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Predicting low premorbid cognitive ability with social determinants: A machine learning approach

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ABSTRACT

Background: Social determinants of health and biological processes are shaped by the exposome, which provides a framework for understanding how social adversity drives molecular and cellular mechanisms underlying Alzheimer's disease risk. Individuals with low premorbid intellectual ability (pIQ ≤70) may be particularly vulnerable to adverse social determinants of health due to reduced cognitive reserve, yet this relationship is understudied.

Methods: Data from the Health and Aging Brain Study–Health Disparities ($n = 2691$) were analyzed. Participants were classified as low pIQ (IQ ≤70) or average pIQ (IQ 90–100) via word reading scores. Using a machine learning approach, an XGBoost model evaluated education, income, Area Deprivation Index (ADI), social support, stress, health status, and worry in prediction of pIQ grouping.

Results: The model achieved and AUC of 0.72 [0.64, 0.81]. Top predictors included worry, ADI, income, high school completion, and tangible support. Low pIQ was associated with greater neighborhood deprivation, lower income, and reduced support resources.

Conclusion: Low pIQ, when combined with SDoH factors reflects a vulnerable psychosocial-cognitive phenotype that may accelerate pathways to cognitive decline potentially through inflammatory mechanisms.

1. Introduction

Social Determinants of Health (SDoH) are modifiable risk factors that impact health outcomes, making them a promising avenue for intervention and study in Alzheimer's Disease (AD) research [1,2]. AD health outcomes reflect the combined influence of both genes and environment, with physical, chemical, and social influences on health, collectively referred to as the *exposome,* being increasingly studied alongside traditional biological considerations [3]. The AD exposome includes exogenous and endogenous exposures, encompassing broad macro-level factors like urban vs. rural living and socioeconomic status, as well as individual-level exposures like diet, infections, and overall health status [3,4]. This broad concept has spurred several grant notices by the National Institute on Aging (NIA) that aim to extend and leverage the established NIA biological research framework [5] to lifestyle, environment, and socioeconomic contexts. Mirroring this increased focus, the amyloid, tau, and neurodegeneration (ATN) biological framework for AD has been revised [6] to include inflammatory/immune mechanisms through astrocytic and microglial activation.

Glial fibrillary acidic protein (GFAP), a key structural protein of astrocytes, which helps maintain the blood–brain barrier (BBB), is a primary biomarker target within this framework. Astrocytes are star-shaped glial cells that maintain homeostasis, primarily by controlling endothelial cell function in the BBB, the selective semipermeable border regulating chemical and solute transfer between the circulatory system and central nervous system [7]. Breakdown of astrocytes increases inflammation and enhances BBB permeability, allowing neurotoxic proteins such as amyloid beta and phosphorylated tau, the hallmark characteristics of AD to cross the BBB and accumulate within the cortex [7]. Inflammation pathways in AD vary from general systemic inflammation to pro-inflammatory cascades, with vascular, innate immune, adaptive immune, and acute phase responses contributing to dynamic disease risk [8].

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1.1. Psychosocial stress and neuroinflammation as a mechanistic pathway

Chronic psychosocial stress and social support play a mechanistic role in cognitive aging [9]. Chronic stress, particularly in the absence of supportive social interactions, triggers hypothalamic pituitary adrenal (HPA) axis dysregulation, leading to prolonged catecholamine (e.g., dopamine, norepinephrine) and glucocorticoid (e.g., cortisol) exposure. Sustained activation of these pathways contributes to systemic inflammation, endothelial dysfunction, BBB compromise, and glial cell activation, creating a cycle of neuroinflammation [10], collateral brain injury [11], and acceleration of neurodegeneration. Chronic stress also drives oxidative stress, hormonal and immune dysregulation, and neurotransmission impairment, which collectively exacerbate AD-related neurodegenerative processes [12]. Conversely, supportive social environments may counteract these effects by promoting synaptic plasticity and neurogenesis, potentially via pleiotropic neuropeptides such as oxytocin, as well as lifestyle and neurotrophic mechanisms critical for synaptogenesis and neuronal repair [13]. Moreover, chronic stress and social support can impact cognitive aging outcomes, with chronic stress and lack of social support being associated with higher subjective memory concerns, lower executive functioning, and higher rates of biological markers of neurodegeneration across several communities [14–17].

A key SDoH measure is the Area Deprivation Index (ADI), a scientifically validated measure of adverse social exposure [18]. ADI indirectly captures and correlates with factors of educational attainment, economic advantage, income, access to healthcare, and overall health status, making ADI a strong indicator of the areas with the highest need to target and tailor public health interventions [9]. Social biological mechanisms involved in the neuropathology of AD suggest that increasing neighborhood disadvantage is associated with the 8.1 increasing the odds of Alzheimer's disease neuropathology for every decile change in ADI (adjusted odds ratio, 1.08; 95 % CI, 1.07–1.09), being in the most disadvantaged decile had a 2.18 increased odds of A.D. neuropathology (adjusted odds ratio, 2.18; 95 % CI, 1.99–2.39) [19]. This is particularly relevant when considering the aggregate impact of chronic adverse exposome exposures and psychosocial stress on brain aging [9]. Adverse SDoH act as upstream stressors that contribute to chronic stress and chronic dysregulation of HPA axis, triggering systemic inflammation, BBB compromise, and glial activation, which together accelerate neurodegeneration. This frames SDoH as a driver of this biological cascade, rather than as parallel correlates, and the exposome provides a scaffold to understand how social adversity translates into molecular and cellular mechanisms of AD risk.

1.2. Premorbid IQ and cognitive vulnerability

Premorbid IQ (pIQ) represents a person's cognitive abilities before experiencing age-related or pathological decline and is commonly used as a benchmark to assess changes in cognitive performance over time. Lifetime intellectual ability shapes differences in living arrangements, employment type, neighborhood quality, and support systems, making pIQ may be an important modifier of SDoH effects on AD risk. Educational attainment, occupational complexity, high income, and engagement in socially, cognitively and physically stimulating activities are thought to buffer against age-related pathophysiological brain changes associated with dementia onset through a proposed construct of cognitive reserve [20,21]. Early biological risks related to low cognitive ability can shape both exposure to and protection from adverse exposome factors across the lifetime [22]. Individuals with low premorbid intellectual ability (pIQ; estimated IQ $\leq$70), within the range associated with intellectual disability [23], may experience disproportionate vulnerability to adverse SDoH, reflecting lowered capacity to withstand neurological damage through reduced cognitive reserve and neurodevelopmental susceptibility [22–25]. Such individuals may live in multigenerational or supervised households, which may buffer some social support risks [26] but introduce others, like socioeconomic disadvantage and caregiver burdens [27]. In contrast, individuals with an average pIQ may live independently, but lack access to socially enriching environments that may mitigate cognitive risk [4,9].

