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SHORT REPORT

Social disadvantage outweighs knowledge in dementia risk

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Abstract

INTRODUCTION: Public health efforts promote dementia knowledge to reduce risk, but it is unclear whether knowledge predicts lower risk compared to social determinants like education and socioeconomic status (SES).

METHODS: We analyzed cross-sectional data from 1730 adults to examine how age, sex, education, SES, family history of dementia, and Alzheimer's disease (AD) knowledge predicted behavioral and health-related dementia risk. We used linear regressions and machine learning to compare the explanatory and predictive value of each factor.

RESULTS: Lower SES and education were the strongest predictors of increased behavioral risk. Health-related risk was associated only with SES. AD knowledge accuracy and confidence were not significantly associated with either index. Machine learning confirmed these patterns, with SES and education emerging as key features.

DISCUSSION: Low SES and education were more strongly linked to dementia risk than AD knowledge. Findings underscore the need for equity-focused strategies beyond public awareness campaigns to improve knowledge.

KEYWORDS

Alzheimer's disease knowledge, dementia, dementia risk, education, socioeconomic status

Highlights

- Social disadvantage was the strongest predictor of dementia risk.
- Lower socioeconomic status (SES) and education predicted increased behavioral risk.
- Only lower SES significantly predicted health-related risk.
- Alzheimer's disease knowledge did not reduce behavioral or health-related risk.

1 | BACKGROUND

Dementia is one of the most pressing global health challenges of the twenty-first century due to its growing prevalence and substantial societal burden.[1] Alzheimer's disease (AD), the most common cause of dementia, accounts for 60% to 80% of all cases.[2,3] Although no cure exists, up to 45% of cases may be preventable through modification of risk factors across the lifespan.[2,3] Understanding the drivers of these risks and their variability across individuals is a critical scientific and public health priority.

Modifiable dementia risk factors include both behavioral and health-related domains, which frequently overlap, but differ in their primary nature. Behavioral risks (e.g., physical inactivity, smoking, social isolation) reflect individual habits but are strongly shaped by structural and social determinants that influence access to supportive environments and healthy choices.[3–6] Health-related risks (e.g., hypertension, diabetes, depression) are clinically diagnosed conditions involving physiological dysregulation or chronic disease, often linked to behavioral patterns.[7,8] Both types of risk are unequally distributed due to structural and social determinants,[4,9,10] with individuals of lower socioeconomic status (SES) and education experiencing higher exposure and greater barriers to prevention and care. Effective dementia prevention requires addressing individual behaviors alongside the structural and social determinants that shape them across the life course.[3,11]

Structural and social determinants are strongly linked to behavioral dementia risk factors. Socioeconomic disadvantage is associated with lower physical activity and reduced smoking cessation.[12,13] Low socioeconomic position, irregular work schedules, and work–family conflict contribute to excessive daytime sleepiness.[14,15] Built-environment factors shape social engagement and loneliness,[16,17] and stronger social support predicts more positive attitudes toward aging.[18] These determinants also influence health-related risks: lower income, neighborhood deprivation, food insecurity, and limited social capital are associated with higher prevalence and poorer control of hypertension,[19] diabetes,[20] and depressive symptoms.[21] Thus, behavioral and health-related risks are shaped by broader social and structural conditions rather than individual choice alone.[9]

Increasing dementia knowledge is often proposed as a risk-reduction strategy, but evidence is mixed. Some campaigns improve knowledge,[22,23] while others showed no change.[24,25] Greater knowledge does not reliably translate into behavior change, particularly among individuals with lower education.[26] Evidence from vascular dementia and cardiovascular risk indicates that knowledge alone is insufficient for sustained lifestyle change, especially among populations with lower education, SES, or limited access to health services.[27–29] Although socioeconomic disadvantage and low education are well-established contributors to dementia vulnerability,[4,30–33] these factors reflect broader structural inequalities shaping cognitive vulnerability beyond individual-level characteristics.[9,34–36] However, their relative importance compared to dementia knowledge, a common target of public health campaigns, remains unclear. No studies have directly quantified the relative contributions of sociodemographic factors (education, SES, age, sex, family history) versus AD knowledge using both explanatory and predictive approaches. Addressing this gap is critical to determine whether knowledge-based interventions can meaningfully reduce risk once upstream social determinants are taken into account.

