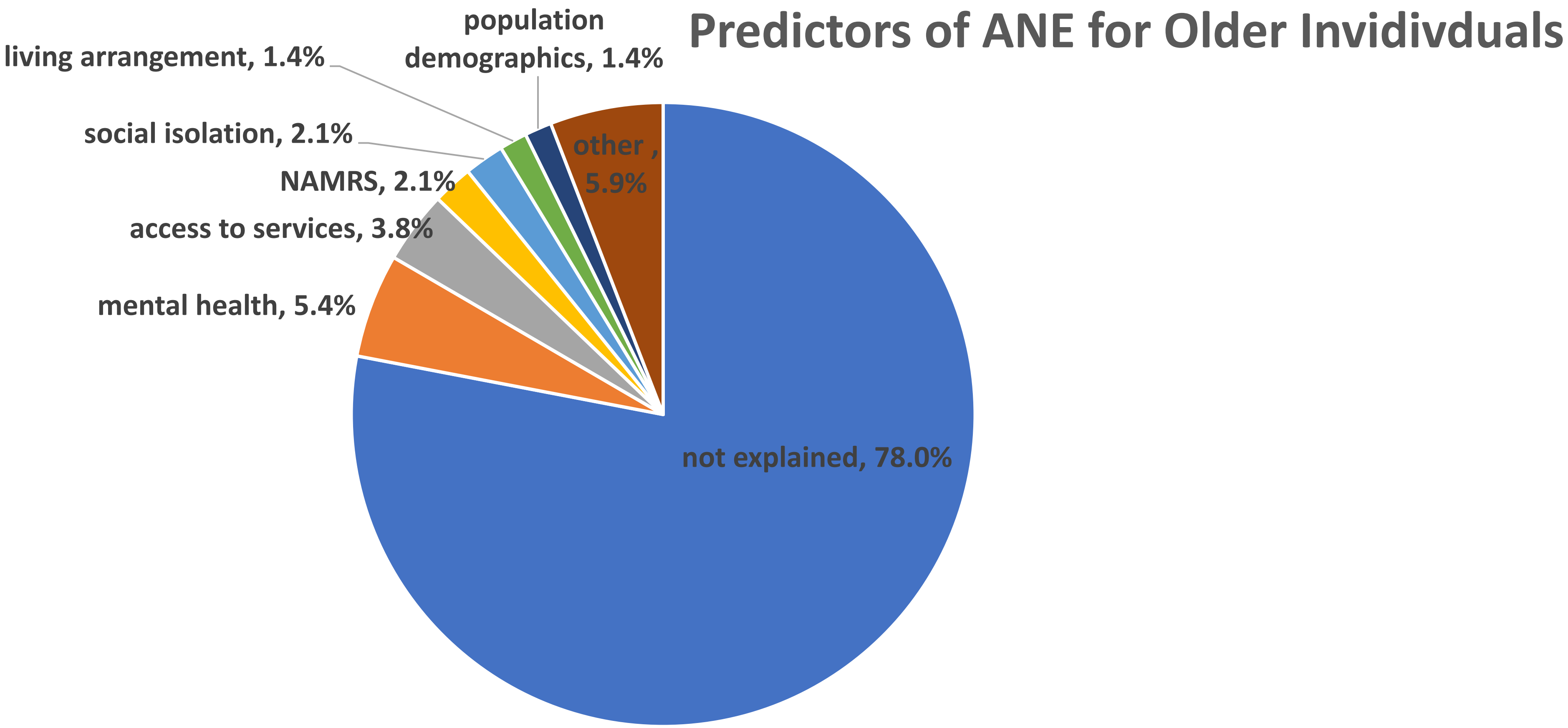
Model Target: Self-Neglect Only



Model Target: Adults with Disabilities



Model Target: Older Adults (only)



Key Findings

- These analyses aimed to elucidate what community factors predict ANE – specifically the annual rate of growth in ANE.
  - As expected, the features (or independent variables) “weigh” in differently depending on the target:
    - ❖All types of ANE ⟷ Employment, housing and health
    - ❖Self-neglect ⟷ Accessible community services
    - ❖Adult w/disability ⟷ Housing and income
    - ❖Older Adults ⟷ Mental health and social isolation

Researcher Implications

- **Conduct rapid studies**
  - For example, using the prepared analytics workflow of APS and community datasets, this project was able to conduct a study of the factors that explain self-neglect in a few days.
  - The use of a big data platform and machine learning algorithms allows for much more complex analyses, including multi-variate counterfactual studies.
- **Add additional historical and real-time datasets**
  - For example, researchers could add COVID-19 data from the CDC and other datasets to study the contributing impact of the Coronavirus on ANE.
- **Conduct community-level studies of adult maltreatment**

Policy Implications

- **Develop targeted policies that focus on the communities that need it most**
  - For example, identify which specific communities in a state need stronger policies to prevent housing crises for disabled adults, and focus limited policy making resources on engaging a more precise/targeted group of stakeholders.
- **Make cost-effective funding decisions**
  - For example, more precisely identify the communities that need more prevention and/or intervention support, first. Then use the data to identify the local agencies and community-based organizations that are best positioned and capable of addressing needs and/or building community assets. By knowing where to go first there are better assurances that funding constraints won't dilute the potential for impact; funding the communities that need it the most maximizes the likelihood for improvement.

Practitioner Implications

- **Develop more precise, targeted prevention and intervention strategies**
  - For example, ACS and IRS data are available at the Census Tract level, so it is possible to create current/up-to-date maps of hotspot communities. Additional datasets can help do the same thing at the county level. These insights could be used for more precise local capacity building, partnering with community-based organizations, targeted resource allocation, etc.
- **Implement real-time monitoring and evaluation**
  - For example, use NAMRS data to longitudinally track efforts in specific communities, as well as view longitudinal changes in ANE rates

Next Steps

- Report on county-level findings
  - Work with states/counties who want to implement this type of approach
- Additional county-level analytics
  - Alignment of APS clients' characteristics & overall community characteristics
- Individual-level predictive analytics
- Incorporate new data sources:
  - Medicare, Medicaid, etc.
  - Police/crime data – Uniform Crime Reporting (UCR)

Questions?

ACL is interested in opportunities to work with state and local partners.

For more information or interest in sharing state and/or local APS data, call or email a member of the project team:

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Contact Us

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