Lower pIQ reflects reduced reserve, lowering the threshold at which adverse SDoH and chronic stress translate into biological dysregulation and clinical decline. This aligns with the Alzheimer's disease research centers (ADRCs) consortium, which offers rationale and guidance for using selected constructs of SDoH in causal pathways and AD risk. Previous work has examined the impact of educational attainment on cognitive reserve across different racial ethnic groups, where higher education attenuated the negative impact of white matter hyper intensity burden on memory ($\beta = -0.03$; 99 % CI: -0.071, -0.002) and language decline ($\beta = -0.024$; 99 % CI:$-$ 0.044, -0.004), as well as the impact of cortical thinning on level of language performance for non-Hispanic White individuals, but not for non-Hispanic Black or Hispanic individuals [28]. This reflects the complex interplay between cognitive and social factors impacting AD outcomes.

Despite these implications, few studies have examined how exposome SDoH factors of AD differ across the pIQ spectrum. To address this gap, we analyzed data from the multi-ethnic Health and Aging Brain Study–Health Disparities (HABS-HD) cohort, categorizing participants into low pIQ ($\equiv$ IQ $\leq$ 70) and average pIQ ($\equiv$ IQ 90–100) groups based on word reading scores. Using a machine learning approach (XGBoost), we modeled SDoH variables education, income, national ADI, social support, chronic stress, health status, and worry, to identify key predictors of pIQ group membership. Our goals were to (1) determine which AD-related SDoH factors differentiate pIQ groups and (2) discuss how these factors may inform risk stratification and targeted intervention strategies for AD in socially vulnerable populations.

2. Methods

2.1. Participants

The Health & Aging Brain Study – Health Disparities (HABS-HD) is an ongoing, longitudinal, community-based study of health disparities in brain health in underrepresented populations [1]. Data Release 6 was processed for this study, previously released in November 2024. Participants for the current study were selected based on the American National Reading Test (AMNART) [2] and Word Accentuation Test (WAT) [3] for Spanish-speakers. Primary language was self-reported. The AMNART is validated in multiple linguistic and cultural contexts; the WAT is a psychometrically sound Spanish adaptation of the AMNART, demonstrating adequate prediction of intelligence in Spanish speakers. Individuals with low or average word reading were grouped by the following parameters: low pIQ; z score $<$ - 2.00 ($\equiv$ IQ $\leq$ 70) and average pIQ; z score = 0.00 $\pm$ 1.00($\equiv$ IQ 90–100). These criterions were selected based on 1) the normal bell curve and associated classification of stanines, and 2) the description of intellectual disability as outlined by the Diagnostic and Statistical Manual of Mental of Mental Disorders-5th Edition (DMS-5) to be an IQ at least 2 SD below the mean [23].

Data availability

This study utilizes the data from the Health and Aging Brain Study-Health Disparities (HABS-HD) cohort study [1]. HABS-HD is a community-based research initiative aimed at examining brain health among representative samples in the Dallas-Fort Worth metropolitan area. The HABS-HD protocol was reviewed and approved by the University of North Texas Health Science Center (UNTHSC) Institutional Review Board with written informed consent obtained from all study participants. The data from HABS-HD is publicly available upon request through the Institute for Translational Research (ITR) at UNTHSC [1].

2.3. Inclusion/exclusion criteria

All procedures are conducted under IRB-approved protocols. Using a community-based participatory research approach [29], participants were recruited from the greater Dallas-Fort Worth community. Participants or their legal authorized representatives (LAR) provide written informed consent. The HABS-HD protocol includes interviews, functional exams, blood draws for clinical labs and biobanking, neuropsychological testing, and 3T MRI scans of the brain. Amyloid and Tau PET scans are ongoing for the full cohort. The study protocol can be conducted in Spanish or English. Data from the study is accessible to the scientific community through the UNTHSC Institute for Translational Research website. Inclusion in HABS-HD requires 1) willingness to provide blood samples, 2) capable of undergoing neuroimaging studies, 3) age 30 and above, and 4) fluent in English or Spanish. Exclusion criteria includes 1) Type 1 diabetes, 2) presence of active infection, 3) current/recent (12 month) cancer (other than skin cancer), 4) current severe mental illness that could impact cognition (other than depression), 5) recent (12 months) traumatic brain injury with loss of consciousness, 6) current/recent alcohol/substance abuse, and 7) active severe medical condition that could impact cognition (e.g., end stage renal failure, chronic heart failure, chronic obstructive pulmonary disease) [29].

2.4. Word-reading protocol

The AMNART [30] consists of 50 words in English that have abnormal spelling-to-sound phonetics. It is a neuropsychological assessment where the participant is scored on how accurately they can read the words. The cumulative score of the test is then used to determine the participant's pIQ. The WAT [31] consists of 30 uncommon words in Spanish that have had the accent removed. It tests the estimated cognitive ability of an individual based on how accurately they accentuate each word. The comprehensive score is then used to determine the participant's pIQ. The performance (z-score) is normalized using the HABS-HD cohort references of years of education (0–7, 8–12, or 13+), age (median split <65 and >66), primary language (English or Spanish), and ethno-racial group.

2.6. Demographic, socioeconomic & environmental factors

SDoH factors were collected through a demographic questionnaire aimed at capturing participants' annual household income, age, sex, and lifelong address history to assess ADI. Social support was determined by the shortened Interpersonal Support and Evaluation List, which is a test consisting of 12 statements with 4 relating to each subgroup (tangible, appraisal, and belonging support) that allows the participant to rank their identification with each statement from "Definitely true" to "Definitely false". Tangible support is the physical aid and financial support that a person feels they can access when in need, appraisal support is the perception of having a trusted person to confide in, and belonging support is the sense of connection. Worry was assessed using the Penn State Worry Questionnaire (PSWQ) [32] which asks participants to rank their identification with each statement from "Not at all typical" to "Very typical of me". Depressive symptoms were assessed using the Geriatric Depression Scale (GDS) [33] that asks participants yes/no questions regarding their feelings about their life. Chronic stress was assessed using the Chronic Burden Scale [29,34] The Chronic Burden Scale captures chronic stress associated with health concerns, difficulties at work, financial strain, relational difficulties, substance use, and caregiving burden.

