Document Title:	Defining Late-Life Poly-victimization and Identifying Associated Mental and Physical Health Symptoms and Mortality
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Document Number:	302238
Date Received:	September 2021
Award Number:	2017-VF-GX-0001

Defining Late-Life Poly-victimization and Identifying Associated Mental and Physical Health Symptoms and Mortality

Final Report

Funding Opportunity Number
NIJ-2017-11185
Submission Date
December 23, 2020

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PROJECT SUMMARY

This project used 5 years of investigation data from the Texas Department of Family and Protective Services, Adult Protective Services Division and the Center for Medicare Services to compare data driven and a priori literature based definitions of elder abuse polyvictimization (PV) in order to derive which best fits the data and assess whether these definitions (i.e. classifications) were associated with differential types of abuse (i.e. physical, neglect, sexual, psychological, financial), morbidity (i.e. anxiety, depression & dementia) and mortality. Structural equation modeling was used to explore the latent class definitions of PV while machine learning algorithms were used to maximize classification of participants into these groups based on victim and perpetrator demographics and APS investigation data. Logistic regressions were used to model the a priori defined PV types, the LCA derived classes and the individual abuse types with Center for Medicare Services health outcomes: death, depression, dementia and anxiety. The sample was majority female, white and English speaking. Dependency on others, others having access to the victims finances and victims with physical limitations were common sample characteristics. The most common confirmed abuse types were physical abuse (~35%) and exploitation (~32%). Approximately 50% of the confirmed perpetrators were the victims biological or step children. Regarding PV, 80% of the cases had a single type of abuse and a single perpetrator. Fifteen-percent had multiple types of abuse and a single perpetrator while a single type with multiple perpetrators (5%) and multiple types of abuse with multiple perpetrators were less common (<1%). A 2-class LCA model provided the best fit to the data and these classes were defined as high vulnerability (43%) and low vulnerability (57%) classes. The high vulnerability (HV) class was characterized by diminished cognition, others with access to the victim's finances, diminished physical ability, dependency on others for care and prior history of APS investigations including self-neglect. The perpetrators were more likely to be friends/caretakers. The HV category was also more likely to

have multiple types of abuse (OR = 1.69, 95% CI = [1.4, 1.9]), multiple perpetrators (OR = 2.5, 95% CI = [2.0, 3.3]) and multiple types with multiple perpetrators (OR = 4.4, 95% CI = [2.3, 9.0]). With respect to the observed counts of each type of abuse, category HV was related to higher counts of exploitation (OR = 2.6, 95% CI = [2.3, 2.9]), medical neglect (OR = 6.4, 95% CI = [5.1, 8.11]), mental health neglect (OR = 6.8, 95% CI = [3.8, 13.0], and physical neglect (OR = 4.1, 95% CI = [3.7, 4.6]). However, HV was related to lower counts of physical abuse (OR = 0.2, 95% CI = [0.17, 0.22]) and emotional abuse (OR = 0.25, 95% CI = [0.21, 0.29]). Multiple types of abuse versus all other PV a priori definitions was predicted by poor explanations of injury (OR = 2.6), limited social networks (OR = 1.7), hazardous living conditions (OR = 1.3) and violence or domestic violence in the home (OR = 1.2). Prior APS investigations (OR = 1.2), rapidly diminishing finances (OR = 1.2), client's cognitive function (OR = 1.1) and concerns about the client's finances (OR = 1.1) were predictive of PV with a single type of abuse and multiple perpetrators. Multiples types of abuse by multiple perpetrators was predicted by poor injury explanation (OR = 1.8), rapidly diminishing finances (OR = 1.5), concerns about the clients finances (OR = 1.2) and other current dangers (OR = 1.2). PV that included multiple types (single or multiple perpetrators) was associated with higher odds of death, depression and dementia. PV with a single type and multiple perpetrators was associated with higher odds of dementia, depression and anxiety. Multiple types and multiple perpetrators was associated with higher odds of death and dementia. Comparatively, the HV class was associated with higher odds of dementia (OR = 9.5), death (OR = 3.5), depression (OR = 2.2) and anxiety (OR = 1.8). For individual abuse types, exploitation, medical neglect, mental health neglect and physical neglect were all associated with higher odds of death, depression, dementia and anxiety. Physical and emotional abuse were associated with decreased odds of death, depression, dementia and anxiety.

PROJECT OBJECTIVES

Elder abuse (**EA**) is pervasive and traumatizing and necessitates a robust public health and criminal justice response. Approximately 30% of abused older adults suffer from multiple concurrent victimizations (i.e. poly-victimization) yet very little is known about this important sub-population.[1] Unlike the child abuse literature within which the term poly-victimization has been empirically defined and its relevance, reach and impact on mental and physical health established, little EA research has focused on defining poly-victimization and studying its related risks.[2]

Currently, EA poly-victimization is operationalized as 2 or more concurrent types of abuse despite lacking empirical evidence supporting this definition.[3,4] This operationalization ignores potentially important combinations of EA and related socioecological factor clusters that may be important for understanding the occurrence of poly-victimization, its health impact and effective prevention and intervention responses. Research is needed to facilitate the development and/or adoption of an evidence-based EA poly-victimization framework similar to those used to study the occurrence, health impact and social service response for child abuse and non-elderly domestic violence victimizations.[2]

The objective of this study is to utilize a large multi-year statewide Adult Protective Services (**APS**) dataset of confirmed EA cases to operationalize EA poly-victimization and assess associations with mental and physical health, mortality and prior exposure to violence. Informed by the child abuse and domestic violence poly-victimization frameworks, both exploratory and a priori perspectives to operationalizing EA poly-victimization will be implemented. Overall, this study explored a broad spectrum of EA occurrences and associations with mental and physical health, mortality.

PROBLEM STATEMENT

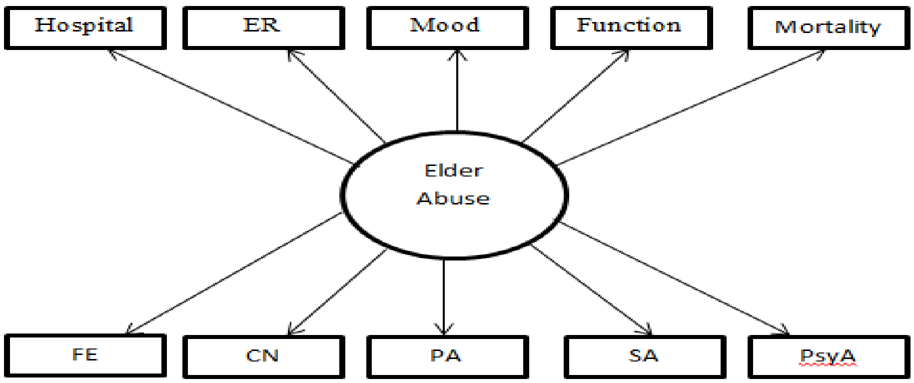
Late-life exposure to multiple forms of elder abuse (EA) and the association with physical health, mental health, mortality and history of violence exposure is grossly understudied.[2] Despite 30-50% of EA victims suffering more than one form of co-occurring abuse or multiple types of abuse in late-life,[1,4,5] there remains no evidence-based operational definition(s) or framework for studying poly-victimization in this population. An interest in describing various aspects of these types of elder abuse has existed for decades[6,7] and much contemporary elder abuse research continues to focus on characterizing the frequency, causes, and consequences of the various types of abuse.[8,9,10,11] This constrains the development of efficient detection and response strategies by social service and criminal justice agencies, leaving many victimized older adults at risk for negative health outcomes and long-term abuse.

LITERATURE REVIEW

Elder Abuse Prevalence and Mortality

EA has been widely conceptualized and studied as an aggregate term for multiple types of late-life violence.[12] Figure 1 below presents a simplistic visual model of EA and its relation to outcomes and individual types of EA (i.e. financial exploitation, caregiver neglect, physical abuse, sexual abuse, and psychological abuse). EA occurs when any single or repeated intentional behavior or omission of behavior, by a person in a position of “trust” with an older adult, causes harm to that older adult.[13] Harm includes injury, distress, discomfort and of course death. Epidemiologic studies report lifetime prevalence rates between 2%-11%[8] with deleterious consequences including increased depression,[14] functional decline,[15] emergency room visits,[16] hospital admissions[17] and 2-3 fold increases in early all-cause mortality compared to non-abused older adults.[18,19] Without hindrance, these inexcusable acts of violence and their consequences are expected to grow proportionately with the rapidly aging US and worldwide population.

Figure 1: Conceptual Model of EA, Consequences and Indicators



Note: Hospital = Hospital Admissions; ER = Emergency Room Visits; Mood = Increased Depression; Function = Physical Function Decline; FE = Financial Exploitation; CN = Caregiver Neglect; PA = Physical Abuse; SA = Sexual Abuse; PsyA = Psychological Abuse.