To address this gap, we used the Neureka app, a digital platform, to assess dementia risk in a large community-based sample.[37,38] Neureka integrates self-report with cognitive and behavioral measures delivered through self-administered science challenges.[37] We analyzed data from 1730 adults to examine associations between sociodemographic factors, dementia knowledge, and two composite indices of modifiable dementia risk: a behavioral index (physical activity, social engagement, loneliness, drowsiness, smoking, attitudes toward aging) and a health-related index (hypertension, diabetes, depressive symptoms). Predictors included age, sex, education, SES, family history of dementia, and dementia knowledge. Regression and machine learning models were used to compare the explanatory and predictive contributions of sociodemographic and knowledge-based factors, with implications for future targeted public health strategies.

RESEARCH in CONTEXT

1. **Systematic Review**: We reviewed the literature using traditional sources (e.g., PubMed) and reference tracking of systematic reviews. While increasing Alzheimer's disease (AD) knowledge is often proposed as a preventive strategy, evidence remains mixed. Some awareness campaigns improve knowledge, but effects on sustained behavior change are inconsistent. No studies have directly compared knowledge to sociodemographic factors as predictors of modifiable dementia risk in healthy adults across a broad age range.
2. **Interpretation**: Low socioeconomic status and education are stronger predictors of behavioral dementia risk than AD knowledge. Using regression and machine learning in a large digital sample, we found that knowledge did not significantly explain or predict risk, whereas social disadvantage consistently did.
3. **Future Directions**: Future research should use longitudinal designs to clarify how knowledge interacts with structural and psychological factors over time. Interventions must be co-developed with vulnerable groups and can be tested using scalable digital tools.

2 | METHODS

2.1 | Participants

From all Neureka app users,[37,38] we included those who completed Risk Factors and Remember This modules. Sixty-seven individuals were excluded due to self-reported dementia or incomplete data, yielding a final sample of 1730 participants (Figure 1A). The sample was 75% female, aged 18 to 88 years (M = 49.81, standard deviation [SD] = 14.11), and spanned 36 countries, primarily the United Kingdom ($n = 1099$), United States ($n = 357$), Ireland ($n = 232$), and Canada (n = 25; Figure 1A). The sample provided > 0.99 power ($\alpha = 0.05$) to detect small-to-moderate effects in multiple linear regression models with up to seven predictors.

The study was approved by the research ethics committee of the School of Psychology, Trinity College Dublin. All participants provided informed consent. Neureka data are stored and processed in accordance with the European Union General Data Protection Regulations.

2.2 | Procedure and instruments

Neureka is a free smartphone app developed by the Gillan Lab at Trinity College Dublin for large-scale brain health research.[37] Participants are recruited through media campaigns, advertisements, research studies, and citizen science initiatives. All users provide informed consent. Eligibility requires age ≥ 18; tasks are self-guided and uncompensated. This study analyzed the Risk Factors and Remember This modules.

The Risk Factors module[38] includes self-reported sociodemographic, medical, and lifestyle data (Table 1). Validated instruments assessed key domains: the Godin–Shephard Leisure-Time Physical Activity Questionnaire,[39] the Lubben Social Network Scale,[40] the University of California Los Angeles (UCLA) Loneliness Scale,[41] and the Center for Epidemiologic Studies Depression Scale (CES-D),[42] and the "Attitudes Toward Own Aging" (ATOA) subscale of the Philadelphia Geriatric Center Morale Scale.[43]

The Remember This module includes the 30 original items of the Alzheimer's Disease Knowledge Scale,[44] without modification. In addition, participants provided True/False responses and rated confidence (0–100%) for each item. Although a repeat assessment is prompted after 2 weeks, only the first completion was analyzed. Two predictors were derived: proportion correct and mean confidence. The full item set is available in Supplementary Material S1 in supporting information.

2.3 | Data analysis

We used statistical and machine learning methods to examine associations among sociodemographic factors, dementia knowledge, and modifiable risks. We estimated effect direction and magnitude and assessed the predictive importance of each predictor group. Regression models quantified associations, whereas machine learning captured non-linear patterns, improved prediction, and identified key contributors.[45] This combined approach enhanced interpretability and robustness. Measures used to operationalize each predictor and risk factor are detailed in Table 1.