2.7. Statistical analysis

A machine learning technique eXtreme Gradient Boosting (XGBoost) was used for this analysis. XGBoost is a supervised machine-learning algorithm that constructs a gradient-boosted decision tree ensemble [35]. In this approach, many simple decision trees are built sequentially, with each tree learning to predict the residual errors from the previous trees. This iterative process "boosts" model performance by combining multiple weak learners into a single strong predictive model, with model parameters optimized using gradient-based methods. Because decision trees partition the data based on predictor values, the resulting ensemble can naturally capture nonlinear relationships, threshold effects, and higher-order interactions among variables without requiring these structures to be prespecified. Compared with conventional regression models, which rely on assumptions of linearity and additivity, XGBoost is particularly well suited for epidemiologic data characterized by heterogeneous predictors, mixed variable types, and complex interdependencies. To ensure the robustness of the findings, its performance was compared to another machine learning method, Random Forest (RF).

During the model building process, highly correlated variables were removed with a Pearson correlation cutoff of $r > 0.75$ and variables with near zero variance were removed. The dataset was partitioned into 80:20 training and test sets based on the PIQ scores. A non-exhaustive 5-fold cross validated hyperparameter grid search was used to reduce overfitting and model complexity. Model validation and hyperparameter optimization were performed exclusively within the training dataset using 5-fold cross-validation. A staged, grid-based tuning strategy was implemented in which key hyperparameters were optimized sequentially, including the number of boosting rounds, learning rate, tree depth, minimum child weight, subsampling fraction, column subsampling, and regularization. A complete list of values considered for all hyperparameters and the final chosen values were reported in Table 1. At each stage, candidate models were evaluated using cross-validated area under the receiver operating characteristic curve (ROC AUC), and the combination of hyperparameters yielding the highest mean cross-validated ROC AUC was retained. The final model was selected based on this criterion and subsequently evaluated on an independent 20 % held-out test set to provide an unbiased estimate of out-of-sample predictive performance.

The test dataset was then fit to the model and evaluated. Features were ranked based on gain, which is the relative contribution of each variable to the overall model fit. Performance metrics for the fitted model included AUC, positive predictive value (PPV), and negative predictive value (NPV). Shapley Additive Explanations were then used to explain the marginal contributions of each feature on the cognitive outcome. SHAP provides a principled approach to interpreting complex machine learning models by quantifying the marginal contribution of each feature to individual predictions [36]. SHAP values attribute differences in model output to each feature in a consistent and locally accurate manner. Importantly, they describe associations learned by the model rather than causal effects, allowing for careful interpretation of feature importance within the context of the fitted model. The mean absolute SHAP value was determined for each feature, which explains the average marginal contribution of that feature to the model prediction.

Table 1
Hyperparameter grid and final selected values for model tuning through 5-fold cross-validation.

Parameter	Tested Values, Final Values Highlighted
Eta	**.01**, 0.015, 0.025, 0.05, 0.1, 0.3
Gamma	**0**, 1, 2, 3, 4, 5, 6
Max depth	2, **3**, 4, 5, 6
Min Child Weight	**1**, 2, 3,4,5
Colsample bytree	0.4, **0.6**, 0.8, 1.0
subsample	0.5, **0.75**, 1.0

3. Results

3.1. Demographic characteristics

Data was analyzed from ($n = 2568$) participants with avg pIQ group (78.2 % of the group are English speakers) and ($n = 123$) individuals with low pIQ (86.0 % are English speakers). Table 2 represents the characteristics of the sample by pIQ. There were no significant differences between the groups in age or sex, although there were a higher percentage of males in the low pIQ group. Individuals in the low pIQ group were more likely to have completed high school or earned a GED. Income was significantly lower in the low pIQ group. Racial-ethnic grouping showed a trend toward significance, with the low pIQ group having a higher proportion of Hispanic and Black individuals and fewer White individuals. To illustrate the underlying distribution of key variables, we conducted exploratory data analysis by plotting the boxplots for income, ADI, worry scale, and tangible support, stratified by pIQ group, in Fig. 1 [37].

3.2. Health status

Reflected in Table 2, there were no significant differences across pIQ groups in self-reported health status. However, the low pIQ group reported significantly higher worry levels on the PSWQ and reported higher levels of neighborhood disadvantage, as indicated by a higher ADI national rank. There were no statistical differences between groups in chronic stress levels.

Table 2
Characteristics of the sample by pIQ.

Characteristic	Average pIQ $N = 2,568$[1]	low pIQ $N = 123$[1]	*p*-value[2]
Age	65.01 (8.67)	65.64 (9.31)	0.5
Sex			0.14
Women	1632 (64 %)	70 (57 %)	
High School Completion			0.001
No high school degree	451 (18 %)	8 (6.5 %)	
High school or GED	2105 (82 %)	115 (93 %)	
Unknown	12	0	
Racial Ethnic Group			0.056
Black	718 (28 %)	42 (34 %)	
Hispanic	868 (34 %)	47 (38 %)	
White	982 (38 %)	34 (28 %)	
Income	74,292.14 (90,310.60)	55,974.07 (56,771.80)	0.011
Unknown	131	9	
Health Status			0.3
Excellent	304 (12 %)	13 (11 %)	
Very good	811 (32 %)	41 (33 %)	
Good	957 (37 %)	37 (30 %)	
Fair	448 (17 %)	30 (24 %)	
Poor	47 (1.8 %)	2 (1.6 %)	
Unknown	1	0	
PSWQ Total	39.42 (14.63)	41.98 (13.19)	0.017
Unknown	6	2	
AD National Rank	55.91 (26.46)	63.20 (25.26)	0.010
Unknown	419	24	
Social Support Total	40.91 (6.35)	40.30 (6.53)	0.2
Unknown	2	0	
Chronic Stress Total	7.76 (6.94)	6.93 (6.42)	0.3
Unknown	4	0	
Appraisal Support	10.20 (1.40)	9.92 (1.49)	0.034
Unknown	5	0	
Belonging Support	10.13 (1.49)	10.06 (1.52)	0.7
Unknown	2	0	
Tangible Support	10.42 (1.46)	10.07 (1.55)	0.004
Unknown	7	0	

[1] Mean (SD); n (%).
[2] Wilcoxon rank sum test; Pearson's Chi-squared test; Fisher's exact test.