Sociocultural Context of EA

Like other acts of violence, EA occurs within a socioecological context. Older victims present with vulnerabilities (i.e. risk factors) that perpetrators exploit for some intrinsic benefit whether it be financial gain, power or some other advantage (microsystem). These acts are often carried out and concealed through the perpetrator disrupting the victim's interactions with outside social connections and support systems (mesosystem).[20] While EA and its individual types of abuse share related risks across the socioecological context,[21] there is now sufficient evidence worldwide demonstrating that some risks are more strongly associated with specific forms of abuse.[22] These findings have encouraged more critical assessments of individual types of abuse to explain the associations between EA, morbidity, and mortality.[2,4,23]

Differential Socioecological Factors and Individual Abuse Types

EA types occur at different rates with financial exploitation, neglect and emotional abuse occurring most often.[8,22] Epidemiologic studies across the countries show significant variation between socioecological factors EA types. Beginning with victim vulnerabilities the following associations are reported: 1) functional dependence with financial exploitation, psychological abuse[8,24,25,26,27] and physical abuse,[28] 2) poor physical health with financial exploitation[26,29,30] and neglect,[8,24,25,31,32] 3) poor mental health with physical[28,30] and psychological abuse,[29] 4); financial problems with financial exploitation,[27] emotional abuse, physical abuse[25] and neglect,[8] 5) race/ethnicity with financial exploitation and psychological abuse[26,33] and 6) low socioeconomic status with all four types of abuse.[22] Perpetrators characteristics also vary with abuse type with mental illness associated with physical[34,35] and psychological abuse[36] and substance abuse associated with financial exploitation and psychological abuse.[22] At the relationship level, physical and psychological abuse are more likely to occur in dyads in which the abuse is the spouse/partner of the older victim.[24,25,26,31,32,37] Socially, having poor social support networks is associated with all forms of abuse whereas victim and perpetrator cohabitation is associated with physical abuse and financial exploitation. [22]

Individual Abuse Types and Related Health Risks

While EA has been associated with specific morbidity and mortality indicators, individual studies of the EA types offer explanation for some of the associations. In two studies Dong et al., found that among the individual types of EA, neglect had the largest association with annual emergency department visits[16] and hospitalizations[3] followed by psychological abuse and financial exploitation, respectively. These studies controlled for various shared and unshared risk factors suggesting that the type of abuse was a significant contributor to the association. However, the hospitalization study found that those with 2 or more types of abuse (i.e. poly-victimization) had higher annual rates of admission compared to the individual types of abuse.[3]

A 5-year all-cause mortality study conducted by Burnett et al. 2016, reported differential mortality between neglect, financial exploitation, psychological abuse, physical abuse and cases with 2 or more types of abuse (i.e. poly-victimization). Similar to the healthcare utilization studies, neglect was associated with the highest 5-year all-cause mortality rate. However, in this study financial exploitation had the second highest mortality rate and was not significantly different from neglect. Interestingly, those with 2 or more types of abuse (i.e. poly-victimization) had the third highest mortality followed by psychological abuse and physical abuse respectively.[4]

These studies did not report the actual number of abuse types or the combinations of abuse types which may explain the inconsistent findings related to poly-victimization.

Evidence of EA Poly-Victimization

EA poly-victimization is grossly understudied and lacks an empirical framework despite estimates suggesting that between 8.9% and 52% of EA incidents include multiple concurrent types of abuse.[1,3,4,5,38,39] The current operational definition of EA poly-victimization focuses on occurrences where there are 2 or more concurrent forms of abuse.[2,3,4] This definition lacks precision and does not account for the potential importance of different abuse combinations.

Cumulative victimizations is a strong predictor of mental and physical health problems in victimized children and non-elderly adults.[2] Evidence within the EA field suggests that the combination of abuse types is also of value. In a study by Mouton et al. (2005), women reporting both physical and verbal abuse (i.e. poly-victimization) at baseline had more depressive symptoms and poorer cognitive function at baseline. However, at 3-years only verbal abuse remained associated with both depression and cognitive decline.[38] Using the same data, Baker et al. (2005) reported that exposure to physical abuse was the most reliable predictor of mortality followed by exposure to both physical and verbal abuse.[39] Jackson and Hafemeister, (2012) have also demonstrated that exposure of financial exploitation with neglect and/or physical abuse was associated with longer exposure to abuse, greater financial loss, co-habitation with the abuser and poorer self-reported health by the victims compared to those only exposed to financial exploitation.[23] These studies urge the development of an EA poly-victimization framework for studying multiple forms of abuse with two main goals: 1) identify data-supported operational definitions of EA-poly-victimization and 2) apply valuation to the operational definitions based on their rate of occurrence, related risks with trauma factors such as morbidity and mortality and their capability to inform social and criminal justice strategies for response and prevention.

Evidence Based Poly-victimization Frameworks

Poly-victimization, as it applies to interpersonal violence, is a term coined by Finkelhor and colleagues,[40] and later elaborated upon as part of the language of the "web of violence" framework proposed by Sherry Hamby and John Grych.[41] In this context, poly-victimization is described broadly as the co-occurrence of multiple types of victimization and the interrelationships between them.[41] In this framework, poly-victimization is distinct from revictimization, which refers to ongoing patterns of victimization over time. The goal of this terminology is to highlight the fact that different types of victimizations occur with different relevance, impact and response needs.[41]

Poly-victimization may be operationalized in multiple ways and has been done so most prominently within the literature on violence experienced by children and adolescents.[40,42,43,44,45,46] Additional examples of the poly-victimization framework, or components of it, can also be found, albeit less frequently, in the literature on interpersonal violence among young and middle-aged adults.[47,48,49,50] The most commonly occurring operationalizations are detailed below.

Dichotomous Operationalizations

Dichotomous measures of exposure to poly-victimization group victims based on some number of types of victimization (i.e. 2 or more versus 1 is the most common). For example, Sabina and Straus (2008) defined poly-victimization as 2 or more versus 3 or more types of dating violence and found that both operationalizations were more strongly associated with negative outcomes than any single type of victimization.[50]

Summative Count Operationalizations

There are several variations on summative count operationalizations. One variation is to count the number of occasions in which one or more types of victimization was experienced - without regard for the number of types that occurred at any given incident.[40,45,47] In this operationalization, physical abuse and emotional abuse, if occurring simultaneously, would count as one single incident. A second variation is to count the number of victimization types experienced - without regard for their co-occurrence with other types.[43,45] In this operationalization, physical abuse and emotional abuse, even if occurring simultaneously, would count as experiencing two different types of victimization. A third variation is to count victimization types / incidents with weights (a constant) added to the count for people who experience certain types of victimization thought to be more severe.[45]

As an example, Finkelhor and colleagues (2005) compared the association between 4 different operationalizations of poly-victimization and traumatic symptomatology (anger / aggression, depression, and anxiety) using data from a sample of 2,030 youth that participated in the Developmental Victimization Survey (DVS).[45] Specifically, they operationalized poly-victimization using: (1) A count of the number of victimization types experienced, (2) A count of the number of occasions in which one or more types of victimization was experienced, (3) A count of victimization types / incidents with weights added to the count for people who experience certain types of victimization thought to be more severe, and (4) A count of the number of victimization types experienced from a reduced set of possible types (34 vs. 12). The authors found evidence that poly-victimization was strongly associated with traumatic symptomatology, and that all operationalizations produced roughly similar results.[45]

Data-Driven Operationalizations

Data-driven operationalizations are generated from the data using some type of statistical or algorithmic procedure. In these circumstances the researcher my only have some vague idea of what the final criteria for poly-victimization will be. As with the summative count operationalizations, there are multiple variations on empirically deriving poly-victimization operationalizations. One method is to use one of the summative counts described above, and then create dichotomous exposure groups by splitting at the mean or median of that count.[43] Similarly, groups may be derived from quantiles of a summative count measures of exposure to victimization types / incidents.[40,43] In a third variation, Adams and colleagues (2016) used latent class analysis (LCA) to empirically derive trauma profiles from a sample of 3,485 youth with confirmed exposure to trauma. This method resulted in a 5-group classification of participants. The groups differed in their relative concentrations of traumatic events experienced, and the number of developmental periods over which the traumatic events occurred. Their results suggest that youth who experience greater numbers of traumatic event types are at greater risk for psychological distress and other negative health and social outcomes.[42]

Additional variations

It should be noted that all of the above methods may be altered in terms of the breadth and number of potential incident types measured,[45,51] the span of time over which potential incident types are measured,[43,47,52] the frequency with which potential incident types are measured within a given timespan,[50] the severity of each potential incident within broad incident type,[50,53] the number and type of perpetrators, and the interaction between all of these attributes.[41] Additionally, all of these dynamics of the violence experienced occur within social and environmental contexts that influence their etiology and effects.[41]

Lessons learned from other interpersonal violence fields

In all of the literature described above, compared to monovictimization (i.e. one type of victimization) measures, virtually all operationalizations of poly-victimization were more highly associated with negative outcomes (predominantly mental health outcomes). However, few of these operationalizations have been directly compared with one another. Therefore, there is currently insufficient evidence to promote any particular operationalization above the others.

New Definitions of EA Poly-victimization

Work completed by Ramsey-Klawsnik et al. (2014) supports the notion that multiple forms of abuse co-occur in approximately one-third of confirmed abuse cases and in a variety of ways. As a result of their work they define EA poly-victimization as an act in which a person 60+ years of age is "harmed through multiple co-occurring or sequential types of elder abuse by one or more perpetrators or when the older adult experiences one type of abuse perpetrated by multiple others with whom the older adult has a personal, professional or care-recipient relationship in which there is a societal expectation of trust."[1] This definition is sufficiently broad and likely captures many of the conceptual forms of EA poly-victimization, but there still remains no evidence regarding which of the many forms are 1) most common in EA, 2) predictive of worse trauma indicators and 3) associated with factors across the socioecological context that are amenable to multi-level social and criminal justice interventions.

Building an EA Poly-Victimization Framework

Acts of violence are often interrelated.[54] Child abuse and domestic violence victims often suffer multiple forms of co-occurring abuse which may have similar etiologies and may arise from similar victim, perpetrator and contextual characteristics.[54] As such, specific victim vulnerabilities may increase the risk for repeat victimizations of a single abuse types as well as increase the likelihood of multiple forms of co-occurring abuse or repeat victimization with new types of abuse. Building evidence for a framework in which poly-victimization occurs and is associated with socioecological variables and morbidity and mortality is critical for studying and intervening in this prevalent and important sub-population of EA victims.

Study Rationale and Hypotheses

Establishing a framework for understanding the relevance and impact of different EA poly-victimization operational definitions is an important paradigm shift in EA research; a similar shift that facilitated progress in understanding the complexities of child abuse[40,45] and domestic violence.[2] This proposal seeks to advance what is known about EA poly-victimization by drawing on existing evidence-informed frameworks and definitions from the child abuse and domestic violence literature, but also exploring the potential for other relevant and impactful definitions of EA poly-victimization. The specific goals of the this study are to: 1) use 5-years of statewide confirmed EA victimizations to identify data-driven and a priori defined EA poly-victimization operational definitions, 2) use a socioecological framework to characterize the victim, perpetrator and relationship associated with data-supported operational definitions and 3) determine whether varied EA poly-victimization violence patterns are differentially associated with mental health, physical health and mortality. Different types of EA can be differentiated by risk factors that underlie mental health, physical health and mortality thus, we hypothesize that a poly-victimization framework that accounts for combinations of abuse and number of perpetrators will be more strongly associated with mental health, physical health and mortality compared to an operational definition(s) that do not account for specific combinations.