Modifiable risk factors[2,3] were grouped into two theoretically defined categories (Figure 1B; Table 1). Behavioral risk included low physical activity, low social engagement, loneliness, drowsiness, smoking, and negative attitudes toward aging.[3,4,26,46,47] Health-related risk included hypertension, diabetes, and depressive symptoms, representing medical or mental health conditions that may be behaviorally influenced but are not solely lifestyle driven.[3,4,11] Variables were reverse-coded as needed so that higher values indicated greater risk. All risk factors were z score standardized and averaged to derive the corresponding risk indices (Figure 1C).

We ran two linear regression models with the behavioral and health-related risk indices as outcomes (Figure 1D). Predictors included age, sex (women as reference), education, SES, family history of dementia, dementia knowledge, and confidence. Standardized betas and R^2 were reported. Univariate models assessed consistency with multivariate results. Predictor correlations and multicollinearity were evaluated using variance inflation factor and tolerance.

To assess predictive performance, we trained Extreme Gradient Boosting (XGBoost) classifiers on binarized risk indices (high vs. low, median split). Performance was evaluated using stratified repeated random splits (10 repeats, 80% training, 20% testing), with hyperparameters tuned via grid search and 5-fold cross-validation within training sets. SHapley Additive exPlanations (SHAP)[48] were used to estimate predictor contributions and direction (Figure 1E). Performance was quantified using area under the curve (AUC; 95% confidence interval [CI]), accuracy, precision, recall, and F1 score. Robustness was examined using alternative 70/30 splits and random forest classifiers under both partitioning schemes.

3 | RESULTS

Participants answered an average of 80% of items correctly (range: 40%–100%; Figure 2A). Item #29 ("Alzheimer's disease cannot be cured") had the highest accuracy, whereas item #2 ("Mental exercise can prevent Alzheimer's disease") had the lowest (Figure 2B). Dementia knowledge was higher among participants with greater education ($r = 0.25$, $p < 0.001$) and older age ($r = 0.20$, $p < 0.001$; Figure 2C). Education was positively associated with SES ($r = 0.34$, $p < 0.001$), and older age with reporting a family history of dementia ($r = 0.30$, $p < 0.001$; Figure 2C). Variance inflation factors (1.03–1.21) and tolerance values (0.83–0.97) indicated no multicollinearity.

In the behavioral risk model ($R^2 = 0.24$, $F = 77.12$, $p < 0.001$), lower SES, lower education, and younger age were associated with higher risk (Figure 3A). SES showed the strongest association (partial $R^2 = 0.24$, $\beta = 0.44$, $p < 0.001$), followed by education (partial $R^2 = 0.05$, $\beta = 0.07$,