3.3. Social and emotional support

The overall social support total (Table 2) was not significantly different across pIQ groups. However, two subcomponents of social support, appraisal and tangible support, were significantly lower in the low pIQ group. There were no significant differences in belonging support across low and avg. pIQ groups.

3.4. SDoH XGBoost model for pIQ group classification

The model achieved an Area Under the Curve (AUC) or 0.72 [0.64, 0.81], Positive Predictive Value (PPV) 0.4 [0.05, 0.85], and Negative Predictive Value (NPV) 0.94 [0.92,0.96] in classifying pIQ group. Fig. 2. displays the features importance plot and receive operating characteristic (ROC) curve for predicting pIQ group membership. The feature importance plot demonstrates that worry, ADI national rank, income, completion of high school, and tangible support are the top 5 predictors in the model performance.

The SHAP plot (Fig. 3) further illustrates the distribution, direction, and magnitude of each feature's contribution to the model's predictions. Factors such as low income, moderate to low tangible support, higher ADI national rank (indicating greater neighborhood disadvantage), moderate worry, older age, and male sex were all associated with low pIQ, each contributing to the model with varying degrees of impact. Additionally, lower appraisal support and higher overall social support were associated with membership in the low pIQ group. High school completion was paradoxically associated with low pIQ, while lower levels of chronic stress were unexpectedly associated with average pIQ.

4. Discussion

Utilizing Alzheimer's disease–related Social Determinants of Health (SDoH) in combination with an XGBoost gradient tree boosting algorithm, we conducted a cross-sectional analysis of participants from the multiethnic, community-based Health and Aging Brain Study–Health Disparities (HABS-HD) to predict premorbid intellectual ability (pIQ). The SDoH-based model achieved an AUC of 0.72 [0.64, 0.81] on 20 % partitioned data, indicating good ability to differentiate individuals by pIQ using SDoH factors alone. Feature importance and SHAP analyses identified worry, national Area Deprivation Index rank, income, high school completion, and tangible social support as the strongest predictors of low pIQ, with additional contributions from age, sex, appraisal support, and chronic stress. These findings indicate that multiple dimensions of social disadvantage and psychosocial context are strongly associated with lower premorbid intellectual ability. The convergence of neighborhood deprivation, economic strain, and altered social and emotional supports in individuals with low pIQ suggests a clustering of social risk factors that may amplify vulnerability to later-life cognitive decline, motivating further investigation into shared biological pathways linking SDoH, cognitive reserve, and neurodegeneration.

In our model, exogenous exposome factors, low income, neighborhood deprivation, and limited access to education and resources, contributed to the predictive value beyond individual-level exposures like health status, stress, and age. This suggests that the association between macro-level risk factors and cognitive ability is robust. These macro-level exposures influence both the likelihood of developing cognitive vulnerabilities earlier in life and the capacity to maintain cognitive health with aging [38,39]. Because health status did not contribute to the model beyond the impact of macro-level factors, our models support that the vulnerabilities in the low pIQ group are not simply a reflection of individual characteristics, but that social disadvantage adds a meaningful contextual layer. This distinction reflects the need for a multi-pronged approach that considers medical, biological, and social risk to address reducing harmful cognitive aging exposures in those with low pIQ. Interventions at the community level, therefore, are important for addressing dementia risk in low pIQ populations.