METHODS

Research Setting

This study was carried out in Houston, Texas and consisted of a large secondary data analysis of statewide Texas Adult Protective Services administrative investigational records of confirmed elder abuse cases and morbidity and mortality outcomes from the Center of Medicare Services data.

Study Population

Only adults 65 years of age and older were included in this study. Eligible data for aims 1-3 consisted of archived APS EA allegations (i.e. emotional/psychological abuse, neglect, financial exploitation, physical abuse, sexual abuse), both community-dwelling and in residential care facilities, within the timeframe of January 1, 2014 and December 31, 2018. All races/ethnicities and genders were included.

Collaborations

Texas Department of Family and Protective Services – Division of Adult Protective Services (APS)

This oversight agency for the state of Texas investigates domestic abuse and neglect of adults aged 18 and older. APS receives referrals from other community agencies, health care providers, family, friends, and the clients themselves at the regional APS agencies and at the state office in Austin. Each reported allegation requires the initiation of an investigation within 24 hours of intake. Each investigation requires a face to face visit to the location where the potential client is living to collect and record evidence for substantiating the alleged circumstances. Face to face visits are prioritized according to severity of the allegation stated in the referral. The most serious, priority one, cases are visited within 24 hours, priority two cases are visited within 3 days, priority three cases are visited within 7 days and priority 4 cases require a visit within 14 days.[55] APS workers conduct in-home and facility investigations and deem a case valid, invalid, or unable to be determined; intervention is provided for between 75% and 85% of the cases that are validated.

Data Sources

Texas APS Administrative Data

Texas APS has an electronic data system which houses their case investigation information for all confirmed and non-confirmed cases of EA. Table 1 provides a comprehensive list of the 57 predictors obtained from APS records.

Abuse Definitions

The Texas Human Resource code Section 48.002 [a] defines the different types of EA investigated by Texas APS.[56] For purposes of this study, these include: 1) Emotional/verbal abuse - “any use of verbal communication or other behavior to humiliate, intimidate, vilify, degrade, or threaten harm”; 2) Physical abuse - “abuse with resulting physical or emotional harm or pain to an elderly person or adult with a disability by the person’s caretaker, family member, or other individual who has an ongoing relationship with the person”; 3) Financial exploitation - “the illegal or improper act or process of a caretaker, family member, or other individual who has an ongoing relationship with a person age 65 or older or an adult with a disability”; and 4) Caregiver neglect - “the failure of a caretaker to provide the goods and/or services, including medical services that are necessary to avoid physical or emotional harm or pain.” [56]

Predictors

Texas APS mandates statewide utilization of the SHIELD investigational protocol to guide all reported investigations of abuse, neglect and exploitation that meet the statute criteria. This protocol includes collection of demographic data, vulnerability factors, danger factors and factors associated with risk of recidivism. This information is used to reach a determination of abuse, neglect and/or exploitation as well as guide protective service planning. The Safety Assessment consists of 7 items which address vulnerabilities to abuse, neglect and exploitation. It also includes 13 factors that assess for dangers that heighten the suspicion of abuse, neglect and exploitation and risk for poor outcomes. The Risk of Recidivism Assessment (RORA) is 28 items and evaluates the client's past history of APS investigations and current factors that may be associated with heightened risk of experiencing recurrent abuse, neglect and exploitation if not addressed.

Center for Medicare Services Health and Mortality Data

The University of Texas School of Public Health Data Repository

Health and mortality related data were obtained from the University of Texas School of Public Health Data/Blue Cross Blue Shield of Texas (UTSPH/BCBSTX) Payment System and Policies Research Program. The mission of the UTSPH/BCBSTX program is to foster research and inform the public, academia and other constituents about health care costs and utilization with the goal of contributing to the discussion on improving efficiency and controlling health care costs in Texas and in the nation. The data are available for use in projects that relate to the program's mission in academic and public policy research, but not for commercial or competitive purposes. For this study, we provided UTSPH/BCBSTX program APS data for linkage.

Data Linkage

An APS dataset of validated was provided to the UTSPH/BCBSTX research program for linkage. The UTSPH/BCBSTX has an internal process for linking data based on first, middle and last name, date of birth, city, zip code, gender, ethnicity, Medicare number, Medicaid number and social security number. However, the APS data does not contain social security number or the Medicare and Medicaid numbers. Therefore, only age, race, gender, date of birth, zip code and first and last name were securely shared through Securstor were provided to UTSPH/BCBSTX for linkage. We recognize that this may result in limitations to reliability of the linkage.

UTSPH/BCBSTX Data Requests

We requested data on whether or not the individuals have ICD-10 codes for specific medical conditions. These are depression, anxiety Alzheimer's disease related dementia. We also requested data on mortality. The time frame for the data request will be 2014-2017. The 2019 CMS data were not available at the time of the request.

UTSPH/BCBSTX Data Use

All analyses between the predictors and outcomes were conducted within the SPH data platform. Since the variables were provided were not our patients, our team was not allowed to access the identifiable data. We provided the data and the SAS code for the respective analyses of the CMS data. The UTSPH/BCBSTX group conducted the matching and ran the analyses within the platform. We were then provided de-identified results on the selected outcomes.

Power/Sample Size Considerations

Traditional power and sample size calculations, while useful in the Frequentist context of null hypothesis testing, are uninformative in the present context of exploring large datasets using machine learning and latent variable modeling. Given sample sizes in the thousands, established conceptualizations of statistical power are of diminished importance even in the context of latent variable modeling, where favorable sample sizes are typically described as including hundreds of individuals[57]. Rather than evaluating statistical significance, machine learning algorithms are primarily concerned with maximizing metrics such as classification accuracy and area under the receiver operating characteristic curve (AUROC) while avoiding overfitting data (achieving a model that is too slavish to a training set that will not perform well on novel data)[58]. In addition, while the present data consists of a vastly greater number of participants than variables, two of the machine learning algorithms that will be utilized in the present study (component-wise gradient boosting and penalized generalized linear modeling) are capable of handling data with more predictors than participants (so-called "$p > n$" problems), further diminishing the role of sample size considerations in these analyses.

Data Preparation

Before analysis, the data was cleaned in a structured, reproducible manner. First, some hands-on cleaning was required in the originally provided Excel files: primarily, header rows were removed for data transport. Each sheet of each Excel file was then loaded and merged on matching characteristics (i.e., person id) to create one large file containing all data. This data set required additional cleaning: variables were declared numeric or categorical, summary counts of confirmed and unconfirmed cases were generated, data from the perpetrators was merged in from additionally provided Excel files. Inconsistencies in categorical variable labeling were then resolved. The data set was then reduced in two steps by first removing the unconfirmed allegations and second removing the cases that only related to self-neglect. Data were then split into two sets. First, a version of the data with only one observation per person was split for analyses that were not equipped to handle multilevel data. The second version of the data retained these observations for the analyses that were equipped to handle multilevel data. This split only affected 4% of the observations in the data, as only 223 of 5,492 observations (after reducing the data) were from individuals already represented in the data.

Analytic Strategy

The maximum available predictor space for the present analyses consisted of 57 variables that may be characterized in three groupings: (1) demographics: age, sex, race, ethnicity, living situation, marital status, primary language, citizenship, and permanent resident status; (2) vulnerability and danger items from the Safety Assessment; and (3) the 28 items from the RORA. An exhaustive list of these predictors, including observed frequencies and measures of central tendency, are provided in Table 1. Further examination of the items demonstrated differential responding across these theoretically similar items, indicating that the different measures may provide different levels of refinement or magnitude with respect to these factors; as such, both were retained in analyses.

The analytic strategy for defining PV followed two paths: (1) a data-driven approach and (2) a theory-driven exploration of an *a priori* definition. The first path utilized methodologies that aim to cluster observations into a smaller set of classes, while the second path utilized machine learning algorithms that can predict pre-defined outcomes from a potentially very large set of variables. The pre-defined categories of PV were: (1) Single Type & Single Perpetrator (STP); (2) Multiple Types / Single Perpetrator (MT); (3) Single Type / Multiple Perpetrators (MP); and (4) Multiple Types / Multiple Perpetrators (MTMP). Another set of variables provided a second potential window into PV: a count of each type of observed confirmed allegations: (1) exploitation, (2) physical abuse, (3) emotional abuse, (4) sexual abuse, (5) physical neglect, (6) medical neglect, and (7) mental health neglect. To establish a link between the methods of the first pathway and PV, the clustered observations were compared to observed outcomes from the second pathway (i.e., pre-defined PV; observed confirmed allegation counts). Table 2 provides a detailed account of the victimization information in the present data.

Latent Class Analysis

Latent Class Analysis (LCA), a type of Structural Equation Modeling (SEM), was used to investigate the degree to which individuals may be probabilistically categorized into hypothesis-driven unmeasured discrete classes of elder abuse victimization.[59,60,61] Information criteria (e.g., AIC, BIC), entropy, and Lo-Mendell-Rubin adjusted likelihood ratio test (LMR-LRT) were used to determine the model fit and the optimal number of classes. Probabilities of class membership based on responses given for each care tool item in the best-fitting models were summarized graphically for critical interpretation.[62] LCA was conducted in MPlus v. 8.4. All predictors were converted to dichotomous two-level factors, generally splitting response options indicating a non-existent vs. existent factor for victimization (e.g., RORA Item 17, concerns about the client's financial situation, describes three options: (a) none, (b) poverty/insufficient resources, and (c) money mismanagement was converted to (a) vs a second option that included both (b) and (c). There were a few variables across measures that reflected similar constructs; for example, Vulnerability Factor 3 and RORA Item 18 both reflect others having access to the client's finances. Additional data cleaning for use in LCA required a small amount of imputation for some of the demographic characteristics: unknown values for sex (26 observations), ethnicity (281 observations), and primary language (101 observations) were imputed to the most frequent category (female, not Hispanic, and English, respectively). One predictor, living situation, was excluded from the LCA model due to convergence issues in estimation.

The latent classes (from LCA) were then compared to the *a priori* conceptualizations of polyvictimization (PV) as well as the observed counts of the different types of victimization. Logistic regression was used to model the two-class solution as a function of one *a priori* PV type or the observed count of one type of victimization.