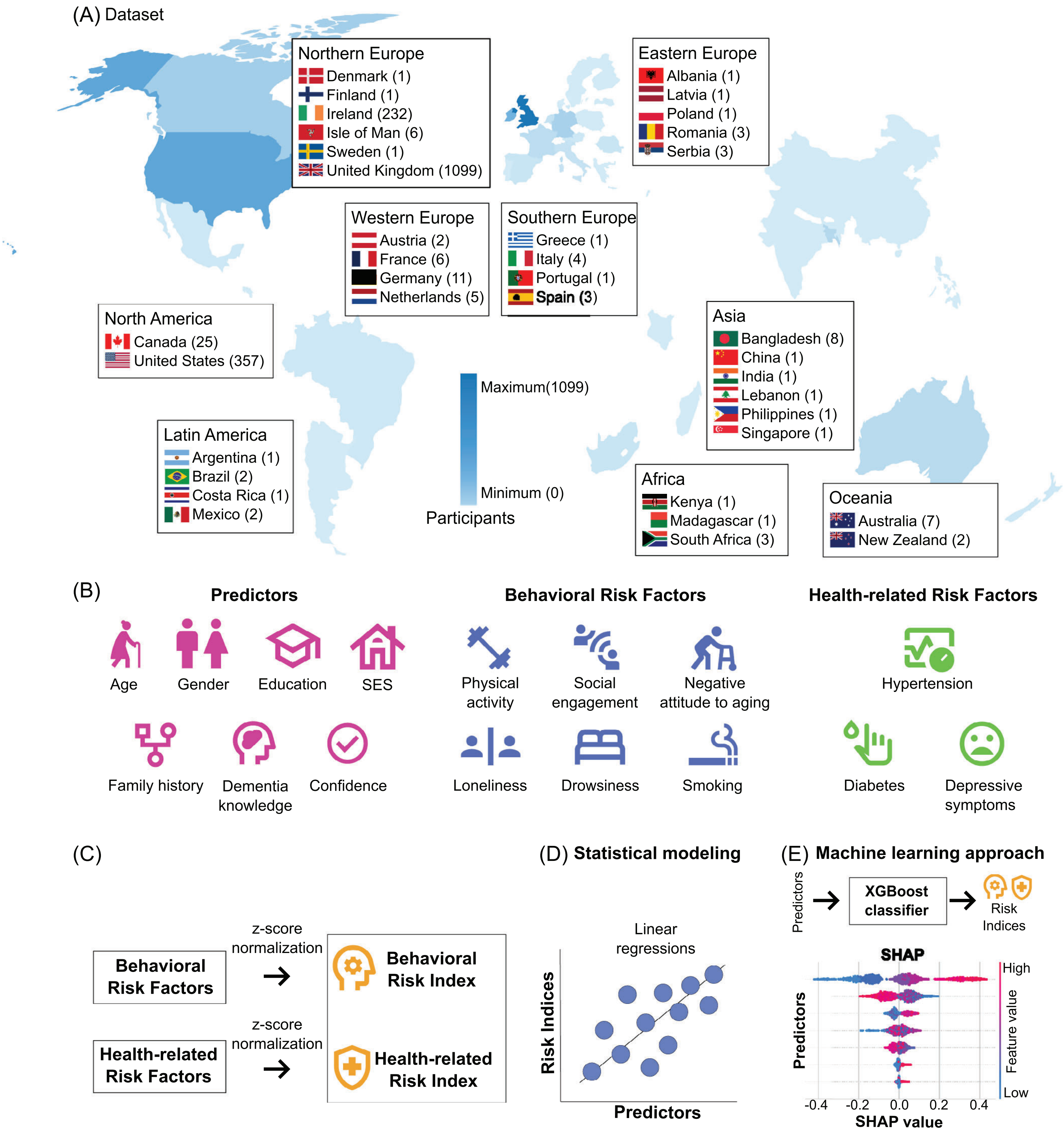

FIGURE 1 Dataset overview and analysis pipeline. A, Data were collected from 1730 participants across 36 countries on six continents. Participant counts per country are shown in brackets. B, Overview of the seven predictors, six behavioral risk factors, and four health-related risk factors included in the study. C, Behavioral and health-related risk factors were standardized using z-score normalization to construct two composite risk indices. D, Two linear regression models—one for each risk index—were conducted using the full set of predictors. E, Two Extreme Gradient Boosting (XGBoost) classifiers—one per index—were trained to predict binarized risk (high vs. low) based on the median split. SHapley Additive exPlanations values were computed to estimate the relative contribution and direction of each predictor to model outputs

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TABLE 1 Measures used to assess predictors and risk factors, with corresponding descriptive data.