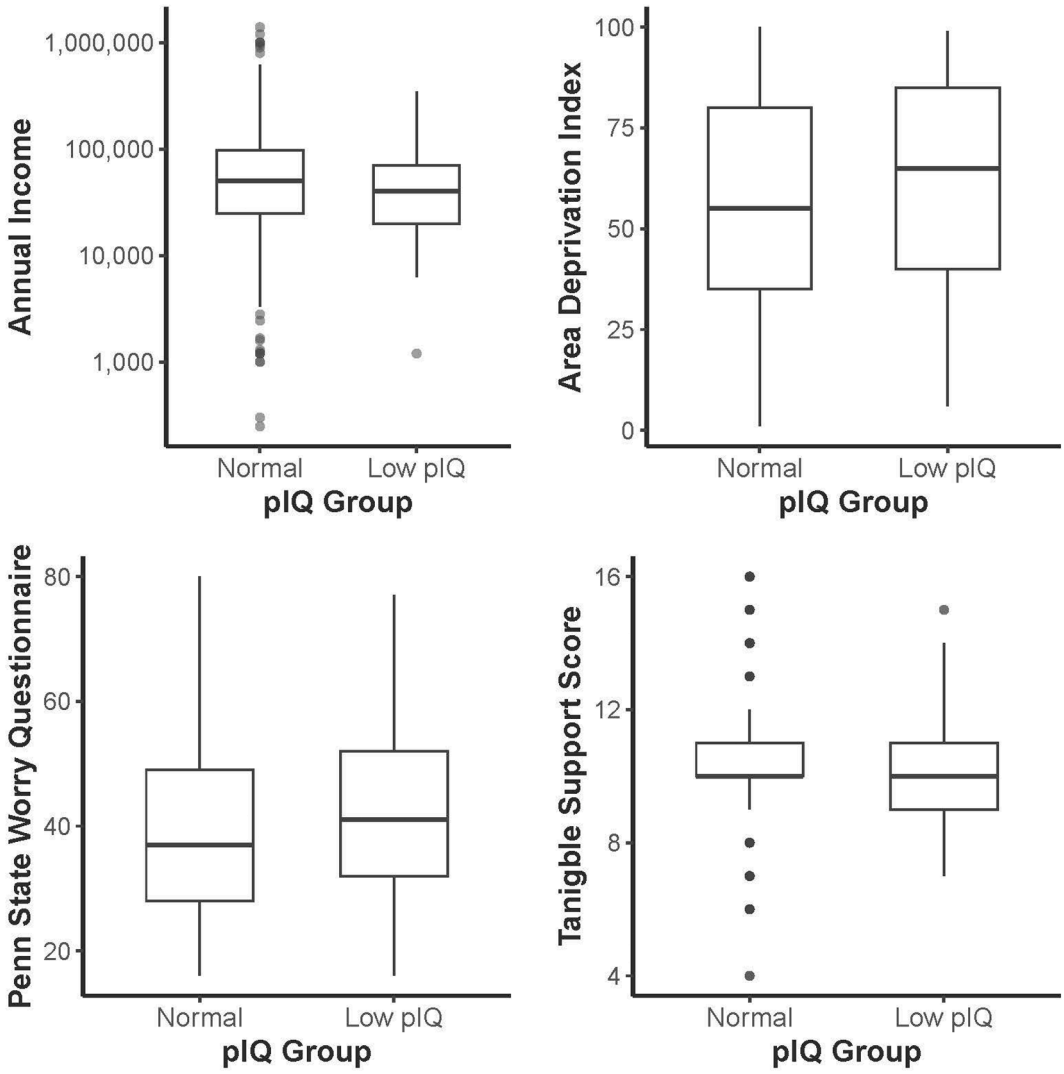

Fig. 1. represents the distribution of income, ADI, worry scale, and tangible support stratified by pIQ group, displayed using boxplots.

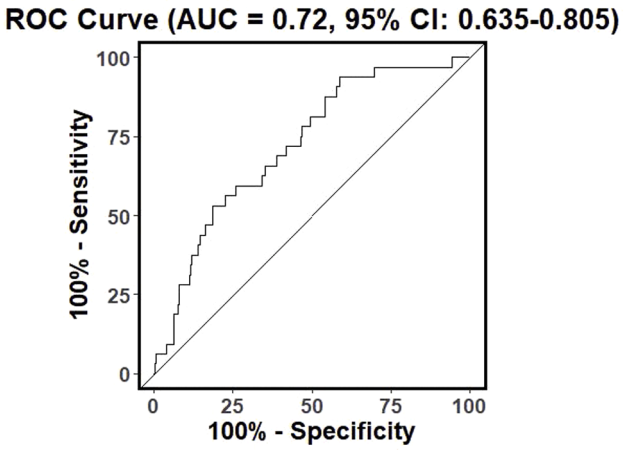

Fig. 2. represents the receiver operating curve (ROC) for the SDoH factors predicting pIQ grouping.

Worry and ADI emerged among the top predictive factors. This link is consistent with prior findings associated with heightened worry with socioeconomic disadvantage, and theories highlight chronic psychological stress promotes proinflammatory phenotypes [34,40]. While a singular environmental factor does not explain macro-level exposome effects on cognitive development and cognitive aging, healthcare access and education are thought to be primary mediators of this relationship [38,39,41–44]. Economically disadvantaged or under-resourced communities have a higher prevalence of individuals with lower cognitive ability, potentially reflecting the cumulative impact of adverse developmental exposures [45]. In turn, lower cognitive ability is associated with reduced compensatory capacity and neurobiological resilience to buffer against AD pathophysiology [20,21,46]. When combined with socioeconomic disadvantage, a low pIQ psychosocial–cognitive profile amplifies AD risk beyond what would be expected from either factor alone.

While our study focused on pIQ, our findings provide nuanced insight into how social support functions differ across cognitive ability levels, with pIQ serving as a proxy for the cognitive functioning associated with intellectual disability (ID). Individuals with a developmentally low pIQ are more likely to be living in group contexts, where emotional support is structurally embedded in daily life, as supported by our SHAP plot findings. This makes traditional support metrics that weigh emotional, social, or appraisal support used in clinical settings less appropriate to estimate social risk in those with low pIQ. Instead, consistent with our findings, tangible support questionnaires and material assistance are critical types of social support for those with