Supervised Machine Learning

An applied machine learning approach for model building and variable selection was used to predict the *a priori* PV categories. This approach has demonstrated effective performance in prior research (Bauer et al., 2019; Suchting, Gowin, Green, Walss-Bass, & Lane, 2018; Suchting, Hebert, Ma, Kendzor, & Businelle, 2019; Walss-Bass, Suchting, Olvera, & Williamson, 2018). The component-wise gradient boosting (CGB) algorithm was used to build a penalized linear model upwards by iteratively fitting the outcome to the entire set of predictors, dummy-coded where necessary (Hofner, Mayr, Robinzonov, & Schmid, 2014). The R package *mboost*[63] was used to perform CGB. The algorithm may be employed on various data structures, from small datasets of only a few variables and participants, to large, "high-dimensional" data where there may be more variables than observations available. In its first iteration, the algorithm identifies the one predictor that best fits that outcome. Each of the subsequent iterations then identifies the one predictor that best fits the residual of the previous iteration. The algorithm repeats until it reaches a *k*-fold cross-validated stopping criterion, chosen via averaging across ten training/test splits of the data. CGB allows for the inclusion of random effects to account for multilevel data (here, a random intercept for repeated observations). This aspect is unique among machine learning algorithms, and it allows cross-validation to occur across individuals. An overall metric describing the performance of the boosted model was provided by the area under the receiver operating characteristic curve (AUC). The variables selected by the mboost algorithm were then put into an unpenalized generalized estimating equation (GEE) model to provide an exploratory idea as to the magnitude of the unpenalized coefficients; however, it must be emphasized that these are purely exploratory in that coefficients generated following a variable selection process are biased, and resulting *p*-values are speculative. Results from both the mboost algorithm and the non-penalized follow-up GEE models, each with a dichotomous outcome, follow from the results that would be derived via logistic regression: model coefficients indicate the log odds of the outcome for a one unit increase in the predictor, and odds ratios provide an index of the increase in the odds of the outcome for every one unit increase in the predictor.

Results

Descriptive Statistics

Table 1 provides a complete account of the descriptive statistics for the predictors in this study. The present sample was over half female (65.10%), non-Hispanic (70.15%), and white (79.80%). Individuals were predominantly English speaking (89.99%) that lived alone (77.85%). Less than half were currently married (30.50%). Most Vulnerability Factors were present in at least 25% of cases, save two that were relatively rare (limited support network: 9.41%; mental health problem/drug dependency: 5.11%). The most prevalent Vulnerability Factor was being dependent on another person for care (38.68%). Danger Factors were relatively rare, with no given factor being reported in more than 5% of cases. The most prevalent Danger Factor was suspected violence in home. Approximately one-third of the RORAs administered to clients described having one or more previous APS investigations. The most prevalent factor identified by the RORA for a current investigation was having other people with access to finances (42.65%). Of the client characteristics described by the RORA, physical limitations were most common (43.35%), followed by concerns about client functioning (25.28%).

Table 2 describes the summary statistics regarding victimization in the present sample. Most cases were characterized as having one perpetrator and one type of victimization (78.38%). Multiple types of victimization were found in 15.03% of cases, with multiple perpetrators being somewhat uncommon (5.69%) and both multiple types & multiple perpetrators being rare (0.89%). Physical abuse was the most common type of victimization (34.55%), followed by exploitation

(32.20%). In about half of all cases (48.70%), the perpetrator(s) included a son, daughter, and/or step-child.

Latent Class Analysis

Solutions for two through five classes were generated from the available predictors in the model. The three-class solution demonstrated lower BIC, adjusted BIC, and higher entropy than the 2-class solution, and both demonstrated a significant LMR-LRT. Higher-numbered class solutions performed worse. When examining the probabilities of classification across items, 2 of the classes in the 3-class solution were nearly identical save for the questions regarding prior APS investigations: one category had them, the other did not. This difference was of little theoretical relevance with respect to PV; for parsimony, the two-class solution was favored for further interpretation and comparison to the *a priori* PV outcome. Graphical examination of the two-class solution (Figure 2) revealed a pattern differentiating the classes. The first class (n = 2274; 43.1%) demonstrated greater vulnerability with respect to functional and clinical status across many of the variables, similar on some others, and not better on any of them. The second class (n = 2995; 56.9%) demonstrated relatively better functional and clinical status. Hereafter the LCA-derived classes are termed “Higher Vulnerability” (H) and “Lower Vulnerability” (L).

As shown in Figure 2, there were larger differences for some predictors relative to the others. The largest differences were in (1) Vulnerability Factor 7: “The alleged victim/client is dependent on another person for care.” (H: 75.9% vs. L: 10.2% probability of endorsement; +65.7%), (2) RORA Item 18: “Other person has access to the client’s finances” (H: 74.0% vs. L: 18.7%; +55.3%), and (3) Vulnerability Factor 2: “Client has diminished cognitive functioning” (H: 55.9% vs. L: 2.8%; =53.1%). This pattern was pervasive across the predictors. Small differences in probability were found for most demographic indices (save age and citizenship status), Danger Factors, and several face-valid RORA Items, particularly 21 (service refusal) and 15 (abuse by other; a condition of the investigation).

As with any data-driven clustering technique, ascribing conceptualizations of PV to the LCA-derived classes was a primary challenge. As noted, the most readily apparent distinction was in that the classes mostly appeared to reflect differences in client vulnerability. To further investigate the relationship between these classes and PV, each observation was probabilistically assigned to one of the two categories, and a series of single-predictor logistic regressions modeled the two-class LCA as a function of (1) the *a priori*, theory-defined PV categories and (2) the observed counts of each type of abuse.

With respect to the *a priori* definitions of PV, those experiencing multiple types of victimization, multiple perpetrators, or both were all more likely to be in the H category (multiple types: OR = 1.68, 95% CI = [1.44, 1.93]; multiple perpetrator: OR = 2.54, 95% CI = [1.99, 3.25]); multiple types & perpetrators: OR = 4.36, 95% CI = [2.29, 9.01]. With respect to the observed counts of each type of abuse, category H was related to higher counts of exploitation (OR = 2.61, 95% CI = [2.34, 2.91]), medical neglect (OR = 6.38, 95% CI = [5.06, 8.15]), mental health neglect (OR = 6.75, 95% CI = [3.75, 12.98], and physical neglect (OR = 4.10, 95% CI = [3.67, 4.60]). However, H was related to lower counts of physical abuse (OR = 0.19, 95% CI = [0.17, 0.22]) and emotional abuse (OR = 0.25, 95% CI = [0.21, 0.29]). Sexual abuse was not related to the two-category outcome, likely due to its rarity (0.22% of observations, none with a higher count than one). The overall pattern demonstrates that although the H category was related to higher vulnerability in terms of cognition, physical limitations, and financial access, the nature of the victimization was typically exploitative or neglectful. Conversely, the victimization in the L category may be directly characterized as abusive. The cumulative evidence here supports the notion that PV may be best characterized by dependency, neglect, and exploitation, rather than abuse.

Supervised Machine Learning - Component-Wise Gradient Boosting

The CGB algorithm was used to derive models of each *a priori* conceptualization of polyvictimization: multiple types, multiple perpetrators, or multiple of each, from the entire set of 56 predictors (73 after dummy coding categorical variables). The optimal number of boosting iterations was determined by 10-fold cross-validation with a shrinkage parameter set to the default *nu* = 0.1. Results from all three models, including penalized coefficients and odds ratios derived from the mboost algorithm as well as the biased coefficients, odds ratios, and p-values from the non-penalized follow-up model, are provided in Table 3.

The model predicting cases with multiple types (MT) of victimization (vs. all other observations) selected 19 of the 73 predictors (after dummy coding), and demonstrated high AUC (0.969). The predictors with the lowest speculative *p*-values were Danger Factor 10 (domestic/family violence suspected in the home), Vulnerability Factor 6 (client has diminished physical functioning), and Vulnerability Factor 1 (client has a limited formal/informal support network). The algorithm did not select any other Vulnerability Factors. The algorithm also selected 3 other Danger Factors, 8 items from the RORA, and a few demographic variables. Most predictors indicated higher odds of experiencing MT of victimization except the demographic variables: a marital status that was unknown or never married; a primary language of English, and living on one's own.

The model predicting cases with multiple perpetrators (MP), but only one type of victimization (vs. all other observations) selected 13 of the 73 predictors and demonstrated substantially lower AUC (0.671). The predictors with the lowest speculative *p*-values were having widowed marital status, RORA Item 19 (at least one identifiable perpetrator, such as a caretaker), and Vulnerability Factor 3 (another person having access to the client's finances). The algorithm selected one other Vulnerability Factor, two Danger Factors, three other RORA items, and a few demographic variables. As with the MT model, the variables related to lower odds of having MP were demographic in nature: female sex, black race, and married marital status.

Finally, the model predicting cases with both multiple types and predictors (MTP) selected 12 of the 73 predictors and demonstrated average AUC (0.746). The predictors with the lowest speculative *p*-values were RORA Item 14 (self-neglect implicated as part of the case, over and above the multiple other types and perpetrators), widowed marital status, and RORA Item 17 (concerns about the client's financial situation). Four Danger Factors, three other RORA Items, and two demographic predictors were selected. No Vulnerability Factors were selected for the MTP model. Only married marital status was related to lower odds of having multiple types and perpetrators.

A set of identifying information was provided to a collaborative state institution with access to Medicare data. This effort was able to match 3,668 individuals to data for four individual-level dichotomous outcomes: present versus absent for (1) death, (2) depression, (3) anxiety, and (4) dementia. In unique models, logistic regression modeled each of these individual-level outcomes as a function of one PV classification variable. These predictors were from one of the three a priori classifications (multiple types/perpetrators/both) or the grouping variable identified via LCA.

Center for Medicare Services Data: Morbidity and Mortality

A set of identifying information was provided to a collaborative state institution with access to Medicare data. This effort was able to match 3,668 individuals to data for four individual-level dichotomous outcomes: present versus absent for (1) death, (2) depression, (3) anxiety, and (4)

dementia. In unique models, logistic regression modeled each of these individual-level outcomes as a function of one polyvictimization classification variable. These predictors were from one of the three *a priori* classifications (multiple types/perpetrators/both) or the grouping variable identified via LCA. The outcomes were then fit as a function of the raw counts of each individual type of victimization (exploitation, physical abuse, physical neglect, emotional abuse, sexual abuse, medical neglect, and mental health neglect).