Measure	Description	Statistics
Predictors		
Education	0 = No formal education 1 = Lower secondary education 2 = Upper secondary education 3 = University/college degree or equivalent 4 = Master's degree or equivalent 5 = PhD or equivalent	*M* = 2.82 SD = 0.99 Range = 0–5
SES	Participants were asked to choose a place in a ladder between 1 and 10, to represent themselves based on money and job in relation to other people in their country of residence	*M* = 5.94 SD = 1.71 Range = 0–10
Family history of dementia	Participants were asked if either of their parents or their siblings have been diagnosed with dementia	Yes = 426 (24.62%) No = 1304 (75.37%)
Health-related index		
Hypertension	Participants answered if they were diagnosed with hypertension by a doctor	Yes = 293 (16.93%) No = 1437 (83.06%)
Diabetes	Participants answered if they were diagnosed with diabetes by a doctor	Yes = 99 (5.72%) No = 1631 (94.27%)
Depression	Center for Epidemiological Studies Depression (CES-D): 20-item self-report to measure depressive symptoms	*M* = 18.23 *SD* = 13.69 Range = 0–60
Behavioral risk index		
Smoking	1. Non-smoker 2. Ex-smoker 3. Current smoker 4. Unknown	Yes (1,2) = 595 (34.39%) No (3,4) = 1135 (65.60%)
Physical activity	Godin-Shephard Leisure-Time Physical Activity Questionnaire: self-report to measure physical activity, specifically strenuous, moderate, and mild exercise	*M* = 32.65 SD = 25.44 Range = 0–120
Social network	Lubben Social Network Scale: self-report measure of social engagement	*M* = 15.59 SD = 6.31 Range = 0–30
Attitute toward own aging	Attitudes Toward Own Aging (ATOA) subscale of the Philadelphia Geriatric Morale Scale: measures self-perception of aging	*M* = 2.87 SD = 1.70 Range = 0–5
Drowsiness	Participants were asked 4 questions about feelings of drowsiness throughout their day: 1. Are you drowsy and lethargic during the day, despite getting enough sleep the night before? 2. Do you sleep 2 or more hours during the day (before 7:00 p.m.)? 3. Are there times when your flow of ideas is disorganized, unclear, or not logical? 4. Do you tend to stare into space for long periods of time?	*M* = 1.21 SD = 1.18 Range = 0–4
Loneliness	UCLA Loneliness Scale: self-report scale that measures loneliness	*M* = 21.12 SD = 15.48 Range = 0—60

Abbreviations: SD, standard deviation; UCLA, University of California Los Angeles.

p = 0.001), and age (partial R^2 = 0.02, β = –0.08, $p < 0.001$), corresponding to large, medium, and small effects, respectively. In the health risk model (R^2 = 0.12, F = 34.34, $p < 0.001$), only SES was a significant predictor (partial R^2 = 0.11, β = 0.34, $p < 0.001$). Sex, family history of dementia, AD knowledge, and confidence were not associated with either index (Figure 3A). This pattern was replicated in univariate analyses.

Machine learning results using XGBoost confirmed these patterns showing that lower SES was linked to higher predicted risk across both indices (Figures 3C, 3B, 3D). For behavioral risk, SES was the strongest predictor, followed by age and education. For health-related risk, SES remained the top predictor, followed by education and age. Predictive performance was consistently higher for the behavioral than for the health risk index in the primary XGBoost models (80/20 split). For behavioral risk, XGBoost achieved an AUC of 0.73 (95% CI [0.67, 0.78]), with accuracy = 0.66 ± 0.02, precision = 0.68 ± 0.02, recall = 0.62 ± 0.03, and $F1$ = 0.65 ± 0.02. Performance was lower for the health risk index (AUC = 0.68, 95% CI [0.62, 0.74]; accu-

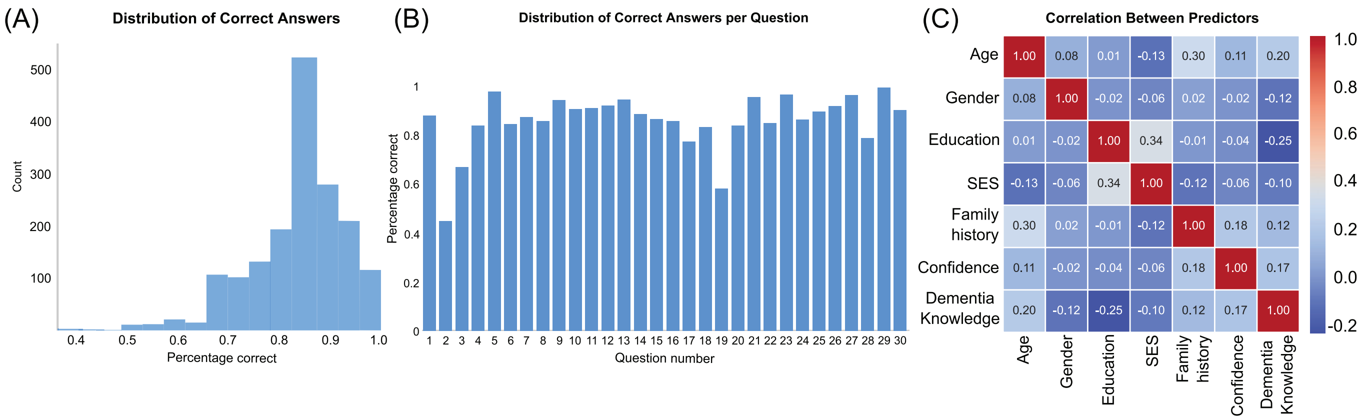

FIGURE 2 Distribution of Alzheimer's disease knowledge questionnaire answers and correlations between predictors. A, General distribution of correct answers across the 1730 participants, and (B) question-specific distribution. C, Correlation matrix between predictors