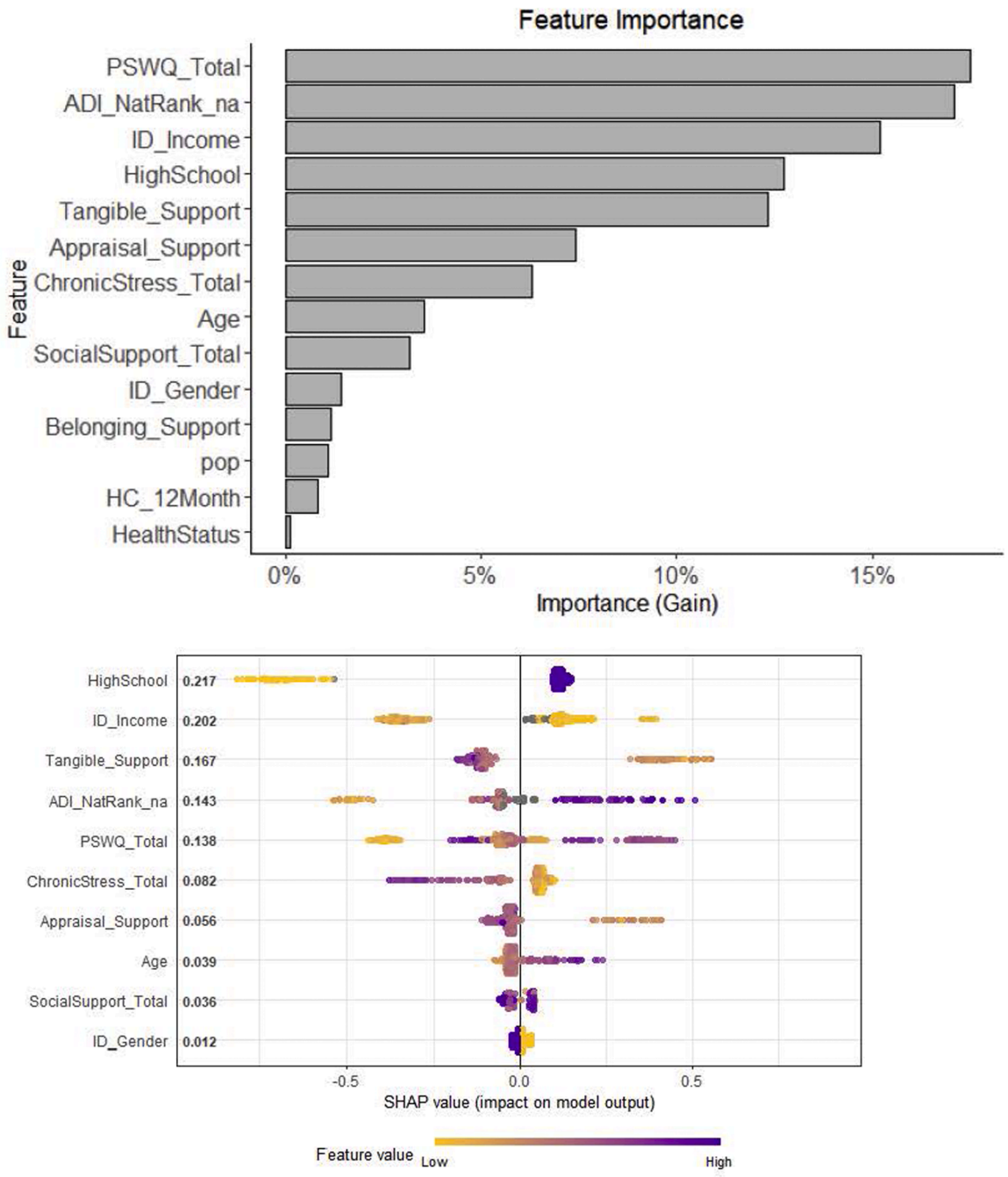

Fig. 3. represents the figure importance plot and the Shapley Additive exPlanations (SHAP) plot. This SHAP plot displays the individual contribution of each feature to the model output. Low pIQ was coded as 1.00 and average pIQ was coded as 0.00, associated with the right and left sides of the x-axis, respectively. Each feature value was coded as either low (yellow) or high (purple) to reflect the distribution of the factor values associated with the pIQ grouping. NHW participants were coded as 0.00 (yellow), NHB as 1.00 (pink), and Hispanic as 2.00 (purple). Males were coded as 0.00 (yellow). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

developmentally low pIQ. For individuals with ID a "cascade of disparities" where risks associated with higher rates of comorbid health conditions [47,48] such as epilepsy, neurological, gastrointestinal, and behavioral or psychiatric disorders are compounded by insufficient attention to health problems by health providers, lower engagement in preventive care and healthy behaviors, inequitable access to healthcare, and challenges in managing chronic conditions, all of which contribute to poorer overall health outcomes [49].

Our paradoxical findings about high school completion and low pIQ group membership reflects cohort characteristics where over 80 % of all participants completed high school, and the variance in high school completion rate between groups reflected a greater distribution of graduates and GED holders in the low pIQ group. Higher rates of chronic stress are unexpectedly associated with average pIQ group membership. Similar to the findings from the Social Support subscale analyses, our results suggest that the nature and sources of chronic stress differ between pIQ groups, where higher IQ levels reflect a greater risk for psychological chronic stress [50]. The Chronic Burden Scale captures chronic stress associated with health concerns, difficulties at work, financial strain, relational difficulties, substance use, and caregiving burden. These types of chronic stressors are differently experienced by individuals with lower pIQ, where individuals with higher cognitive

functioning may engage in more complex work, social, or caregiving roles, exposing them to a wider range of stressors. For individuals with a lower pIQ the experience of chronic stress may depend more heavily on specific contexts rather than on a broad range of life demands. Our findings underscore the need for more inclusive and adaptive measures of chronic stress, ensuring that stress-related risk factors for physical and mental health are adequately captured across the cognitive spectrum.

Future analyses will leverage the longitudinal design of HABS-HD to evaluate whether the SDoH profile identified here predicts cognitive decline, AD-related biomarker trajectories, or incident mild cognitive impairment and dementia, and whether these associations differ by premorbid intellectual ability. Based on our model, we predict that individuals with low premorbid ability and high social disadvantage (e.g., low income, high ADI, incomplete high school) will show greater neuroinflammatory burden and faster cognitive decline. This priori is supported by our previously published characterization of AD biomarkers, where higher level of neurodegeneration and phosphorylated tau was observed in those with low pIQ [51]. Conversely, modifiable supports, including tangible supports, bridge programming through secondary and post-secondary education, group housing contexts that provide social support, and caregiver resources, may mitigate risk and represent intervention-relevant targets to slow or prevent AD progression in vulnerable populations.

5. Limitations and future directions

Our results provide insight into how relative social disadvantage intersects with cognitive risk, but several limitations should be noted. First, the cross-sectional design precludes statements about causality or how these factors interact over time to shape lifetime risk. Second, we used word-reading as a proxy for premorbid IQ. While this is a common approach in cognitive assessment, it does not fully capture the complexity of developmentally low IQ, potentially underestimating variation in cognitive reserve. Third, sample composition and the relatively small size of the low pIQ group limits generalizability, and the distribution of education and income in this community sample may not reflect broader populations or other geographic contexts. Fourth, regarding the machine learning approach, although cross-validation and an independent test set were utilized for the analysis, although we implemented cross-validation and evaluated performance on an independent test set, overfitting remains a possibility given model complexity. Model performance was modest, indicating that SDoH predictors explain only part of the variability in cognitive outcomes, and SHAP values reflect associations learned by the model rather than causal effects. Finally, replication in larger, independent samples is necessary to validate and expand upon these findings and better understand how premorbid cognitive ability and social disadvantage intersects with AD risk across the lifespan.

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Generative AI statement

No generative AI or AI-assisted technologies were used in the preparation of this manuscript or the figures contained within.

Ethics statement

This study involves data from human participants and was approved by the North Texas IRB (#2016-128). Participants (or their legal authorized representatives [LAR]) provided written informed consent.

Data availability

The original contributions presented in the study are publicly available. This data can be found at: University of North Texas Health Science Center (UNTHSC) Institute for Translational Research (ITR), https://apps.unthsc.edu/itr/researchers

Consent statement

Informed consent from all participants or their legally authorized representatives were obtained prior to inclusion.