Results for these analyses are summarized in Table X. For clarity, the findings for mortality are described here; interpretation for the other outcomes follows from the logic described here. Regarding mortality, the MT and MTP *a priori* polyvictimization classifications were related to a higher probability of death as recorded in the statewide database (MT: OR = 1.37, $p = 0.001$; MTP: OR = 2.14, $p = 0.008$). This relationship was not supported for multiple perpetrators (MP: OR = 1.18, $p = 0.256$). These results suggest that experiencing multiple types of victimization may be more influential toward mortality than experiencing victimization from multiple perpetrators. The Higher Vulnerability class identified via LCA was related to a higher probability of death (OR = 3.45, $p < 0.001$) relative to the Lower Vulnerability class. With respect to the individual types of victimization, higher counts of four types were related to higher probability of death (exploitation: OR = 1.19, $p = 0.007$; medical neglect: OR = 1.75, $p < 0.001$; mental health neglect: OR = 1.98, $p = 0.002$; physical neglect: OR = 1.60, $p < 0.001$). Conversely, higher counts of two types were related to lower probability of death (physical abuse: OR = 0.42, $p < 0.001$; emotional abuse: OR = 0.523, $p < 0.001$), and sexual abuse was not related ($p = 0.956$).

DISCUSSION

The child abuse literature and interpersonal violence fields have long-since demonstrated the importance of considering the presence of abuse polyvicitmization and its effects on the victims health and wellbeing.[42,45,] Although described in studies prior to 2012 (Mouton, 2004; Baker 2009), seeking to understand the term polyvictimization (PV) in the context of elder abuse and its association with late-life morbidity and mortality is a relatively new endeavor among elder abuse researchers and practitioners (Ramsey-Klawsnik, 2017).[1,3,5,38,39] Currently, there is no single definition of PV in elder abuse and giving a nod to the child abuse literature, there is good reason why applying a single definition could be more harmful than helpful. The current study sought to determine whether a single definition of PV or a more inclusive definition of PV, such as that provided by Ramsey-Klawnik and Heisler, 2014, should be considered.[1] Data-driven and literature-based PV definitions were explored in relation to prevalence, socioecological profiles and their associations with morbidity (i.e. depression, dementia and anxiety) and mortality. The findings from the current study suggest that multiple types of PV are related to poor health, mental health and mortality and therefore a broad and inclusive definition of PV is relevant. The details and implications of these new findings for the field are discussed below.

Like child abuse, the phenomenon of elder abuse presents in many different ways that include multiple co-occurring types, single type of abuse committed by multiple people, multiple types committed by a single person and other combinations[40,42,43,44,45,46]. Ramsey-Klawsnik and Heisler, 2014 define PV broadly as, “multiple co-occurring or sequential types of abuse by one or more perpetrators or when and older adult experiences one type of abuse by multiple others with whom the older adult has a personal, professional or care-recipient relationship in which there is a societal expectation of turs”.[1] This definition was based on the review of the literature and therefore includes the most commonly used definition of abuse which is “co-occurring abuse”.[2,3,4,38,39,83]

In the current study, we modeled this PV definition with the exception of sequential types of abuse. Our PV categories were multiple types of abuse by a single perpetrator (15.03%), single type of abuse by multiple perpetrators (5.69%), and multiple types of co-occurring abuse by multiple perpetrators (0.89%). This resulted in a prevalence of 22% of the confirmed cases fitting the definition of PV. Like general elder abuse, prevalence of PV varies across studies with the largest variation related to cognitive status of the victim. In a nationally representative study of cognitively intact older adults in the U.S., the prevalence of PV, based on self-report, was 1.7%.[64] Our study aligns closer with the study by Wiglesworth et al., 2010 which reported a PV prevalence of 31%.[65] Unlike Williams et al.,[64] both Wiglesworth et al., 2010[65] and the current study included individuals with diminished cognition which could explain the higher prevalence estimates. Additionally, the current study also included more PV types than the single "co-occurring" abuse definition and therefore, may have resulted in higher estimates than other studies such as Mouton et al., 2005 (PV prevalence, 8.8%)[38] and the Iowa Medicaid Waiver study (PV prevalence, 4%). Other reasons for the differing prevalence include the common differences in defining abuse, criteria for validation and sampling frames.

An important finding from the latent class analysis was that individuals considered to have high levels of vulnerability to abuse, neglect and exploitation had significantly higher odds of experiencing one of the three types of a priori defined PV and certain types of abuse. Demographically, the high vulnerability group was older in age and fewer were currently married. This coupled with the findings that these individuals were more likely to present with diminished cognition, higher medical burdens and diminished physical functioning helps explain why this group also had higher odds of being dependent on others. Dependency on others is a strong risk factor for all types of elder abuse.[8,24,25,26,27] This is often due to limited ability to carry out necessary basic and instrumental activities of daily living such as bathing, cooking, dressing and handling ones finances. Inability to carry out basic activities of daily living explains why individuals assigned to this class were more likely to be suffering from medical, mental health and physical neglect. In a national study of PV correlates based on "co-occurring" abuse, individuals with impaired activities of daily living has a 2.5 fold increase in the likelihood of PV.[64] Impairments in more instrumental activities of daily living such as financial management may explain why there was more access to the victim's finances in this class and why this class was strongly defined by financial exploitation. Numeracy is one of the first skills to diminish with cognitive decline, especially when related to dementia.[66] This results in the need for financial management support.

Interestingly, the odds of physical abuse and emotional abuse were less likely in this class, but this could be explained by the notion that many of the victims in this class did have cognitive declines and may not have been able to or were unwilling to self-report abuse. Moreover, the evidence of physical abuse could have dissipated by the time of the investigation or could have been masked by the aging process or signs and symptoms of the medical and physical neglect findings.

Several findings emerged from the machine learning classifications. When older victims present with a poorly explained injuries, limited social networks, hazardous living conditions and a history of violence (either intimate partner or domestic violence) they are more likely to be experiencing multiple types of abuse by a single perpetrator. This paints an all too familiar situational picture in which an older adult with a limited social network is dependent on someone who they have an established history of violence with. Commonly, the desire to remain living in their home and protection of their loved overs, no matter how contentious the relationship, overrides the history of violence and the occurring abuse. This is supported by the lack of willingness to self-report abuse and to cooperate with prosecution of alleged abusers, especially when they are family. Of course, attempts to conceal abuse related injuries occurs regardless of the number of perpetrators. However, when inconsistencies or poor explanations of injuries occur, this should be considered as either a sign of concealment or lack of caregiving attention. Regarding concealment, the physical injuries could be a sign of physical abuse which is often occurs in conjunction with neglect. Jackson & Hafemeister (2012) showed this to be true in their study of pure versus hybrid financial exploitation.[23] In the current study, both physical abuse and financial exploitation are the most common forms of abuse. With a limited social network there may be fewer potential perpetrators, but it also means that there are fewer people to be aware of the abuse and therefore, multiple types can be occurring with very little detection and scrutiny.

The single type of abuse and multiple perpetrators PV category was primarily explained by having prior APS involvement, rapidly diminishing finances, concerns about the client's cognitive function and concerns about the client's finances. This appears to be a classic presentation of ongoing financial exploitation. Financial exploitation is extremely difficult to investigate and often results in no resolution, even if validated, because older adults don't want to press charges. When this happens the perpetrator may stay in their life and continue to take the older adults money. When prior APS involvement does not result in consequences, this opens the door to continued exploitation by one person and potentially sends a signal to others that this person is vulnerable, perhaps due to cognitive declines, there is money to be easily accessed and the system response is weak. Moreover, as Dong et al. 2013 has shown, prior validation of self-neglect results in a subsequent 3-year higher odds of financial exploitation.[67] Cases of self-neglect are more likely to be re-referred to APS and many self-neglecters are experiencing declines in cognitive function leading to self-neglect and dependency on others for care; all of which makes them vulnerable to exploitation.

This is the first study to purposely assess the links between PV and morbidity and mortality. Multiples types of co-occurring abuse, regardless of the number of perpetrators is associated with increased odds of death, dementia and depression. Multiple studies assessing child abuse PV and outcomes have shown that the cumulative effect of abuse has profound impacts on mental health and survival. It seems that the same is true here, however, we are not arguing that being abused leads to dementia or depression. It is plausible that depression may serve as a risk factor and an outcome of multiple types of abuse where as it is improbable that abuse leads to dementia. In fact, Wiglesworth et al., 2010 show that dementia is a risk factor for elder abuse. Baker et al. 2009 also showed that women who experienced verbal and physical abuse were more likely to be less optimistic, more depressed, and hostile and express negative ambivalence in emotional responses. When there is a single type of abuse, but multiple perpetrators there are higher odds of dementia, depression and anxiety, but no significant increase in death. This is consistent with the idea that the cumulative effect of multiple types of abuse is more important than the number of abusers.

It is not surprising that the high vulnerability group had a higher odds of dementia, death, depression and anxiety, respectively. This group has high medical burdens, lower cognitive and physical function and more dependency on others (i.e. less control over their situation). All of which are associated with the predicted outcomes.

Although there are few mortality studies in elder abuse, they are consistent in stating that individuals who experience elder abuse have a higher odds of dying (Lachs et al., 1998, Dong et al, 2009; Burnett et al., 2018). What is less understood is the association of individual types of abuse with morbidity and mortality outcomes. We found that the presence of exploitation and caregiver neglect were strongly associated with higher odds of mortality while those experiencing physical and/or emotional abuse had a lower odds of mortality. This is consistent with the mortality findings reported by Burnett et al., 2018 where individual non-polyvictimization categories were modeled against 5-year survival. Caregiver neglect had the lowest survival followed by exploitation (the differences was not significant). Likewise, physical and emotional abuse had the highest survival rates. These same patterns follow for the other outcomes of depression, dementia and anxiety.

This study provides the first in-depth characterization study of elder abuse PV and relations with morbidity and mortality outcomes. It not only provides new insight into the reasoning why PV should be defined broadly and inclusive of more than just co-occurring abuse, but it also provides new evidence linking a priori PV categories to latent profiles that can be used to guide investigations and morbidity and mortality outcomes that should be considered when designing protective services plans for current and future remediation and prevention of elder abuse. The idea that a cumulative effect of abuse types is related to worse outcomes parallels that of child abuse and should provide impetus to implement trauma-informed practices into the service delivery so that client-centered approaches are maximized to meet the needs of the victim and lower risks of recurrent abuse. Characterizing the PV groups and linking them to morbidity and mortality outcomes may have implications for changing investigation practices, protective service delivery and justice response pathways. However, the application of these findings for the field of elder abuse as well as the justice system need further consideration.

While this study provides new data for the field, the findings should be considered in light of a few strengths and limitations. First, these data do come from a statewide APS program in which uses a standardized assessment process following intensive investigator training. However, the data do not represent a national sample of older adults and thus, generalizability may be limited. The definitions of abuse, neglect and exploitation used in this study require the relationship between the victim and the perpetrator to be based on a foundation of “trust” which is consistent with national definitions of elder abuse, but in terms of financial exploitation may depart from other APS programs where fraud and scams may be allowable for investigation and therefore, inclusive of differing victim and perpetrator characteristics. A major strength of this study is also the use of robust exploratory analyses that rely on data-driven approaches to groupings and classifications rather than investigator defined groups. This reduces some of the biases, but may also error on the side of lacking valuable investigator knowledge about important variables to be included in modeling. However, this study did choose analyses that allow for maximal use of the data and utilization of modeling algorithms such as variants of supervised machine learning that can handle large datasets while controlling for multiple comparisons. The use of the Center for Medicare Services data also added to the robustness of the outcome data, but those models were limited to single predictors and therefore, further moderated and adjusted analyses need to be conducted test the stability of the morbidity and mortality findings in relation to PV types, LCA categories and individual types of abuse, neglect and exploitation. The lack of standardized measures in the field of elder abuse remains a limitation to the field especially given the variation in measures used across APS program. This study should be replicated within the National Adult Maltreatment System (NAMRS) across the APS programs that have adopted and implemented the SHIELD investigation protocol for better understanding of study generalizability.

References

[1] Ramsey-Klawsnik H & Heisler C. Polyvictimization in later life. Victimization of the Elderly and Disabled. May/June 2014. Pgs. 3-4 and 15-16.

[2] Hamby, S., PhD, Smith, A., Ba, Mitchell, K., PhD, & Turner, H., PhD. (2017). Poly-victimization and resilience portfolios: Trends in violence research that can enhance the understanding and prevention of elder abuse. *Journal of Elder Abuse & Neglect*, *28*(4-5), 217–234. https://doi.org/10.1080/08946566.2016.1232182

[3] Dong X & Simon MA. Elder abuse as a risk factor for hospitalization in older persons. JAMA Internal Medicine, 2013;173(10):911-917.

[4] Burnett J, Jackson SL, Sinha A, Aschenbrenner AR, Xia R, Murphy KP & Diamond PM. Differential Mortality across Five Types of Substantiated Elder Abuse. Journal of Elder Abuse and Neglect, 2016; 28:2, 59-75.

[5] Choi N, Kulick DB & Mayer J. Financial exploitation in elders: analysis of risk factors based on county adult protective services data. JEAN, 1999, 19(3):39-62.

[6] Hwalek, M., Sengstock, M. C., & Lawrence, R. (1984). *Assessing the probability of abuse of the elderly*. Presented at the 37th Annual Meeting of the Gerontological Society of America, Wayne State University. Retrieved from http://eric.ed.gov/?id=ED257016

[7] U.S. House Select Committee on Aging. (1981). *Elder Abuse: an Examination of a Hidden Problem*. U.S. Government Printing Office.

[8] Acierno, R., Hernandez, M. A., Amstadter, A. B., Resnick, H. S., Steve, K., Muzzy, W., & Kilpatrick, D. G. (2010). Prevalence and correlates of emotional, physical, sexual, and

financial abuse and potential neglect in the United States: The National Elder Mistreatment Study. American Journal of Public Health, 100, 292–297. doi:10.2105/AJPH.2009.163089

[9] Cannell, M. B., Manini, T., Spence-Almaguer, E., Maldonado-Molina, M., & Andresen, E. M. (2014). U.S. Population Estimates and Correlates of Sexual Abuse of Community-Dwelling Older Adults. *Journal of Elder Abuse & Neglect*, *26*(4), 398–413. https://doi.org/10.1080/08946566.2013.879845

[10] Dong, X. Q. (2015). Elder Abuse: Systematic Review and Implications for Practice. *Journal of the American Geriatrics Society*, *63*(6), 1214–1238. https://doi.org/10.1111/jgs.13454

[11] Lachs, M. S., & Pillemer, K. A. (2015). Elder Abuse. *The New England Journal of Medicine*, *373*(20), 1947–1956. https://doi.org/10.1056/NEJMra1404688

[12]Goergen, T., & Beaulieu, M. (2013). Critical concepts in elder abuse research. International Psychogeriatrics/IPA, 25(8), 1217–1228. doi:10.1017/S1041610213000501

[13] National Center on Elder Abuse. Elder Abuse Types and Definitions March 15, 2017. https://ncea.acl.gov/faq/index.html#faq1

[14] Nerenberg L. (2000). Forgotten victims of financial crime and abuse: Facing the challenge. Journal of Elder Abuse and Neglect, 12, 49-72.

[15] Dong, X., Simon, M., & Evans, D. (2012). Decline in physical function and risk of elder abuse reported to social services in a community-dwelling population of older adults. Journal of the American Geriatrics Society, 60(10), 1922–1928. doi:10.1111/j.1532-415.2012.04147.x

[16] Dong X & Simon MA. Association between elder abuse and use of ED: findings from the Chicago Health and Aging Project. American Journal of Emergency Medicine, 2013, 31: 693-698.

[17]Dong X & Simon MA. Elder abuse as a risk factor for hospitalization in older persons. JAMA Internal Medicine, 2013;173(10):911-917.

[18] Lachs, M. S., Williams, C. S., O'Brien, S., Pillemer, K. A., & Charlson, M. E. (1998). The mortality of elder mistreatment. JAMA: The Journal of the American Medical Association, 280(5), 428–432. doi:10.1001/jama.280.5.428

[19]Dong, X., Simon, M., Mendes de Leon, C., Fulmer, T., Beck, T., Hebert, L., & Evans, D. (2009). Elder self-neglect and abuse and mortality risk in a community-dwelling population. JAMA: The Journal of the American Medical Association, 302(5), 517–526. doi:10.1001/jama.2009.1109

[20] Jackson SL & Hafemesiter TL. Theory-based models enhancing the understanding of four types of elder maltreatment. International Review of Victimology, 2016, 1-32.

[21] Johannesen, M., & LoGiudice, D. (2013). Elder abuse: A systematic review of risk factors in community-dwelling elders. Age and Ageing, 42, 292–298. doi:10.1093/ageing/afs195

[22] Pillemer K, Burnes D, Riffin C & Lachs MS. Elder Abuse: Global situations, risk factors and prevention strategies. Gerontologist, 2016, 56(S2):S194-S205.

[23] Jackson, S. L., & Hafemeister, T. L. (2012). Pure financial exploitation vs. Hybrid financial exploitation co-occurring with physical abuse and/or neglect of elderly persons. *Psychology of Violence*, *2*(3), 285. https://doi.org/10.1037/a0027273

[24] Amstadter, A. B., Zajac, K., Strachan, M., Hernandez, M. A., Kilpatrick, D. G., & Acierno, R. (2011). Prevalence and correlates of elder mistreatment in South Carolina: The South Carolina elder mistreatment study. Journal of Interpersonal Violence, 26, 2947–2972. doi:10.1177/0886260510390959

[25] Burnes, D., Pillemer, K., Caccamise, P., Mason, A., Henderson, C. R., & Lachs, M. S. (2015). Prevalence of and risk factors for elder abuse and neglect in the community: A population-based study. Journal of the American Geriatrics Society (JAGS), 65,1906–1912. doi:10.1111/jgs.13601

[26] Laumann, E. O., Leitsch, S. A., & Waite, L. J. (2008). Elder mistreatment in the United States: Prevalence estimates from a nationally representative study. The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences, 63, S248–S254. doi:10.1093/geronb/63.4.S248

[27] Peterson, J. C., Burnes, D. P., Caccamise, P. L., Mason, A., Henderson, C. R., Jr., Wells, M. T., … Lachs, M. S. (2014). Financial exploitation of older adults: A population-based prevalence study. Journal of General Internal Medicine, 29, 1615–1623. doi:10.1007/s11606-014-2946-2

[28] Wu, L., Chen, H., Hu, Y., Xiang, H., Yu, X., Zhang, T., … Wang, Y. (2012). Prevalence and associated factors of elder mistreatment in a rural community in People's Republic of China: A cross-sectional study. PLoS One, 7, e33857. doi:10.1371/journal.pone.0033857

[29] O'Keeffe, M., Hills, A., Doyle, M., McCreadie, C., Scholes, S., Constantine, R., … Erens, B. (2007). UK study of abuse and neglect of older people: Prevalence survey report. London: Department of Health.

[30] Podnieks, E. (1993). National survey on abuse of the elderly in Canada. Journal of Elder Abuse & Neglect, 4, 4–58. doi:10.1300/J084v04n01_02

[31] Lowenstein, A., Eisikovits, Z., Band-Winterstein, T., & Enosh, G. (2009). Is elder abuse and neglect a social phenomenon? Data from the first national prevalence survey in Israel. Journal of Elder Abuse & Neglect, 21, 253–277. doi:10.1080/08946560902997629

[32] Pillemer, K., & Finkelhor, D. (1988). The prevalence of elder abuse: A random sample survey. The Gerontologist, 28, 51–57.doi:10.1093/geront/28.1.51

[33] Beach, S. R., Schulz, R., Castle, N. G., & Rosen, J. (2010). Financial exploitation and psychological mistreatment among older adults: Differences between African Americans and non-African Americans in a population-based survey. The Gerontologist. Advance online publication. doi:10.1093/geront/gnq053

[34] Coyne, A. C., Reichman, W. E., & Berbig, L. J. (1993). The relationship between dementia and elder abuse. The American Journal of Psychiatry, 150, 643–646. doi:10.1176/ajp.150.4.643

[35] Paveza, G. J., Cohen, D., Eisdorfer, C., Freels, S., Semla, T., Ashford, J. W., … Levy, P. (1992). Severe family violence and Alzheimer's disease: Prevalence and risk factors. The Gerontologist, 32, 493–497.