CRediT authorship contribution statement

Lubnaa Badriyyah Abdullah: Writing – review & editing, Writing – original draft, Conceptualization. **Ibshar Khandakar:** Writing – review & editing, Methodology, Formal analysis. **Ashley Douglas:** Writing – review & editing. **Robert Nance:** Writing – review & editing. **Zhengyang Zhou:** Supervision, Methodology. **James Hall:** Writing – review & editing, Supervision. **Sid O'Bryant:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

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References

[1] Livingston G, Huntley J, Sommerlad A, et al. Dementia prevention, intervention, and care: 2020 report of the Lancet Commission. Lancet 2020;396(10248):413–46. https://doi.org/10.1016/S0140-6736(20)30367-6.
[2] Majoka MA, Schimming C. Effect of social determinants of health on cognition and risk of Alzheimer disease and related dementias. Clin Ther 2021;43(6):922–9. https://doi.org/10.1016/j.clinthera.2021.05.005.
[3] Finch CE, Kulminski AM. The Alzheimer's Disease exposome. Alzheimers Dement 2019;15(9):1123–32. https://doi.org/10.1016/j.jalz.2019.06.3914.
[4] Li K, Shacham E, Brown D, et al. Association of environmental exposome and cognitive function among older adults with and without preclinical Alzheimer's disease. Alzheimers Dement 2025;21(6):e70373. https://doi.org/10.1002/alz.70373.
[5] Jack Jr CR, Bennett DA, Blennow K, et al. A/T/N: an unbiased descriptive classification scheme for Alzheimer disease biomarkers. Neurology 2016;87(5):539–47. https://doi.org/10.1212/WNL.0000000000002923.
[6] Jack Jr CR, Andrews JS, Beach TG, et al. Revised criteria for diagnosis and staging of Alzheimer's disease: alzheimer's Association Workgroup. Alzheimers Dement 2024;20(8):5143–69. https://doi.org/10.1002/alz.13859.
[7] Daneman R, Prat A. The blood-brain barrier. Cold Spring Harb Perspect Biol 2015;7(1):a020412. https://doi.org/10.1101/cshperspect.a020412.