[36] Vandeweerd, C., Paveza, G. J., & Fulmer, T. (2006). Abuse and neglect in older adults with Alzheimer's disease. The Nursing Clinics of North America, 41, 43–55. doi:10.1016/j.cnur.2005.09.004

[37] Soares, J., Barros, H., Torres-Gonzales, F., Ioannidi-Kapolou, E., Lamura, G., Lindert, J., … Macassa, G. (2010). Abuse and health in Europe. Kaunas: Lithuanian University of Health Sciences Press.

[38] Mouton, C. P., Rodabough, R. J., Rovi, S. L., Hunt, J. L., Talamantes, M. A., Brzyski, R. G., & Burge, S. K. (2004). Prevalence and 3-year incidence of abuse among postmenopausal women. American Journal of Public Health, 94(4), 605–612. doi:10.2105/AJPH.94.4.605

[39] Baker, M. W., LaCroix, A. Z., Wu, C., Cochrane, B. B., Wallace, R., & Woods, N. F. (2009).

Mortality risk associated with physical and verbal abuse in women aged 50 to 79. Journal of the American Geriatrics Society, 57(10), 1799–1809. doi:10.1111/j.1532-5415.2009.02429.x

[40]Finkelhor, D., Ormrod, R. K., & Turner, H. A. (2007). Poly-victimization: a neglected component in child victimization. *Child Abuse & Neglect*, *31*(1), 7–26. https://doi.org/10.1016/j.chiabu.2006.06.008

[41] Hamby, S., & Grych, J. (2013a). The Causes of Interconnection. In *The Web of Violence: Exploring Connections Among Different Forms of Interpersonal Violence* (pp. 28–49). Springer. https://doi.org/10.1007/ 978-94-007-5596-3

[42] Adams, Z. W., Moreland, A., Cohen, J. R., Lee, R. C., Hanson, R. F., Danielson, C. K., … Briggs, E. C. (2016). Polyvictimization: Latent profiles and mental health outcomes in a clinical sample of adolescents. *Psychology of Violence*, *6*(1), 145–155. https://doi.org/10.1037/a0039713

[43] Collings, S. J., Penning, S. L., & Valjee, S. R. (2014). Lifetime poly-victimization and posttraumatic stress disorder among school-going adolescents in Durban, South Africa. *Journal of Psychiatry & Neuroscience: JPN*, *17*(5), 1–5.

[44] Felitti, V. J., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V., … Marks, J. S. (1998). Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The Adverse Childhood Experiences (ACE) Study. *American Journal of Preventive Medicine*, *14*(4), 245–258. Retrieved from http://www.sciencedirect.com/science/article/pii/S0749379798000178

[45] Finkelhor, D., Ormrod, R. K., Turner, H. A., & Hamby, S. L. (2005). Measuring poly-

victimization using the Juvenile Victimization Questionnaire. *Child Abuse & Neglect*, *29*(11), 1297–1312. https://doi.org/10.1016/j.chiabu.2005.06.005

[46] Hamby, S., PhD, Smith, A., Ba, Mitchell, K., PhD, & Turner, H., PhD. (2016). Poly-victimization and resilience portfolios: Trends in violence research that can enhance the understanding and prevention of elder abuse. *Journal of Elder Abuse & Neglect*, *28*(4-5), 217–234. https://doi.org/10.1080/08946566.2016.1232182

[47] Cuevas, C. A., Sabina, C., & Picard, E. H. (2010). Interpersonal victimization patterns and psychopathology among Latino women: Results from the SALAS study. *Psychological Trauma: Theory, Research, Practice and Policy*, *2*(4), 296. Retrieved from http://psycnet.apa.org/journals/tra/2/4/296/

[48] Graham-Bermann, S., Sularz, A. R., & Howell, K. H. (2011). Additional adverse events among women exposed to intimate partner violence: Frequency and impact. *Psychology of Violence*, *1*(2), 136. Retrieved from http://psycnet.apa.org/journals/vio/1/2/136/

[49] Krebs, C., Breiding, M. J., Browne, A., & Warner, T. (2011). The Association Between Different Types of Intimate Partner Violence Experienced by Women. *Journal of Family Violence*, *26*(6), 487–500. https://doi.org/10.1007/s10896-011-9383-3

[50] Sabina, C., & Straus, M. A. (2008). Polyvictimization by dating partners and mental health among U.S. college students. *Violence and Victims*, *23*(6), 667–682. Retrieved from https://www.ncbi.nlm.nih.gov/pubmed/19069560

[51] Hamby, S., Finkelhor, D., Turner, H., & Ormrod, R. (2010). The overlap of witnessing partner violence with child maltreatment and other victimizations in a nationally representative

survey of youth. *Child Abuse & Neglect*, *34*(10), 734–741. https://doi.org/10.1016/j.chiabu.2010.03.001

[52] Finkelhor, D., Turner, H., Hamby, S. L., & Ormrod, R. (2011). Polyvictimization: Children's Exposure to Multiple Types of Violence, Crime, and Abuse. *National Survey of Children's Exposure to Violence*. Retrieved from http://scholars.unh.edu/ccrc/25/

[53] Burnes, D., Pillemer, K., & Lachs, M. S. (2016). Elder Abuse Severity: A Critical but Understudied Dimension of Victimization for Clinicians and Researchers. *The Gerontologist*. https://doi.org/10.1093/geront/gnv688

[54] Hamby et al., Chapter 2: Tracing the threads of the web: the epidemiology of interconnections among forms of violence and victimization.

[55] Texas Department of Family and Protective Services. March 15, 2017. Allegation Priorities. https://www.dfps.state.tx.us/Handbooks/APS/Files/APS_pg_1600.asp

[56] Texas Department of Family and Protective Services. March 15, 2017. Texas human resource codes. Retrieved from http://www.statutes.legis.state.tx.us/Docs/HR/htm/HR.48.htm

[57] Tabachnick, B. G., & Fidell, L. S. (2001). *Using multivariate statistics* (4th ed.). Needham Heights, MA: Allyn & Bacon.

[58] Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). New York, NY: Springer.

[59] Vaughn MG, DeLisi M, Beaver KM et al. Identifying latent classes of behavioral risk based on early childhood: Manifestations of self-control. Youth Violence Juv Justice 2009;7:16–31.

[60] Herman KC, Ostrander R, Walkup JT et al. Empirically derived subtypes of adolescent depression: Latent profile analysis of co-occurring symptoms in the Treatment for Adolescents with Depression Study (TADS). J Consult Clin Psychol 2007;75:716–728.

[61] Muthen B. Should substance use disorders be considered as categorical or dimensional? Addiction 2006;101(Suppl 1):6–16.

[62] Nylund KL, Asparouhov T, Muthen BO. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. Struct Equ Modeling 2007;14:535–569.

[63] T. Hothorn, P. Buehlmann, T. Kneib, M. Schmid, and B. Hofner (2016). mboost: Model-Based Boosting, R package version 2.6-0, http://CRAN.R-project.org/package=mboost.

[64] J.L. Williams, E.H.Racette, M. A. Hernandez-Tejada & R. Acierno. (2020). Prevalence of polyvictimization in the United States: Data from the national elder mistreatment study. Journal of Interpesonal Violence, 2020. Vol. 25 (21-22). 4517-4532.

[65] Wiglesworth, A., Mosqueda, L., Mulnard, R., Liao, S., Gibbs, L., & Fitzgerald, W. (2010). Screening for abuse and neglect of people with dementia. Journal of the American Geriatrics Society, 58, 493-500.

[66] Wood, S. A., Liu, P. J., Hanoch, Y., & Esteves-Cores, S. (2016). Importance of numeracy as a risk factor for elder financial exploitation in a community sample. J Gerontol B Psychol Sci Soc Sci, 71(6), 978–986. doi:10.1093/geronb/gbv041

[67] Dong, X., Simon, M., & Evans, D. (2013). Elder self-neglect is associated with increased risk for elder abuse in a community-dwelling population: Findings from the Chicago health and aging project. Journal of Aging & Health, 25(1), 80–96. doi:10.1177/0898264312467373

Table 1. Predictor Space Descriptive Statistics.							
Demographic Variables	**Details**	N	%	N	%	N	%
Age (Median Split)	Median Split: <= 76 vs. > 76 Continuous: Mean = 77 (SD = 8.07)	<= 76		> 76			
		2542	48.20%	2727	51.80%		
Sex	Male/Female/Unknown	Male		Female		Unknown	
		1839	34.90%	3430	65.10%	26	0.49%
Race	Black/Other/White	Black		Other		White	
		757	14.36%	308	5.84%	4204	79.80%
Ethnicity	Hispanic/Not Hispanic/Unknown	Hispanic		Not Hispanic		Unknown	
		1291	24.50%	3696	70.15%	282	5.35%
Living Situation	Alone/Nursing Home/With Relatives/Other	Alone		Nursing/Assisted		Relative/Other	
		4102	77.85%	562	10.67%	605	11.48%
Marital Status	Divorced/Married/Never Married/Separated/Widowed/Unknown	Married		Div/Wid/Sep/Never		Unknown	
		1608	30.50%	1946	66.25%	1715	3.25%
Primary Language	English/Spanish/Other	English		Spanish		Other	
		4742	89.99%	424	8.05%	103	1.95%
Citizen	No/Yes	0		1			
		4222	80.10%	1047	19.90%		
Permanent Resident	No/Yes	0		1			
		5179	98.30%	90	1.70%		
APS Measure Variables	**Details**	NOT PRESENT		PRESENT			
Vulnerability Factor 1	Limited Support Network	4773	90.59%	496	9.41%		
Vulnerability Factor 2	Diminshed Cognitive Functioning	3907	74.15%	1362	25.85%		
Vulnerability Factor 3	Another Person May Access Finances	3323	63.07%	1946	36.93%		
Vulnerability Factor 4	Mental Health Problem or Drug/Alcohol Dependency	5000	94.89%	269	5.11%		
Vulnerability Factor 5	Significant Untreated, Suspected, or Diagnosed Condition	2495	47.35%	2774	52.65%		