[8] Megha KB, Joseph X, Akhil V, Mohanan PV. Cascade of immune mechanism and consequences of inflammatory disorders. Phytomedicine 2021;91:153712. https://doi.org/10.1016/j.phymed.2021.153712.
[9] Adkins-Jackson PB, George KM, Besser LM, et al. The structural and social determinants of Alzheimer's disease related dementias. Alzheimers Dement 2023;19(7):3171–85. https://doi.org/10.1002/alz.13027.
[10] Non AL, Rimm EB, Kawachi I, Rewak MA, Kubzansky LD. The effects of stress at work and at home on inflammation and endothelial dysfunction. PLoS One 2014;9(4):e94474. https://doi.org/10.1371/journal.pone.0094474.
[11] Yuan Y, Sun J, Dong Q, Cui M. Blood-brain barrier endothelial cells in neurodegenerative diseases: signals from the "barrier". Front Neurosci 2023;17:1047778. https://doi.org/10.3389/fnins.2023.1047778.
[12] Juszczyk G, Mikulska J, Kasperek K, Pietrzak D, Mrozek W, Herbet M. Chronic stress and oxidative stress as common factors of the pathogenesis of depression and Alzheimer's Disease: the role of antioxidants in prevention and treatment. Antioxidants (Basel) 2021;10(9). https://doi.org/10.3390/antiox10091439.
[13] Shin MH, Yin ZZ, Yoon KN, Quan QL, Lee DH, Chung JH. Oxytocin enhances neurogenesis and synaptic plasticity to attenuate age-related cognitive decline in aged mice. IBRO Neurosci Rep 2025;19:774–80. https://doi.org/10.1016/j.ibneur.2025.10.008.
[14] Perry BL, McConnell WR, Coleman ME, Roth AR, Peng S, Apostolova LG. Why the cognitive "fountain of youth" may be upstream: pathways to dementia risk and resilience through social connectedness. Alzheimers Dement 2022;18(5):934–41. https://doi.org/10.1002/alz.12443.
[15] Lee JK, Johnson L, Hall JR, et al. Chronic stress, social support, and Alzheimer's blood-based biomarkers in the HABS-HD study. Alzheimers Dement 2025;21(3):e70043. https://doi.org/10.1002/alz.70043.
[16] Hithersay R, Startin CM, Hamburg S, et al. Association of dementia with mortality among adults with Down syndrome older than 35 years. JAMA Neurol 2019;76(2):152–60. https://doi.org/10.1001/jamaneurol.2018.3616.
[17] Clark AL, Thomas KR, Ortega N, et al. Empirically derived psychosocial-behavioral phenotypes in Black/African American and Hispanic/Latino older adults enrolled in HABS-HD: associations with AD biomarkers and cognitive outcomes. Alzheimers Dement 2024;20(2):1360–73. https://doi.org/10.1002/alz.13544.
[18] Petterson S. Deciphering the neighborhood Atlas Area Deprivation Index: the consequences of not standardizing. Health Aff Sch 2023;1(5):qxad063. https://doi.org/10.1093/haschl/qxad063.
[19] Powell WR, Buckingham WR, Larson JL, et al. Association of neighborhood-level Disadvantage with Alzheimer Disease neuropathology. JAMA Netw Open 2020;3(6):e207559. https://doi.org/10.1001/jamanetworkopen.2020.7559.
[20] Stern Y. What is cognitive reserve? Theory and research application of the reserve concept. J Int Neuropsychol Soc 2002;8(3):448–60.
[21] Pettigrew C, Soldan A. Defining cognitive reserve and implications for cognitive aging. Curr Neurol Neurosci Rep 2019;19(1):1. https://doi.org/10.1007/s11910-019-0917-z.
[22] Tchoua P.P., Clarke E., Wasser H., et al. The interaction between social determinants of health, health behaviors, and child's intellectual developmental diagnosis. *medRxiv*. 2024;doi:10.1101/2024.05.23.24307804.
[23] Black DW, Grant JE. DSM-5® guidebook: the essential companion to the diagnostic and statistical manual of mental disorders. American Psychiatric Pub; 2014.
[24] Stone MR, Faulkner GE. Outdoor play in children: associations with objectively-measured physical activity, sedentary behavior and weight status. Prev Med 2014;65:122–7. https://doi.org/10.1016/j.ypmed.2014.05.008.
[25] Iezzoni LI, Rao SR, Ressalam J, et al. Physicians' Perceptions of people with disability and their health care. Health Aff 2021;40(2):297–306. https://doi.org/10.1377/hlthaff.2020.01452.
[26] Lee H, Ryan LH, Ofstedal MB, Smith J. Multigenerational households during childhood and trajectories of cognitive functioning among U.S. Older adults. J Gerontol B 2021;76(6):1161–72. https://doi.org/10.1093/geronb/gbaa165.
[27] Theng B, Tran JT, Serag H, et al. Understanding caregiver challenges: a comprehensive exploration of available resources to alleviate caregiving burdens. Cureus 2023;15(8):e43052. https://doi.org/10.7759/cureus.43052.
[28] Avila JF, Renteria MA, Jones RN, et al. Education differentially contributes to cognitive reserve across racial/ethnic groups. Alzheimers Dement 2021;17(1):70–80. https://doi.org/10.1002/alz.12176.
[29] O'Bryant SE, Johnson LA, Barber RC, et al. The Health & Aging Brain among Latino elders (HABLE) study methods and participant characteristics. Alzheimers Dement (Amst) 2021;13(1):e12202. https://doi.org/10.1002/dad2.12202.
[30] O'Bryant SE, Edwards M, Johnson L, Hall J, Gamboa A, O'Jile J. Texas Mexican American adult normative studies: normative data for commonly used clinical neuropsychological measures for English- and Spanish-speakers. Dev Neuropsychol 2018;43(1):1–26. https://doi.org/10.1080/87565641.2017.1401628.
[31] Sierra Sanjurjo N, Montanes P, Sierra Matamoros FA, Burin D. Estimating intelligence in Spanish: regression equations with the word accentuation test and demographic variables in Latin America. Appl Neuropsychol Adult 2015;22(4):252–61. https://doi.org/10.1080/23279095.2014.918543.
[32] Meyer TJ, Miller ML, Metzger RL, Borkovec TD. Development and validation of the Penn State worry Questionnaire. Behav Res Ther 1990;28(6):487–95. https://doi.org/10.1016/0005-7967(90)90135-6.
[33] Yesavage JA, Brink TL, Rose TL, et al. Development and validation of a geriatric depression screening scale: a preliminary report. J Psychiatr Res 1982;17(1):37–49. https://doi.org/10.1016/0022-3956(82)90033-4.
[34] Bromberger JT, Matthews KA. A longitudinal study of the effects of pessimism, trait anxiety, and life stress on depressive symptoms in middle-aged women. Psychol Aging 1996;11(2):207–13. https://doi.org/10.1037//0882-7974.11.2.207.
[35] Chen T. XGBoost: a scalable tree boosting system. Cornell University; 2016.
[36] Lundberg SM, Lee S-I. A unified approach to interpreting model predictions. Adv Neural Inf Process Syst 2017;30.
[37] Tukey JW, Mosteller F. Data analysis and regression. Reading: Addison-Wesley; 1977.
[38] Xiang X, Cho J, Sun Y, Wang X. Childhood adversity and cognitive impairment in later life. Front Psychol 2022;13:935254. https://doi.org/10.3389/fpsyg.2022.935254.
[39] Hackman DA, Farah MJ, Meaney MJ. Socioeconomic status and the brain: mechanistic insights from human and animal research. Nat Rev Neurosci 2010;11(9):651–9. https://doi.org/10.1038/nrn2897.
[40] Baum A, Garofalo JP, Yali AM. Socioeconomic status and chronic stress. Does stress account for SES effects on health? Ann N Y Acad Sci 1999;896:131–44. https://doi.org/10.1111/j.1749-6632.1999.tb08111.x.
[41] Noble KG, McCandliss BD, Farah MJ. Socioeconomic gradients predict individual differences in neurocognitive abilities. Dev Sci 2007;10(4):464–80. https://doi.org/10.1111/j.1467-7687.2007.00600.x.
[42] National Institute of Child H. Human Development Early Child Care Research N. Duration and developmental timing of poverty and children's cognitive and social development from birth through third grade. Child Dev 2005;76(4):795–810. https://doi.org/10.1111/j.1467-8624.2005.00878.x.
[43] Wang X., Bakulski K.M., Paulson H.L., Albin R.L., Park S.K. Associations of healthy lifestyle and socioeconomic status with cognitive function in U.S. Older adults. *medRxiv*. 2023;doi:10.1101/2023.01.24.23284961.
[44] McMaughan DJ, Oloruntoba O, Smith ML. Socioeconomic status and access to healthcare: interrelated drivers for healthy aging. Front Public Health 2020;8:231. https://doi.org/10.3389/fpubh.2020.00231.
[45] Muhammad T, Srivastava S, Sekher TV. Assessing socioeconomic inequalities in cognitive impairment among older adults: a study based on a cross-sectional survey in India. BMC Geriatr 2022;22(1):389. https://doi.org/10.1186/s12877-022-03076-6.
[46] Abdullah L, Zhou Z, Hall J, Petersen M, Zhang F, O'Bryant S. Association of Alzheimer's disease biomarkers with low premorbid intellectual functioning in a multi-ethnic community-dwelling cohort: a cross-sectional study of HABS-HD. J Alzheimers Dis 2025:13872877251322966. https://doi.org/10.1177/13872877251322966.
[47] Lineberry S, Bogenschutz M, Broda M, Dinora P, Prohn S, West A. Co-occurring mental illness and behavioral support needs in adults with intellectual and developmental disabilities. Community Ment Health J 2023;59(6):1119–28. https://doi.org/10.1007/s10597-023-01091-4.
[48] Samarasekera S. Managing patients with intellectual disability and epilepsy in the acute medical setting. Clin Med 2024;24(2):100039. https://doi.org/10.1016/j.clinme.2024.100039.
[49] Krahn GL, Fox MH. Health disparities of adults with intellectual disabilities: what do we know? What do we do? J Appl Res Intellect Disabil 2014;27(5):431–46. https://doi.org/10.1111/jar.12067.
[50] Karpinski RI, Kinase Kolb AM, Tetreault NA, Borowski TB. High intelligence: a risk factor for psychological and physiological overexcitabilities. Intelligence 2018;66:8–23. https://doi.org/10.1016/j.intell.2017.09.001.
[51] Abdullah LB, Zhou Z, Alliey NA, Barber R, Hall J, O'Bryant S. Low premorbid IQ may exacerbate the cognitive effects of apolipoprotein epsilon4 (APOE epsilon4): a multi-ethnic cross-sectional study from HABS-HD. Front Neurol 2025;16:1627525. https://doi.org/10.3389/fneur.2025.1627525.