Vulnerability Factor 6	Diminished Physical Functioning	3178	60.32%	2091	39.68%		
Vulnerability Factor 7	Dependent on Another Person for Care	3231	61.32%	2038	38.68%		
Danger Factor 1	Impeded Assessment of Client's Situation	5238	99.41%	31	0.59%		
Danger Factor 2	Hazardous Physical Living Conditions	5213	98.94%	56	1.06%		
Danger Factor 3	Experienced Serious Physical Injury	5157	97.87%	112	2.13%		
Danger Factor 4	Questionable Explanation for Observed Injury	5260	99.83%	9	0.17%		
Danger Factor 5	Immediate Care Not Met (Physical or Mental Health)	5158	97.89%	111	2.11%		
Danger Factor 6	Immediate Care Not Met & Threatens Others (Mental Health)	5256	99.75%	13	0.25%		
Danger Factor 7	Risky Cognitive Status	5211	98.90%	58	1.10%		
Danger Factor 8	Financial Assets Rapidly Diminishing	5202	98.73%	67	1.27%		
Danger Factor 9	Suspected Sexual Abuse	5265	99.92%	4	0.08%		
Danger Factor 10	Suspected Violence in Home	5029	95.45%	240	4.55%		
Danger Factor 11	Unwilling Caretaker	5232	99.30%	37	0.70%		
Danger Factor 12	Absent Other Factors, History of Abuse/Neglect/Exploitation	5230	99.26%	39	0.74%		
Danger Factor 13	Other Current Danger Factor	5200	98.70%	69	1.31%		
RORA Item 1	None vs. One or More Previous APS Investigations	3491	66.26%	1778	33.74%		
RORA Item 2	Prior - Self Neglect Allegation	3860	73.26%	1409	26.74%		
RORA Item 3	Prior - Abuse/Neglect/Exploitation Required Emergency Services	5190	98.50%	79	1.50%		
RORA Item 4	Prior - Resulted in Client Receiving a Diagnosis or Treatment	5186	98.42%	83	1.58%		
RORA Item 5	Prior - Validated APS Investigation (Any Type)	4120	78.19%	1149	21.81%		
RORA Item 6	Prior - Abuse/Neglect/Exploitation Validated (Expect Self-Neglect)	4981	94.53%	288	5.47%		
RORA Item 7	Prior - Client Lacking Capacity	4881	92.64%	388	7.36%		
RORA Item 8	Prior - Client Physically Impaired	4686	88.94%	583	11.06%		

RORA Item 9	Prior - Abuse/Neglect/Exploitation by Spouse or Paramour	5072	96.26%	197	3.74%		
RORA Item 10	Current - Client Displayed Inappropriate Affect or Extreme Behavior	5192	98.54%	77	1.46%		
RORA Item 11	Current - Home Health/Provider Services Received Previously	4643	88.12%	626	11.88%		
RORA Item 12	Current - Client Previously Refused Services	5170	98.12%	99	1.88%		
RORA Item 13	Current - Abuse/Neglect/Exploited Previously by Another Person	5197	98.63%	72	1.37%		
RORA Item 14	Current - Self-Neglect Part of the Investigation	3477	65.99%	1792	34.01%		
RORA Item 15	Current - Abuse/Neglect/Exploited by Another Person	57	1.08%	5212	98.92%		
RORA Item 16	Current - Hazardous Living Conditions	5133	97.42%	136	2.58%		
RORA Item 17	Current - Concerning Financial Situation	4451	84.48%	818	15.52%		
RORA Item 18	Current - Other May Access Finances	3022	57.35%	2247	42.65%		
RORA Item 19	Current - Alleged Perpetrator Includes a Specific Person (e.g., Caretaker)	3964	75.23%	1305	24.77%		
RORA Item 20	Current - Primary Caretaker has Realistic Expectations of Client	3944	74.85%	1325	25.15%		
RORA Item 21	Current - Client has Capacity to Consent but Refuses Services	4872	92.47%	397	7.53%		
RORA Item 22	Characteristics - Physical Limitations	2985	56.65%	2284	43.35%		
RORA Item 23	Characteristics - Current/Prior Diagnosed Mental Health Concern	4525	85.88%	744	14.12%		
RORA Item 24	Characteristics - Diagnosed with Intellectual/Developmental Disability	5200	98.69%	69	1.31%		
RORA Item 25	Characteristics - Concerns about Client's Cognitive Functioning	3937	74.72%	1332	25.28%		
RORA Item 26	Characteristics - Client is Socially Isolated	5066	96.15%	203	3.85%		
RORA Item 27	Characteristics - Client is Receiving Medicaid	4034	76.56%	1235	23.44%		
RORA Item 28	Characteristics - Client has/had an Alcohol/Drug Problem	5135	97.46%	134	2.54%		

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Table 2. Victimization Descriptive Statistics		
Variable	**N**	**%**
Polyvictimization Classification		
One Perpetrator & Type	4130	78.38%
Multiple Perpetrators	300	5.69 %
Multiple Types	792	15.03 %
Multiple Perpetrators & Types	47	0.89 %
Confirmed Abuse Type Counts		
Exploitation		
0	3572	67.79%
1	1541	29.24%
2+	156	2.96%
Physical Abuse		
0	3448	65.43%
1	1774	33.66%
2+	47	0.89%
Emotional Abuse		
0	4011	76.12%
1	1219	23.13%
2+	39	0.74%
Sexual Abuse		
0	5257	99.77%
1	12	0.22%
Medical Neglect		
0	4799	91.08%
1	385	7.30%
2+	85	1.61%
Mental Health Neglect		
0	5195	98.59%
1	70	1.32%
2+	4	0.07%
Physical Neglect		
0	3765	71.45%
1	1139	21.61%
2+	365	6.92%
Number of Perpetrators		
1	4477	84.96%
2	714	13.55%
3	65	1.23%
4+	13	0.24%
Perpetrator Relationship		

Daughter/Son/Step-Child	2566	48.70 %
Other	2703	51.30 %

Table 3. Supervised Machine Learning Results					
Multiple Types vs. All Other Observations	**Boosted Model**		**Follow-Up Non-Penalized Model**		
Predictor	**Penalized Coefficient**	**Penalized Odds Ratio**	**Biased Coefficient**	**Biased Odds Ratio**	**Biased p-Value**
Danger Factor 10	0.203	1.225	0.772	2.163	< 0.001
Vulnerability Factor 6	0.054	1.056	0.351	1.421	< 0.001
Vulnerability Factor 1	0.161	1.174	0.437	1.548	< 0.001
RORA Item 16	0.278	1.321	0.713	2.041	< 0.001
RORA Item 6	0.095	1.099	0.364	1.439	0.003
Danger Factor 13	0.146	1.157	0.787	2.198	0.005
Danger Factor 4	0.941	2.562	3.048	21.067	0.006
RORA Item 7	0.148	1.160	0.360	1.433	0.006
RORA Item 9	0.104	1.110	0.383	1.467	0.015
RORA Item 17	0.033	1.033	0.238	1.269	0.018
Marital Status - Never Married	-0.054	0.948	-0.508	0.602	0.019
Danger Factor 5	0.176	1.193	0.444	1.559	0.039
RORA Item 23	0.007	1.007	0.198	1.219	0.063
Marital Status - Unknown	-0.031	0.970	-0.153	0.858	0.079
Primary Language - English	-0.066	0.936	-0.204	0.815	0.091
RORA Item 8	0.100	1.105	0.202	1.224	0.095
Ethnicity - Unknown	-0.014	0.986	-0.297	0.743	0.145
RORA Item 26	0.063	1.065	0.223	1.250	0.194
Living Situation - By Themselves	-0.043	0.958	-0.091	0.913	0.329
Multiple Perpetrators vs. All Other Observations	**Boosted Model**		**Follow-Up Non-Penalized Model**		
Predictor	**Penalized Coefficient**	**Penalized Odds Ratio**	**Biased Coefficient**	**Biased Odds Ratio**	**Biased p-Value**
Marital Status - Widowed	0.038	1.039	0.438	1.550	0.001
RORA Item 19	0.088	1.092	0.374	1.454	0.003
Vulnerability Factor 3	0.065	1.068	0.405	1.499	0.006
RORA Item 17	0.088	1.092	0.326	1.385	0.021
Danger Factor 13	0.032	1.032	0.851	2.342	0.027
Citizen - Yes	0.017	1.018	0.291	1.338	0.034
RORA Item 3	0.161	1.175	0.575	1.777	0.060
Danger Factor 8	0.214	1.239	0.625	1.868	0.063
Race - Black	-0.030	0.970	-0.307	0.736	0.095
Sex - Female	-0.052	0.950	-0.204	0.815	0.105
RORA Item 25	0.103	1.109	0.274	1.315	0.127
Marital Status - Married	-0.104	0.901	-0.175	0.839	0.272
Vulnerability Factor 2	0.012	1.012	0.110	1.116	0.565

Multiple Types & Perpetrators vs. All Other Observations	**Boosted Model**		**Follow-Up Non-Penalized Model**		
Predictor	**Penalized Coefficient**	**Penalized Odds Ratio**	**Biased Coefficient**	**Biased Odds Ratio**	**Biased p-Value**
RORA Item 14	0.014	1.014	0.741	2.098	0.015
Marital Status - Widowed	0.040	1.040	0.722	2.059	0.023
RORA Item 17	0.189	1.209	0.691	1.996	0.039
Danger Factor 13	0.181	1.199	1.322	3.751	0.040
RORA Item 19	0.055	1.057	0.551	1.735	0.054
Citizen - Yes	0.045	1.046	0.589	1.802	0.062
Danger Factor 4	0.560	1.751	1.394	4.031	0.097
Danger Factor 8	0.419	1.520	0.943	2.568	0.115
RORA Item 25	0.036	1.037	0.459	1.582	0.143
RORA Item 16	0.165	1.180	0.519	1.680	0.289
Marital Status - Married	-0.053	0.948	-0.291	0.748	0.510
Danger Factor 11	0.047	1.048	0.385	1.470	0.573

Figure 2: Top Latent Class Analysis Predictors of Based on APS Investigational Data Including Demographics, Safety Assessment and Risk of Recidivism Assessment

Group 1= High Vulnerability; **Group 2** = Low Vulnerability

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