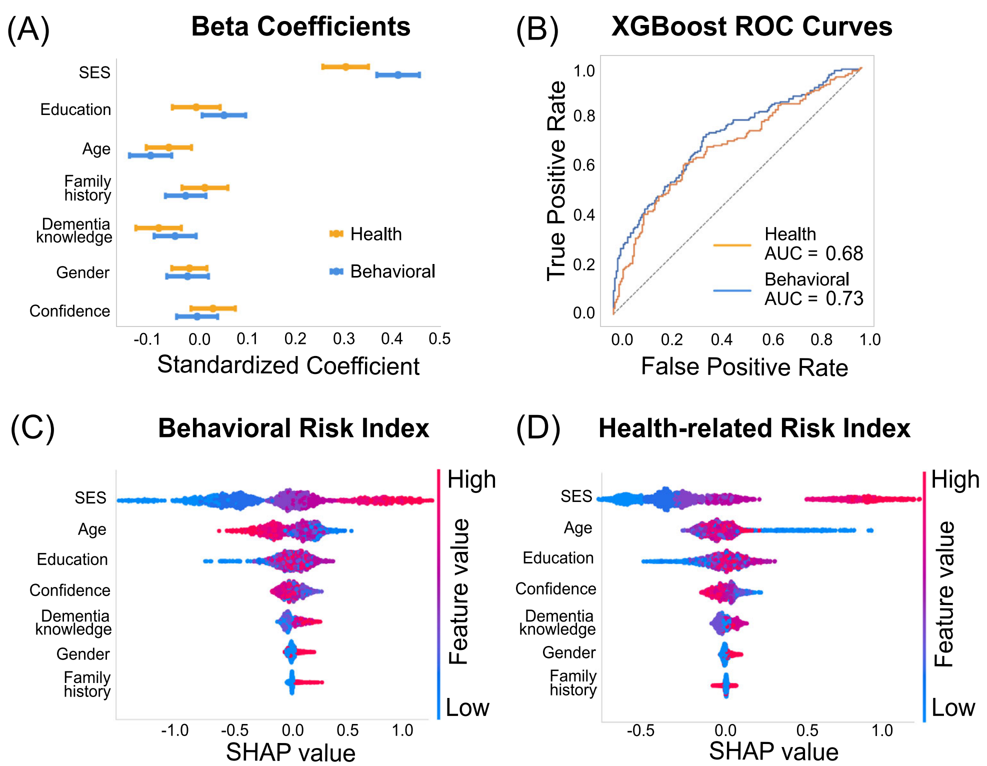

FIGURE 3 Results from linear regression and Extreme Gradient Boosting (XGBoost) models using the 80% training and 20% testing partition. A, Standarized beta values for each predictor from the linear regression models. B, Receiver operating characteristic (ROC) curves for the XGBoost models predicting high versus low risk for each index. C, D, SHapley Additive exPlanations (SHAP) summary plots showing the contribution and impact of each predictor on the behavioral risk index and health-related risk index, respectively. Each point represents a participant; color indicates the value of the predictor (red = high, blue = low), and SHAP values on the *x* axis indicate the direction and magnitude of the predictor's influence. Wider distributions reflect greater overall importance to the model

racy = 0.65 ± 0.01; precision = 0.69 ± 0.03; recall = 0.48 ± 0.02; *F1* = 0.56 ± 0.01). Validation with random forest models under the same 80/20 scheme showed a similar pattern, with higher performance for behavioral risk (AUC = 0.72, 95% CI [0.66, 0.77]) than for health risk (AUC = 0.67, 95% CI [0.61, 0.72]). Predictor rankings were consistent across XGBoost and random forest models.

Results from alternative 70/30 splits, consistent with the 80/20 partition, are reported in S2 in supporting information. Figure S1 in supporting information shows receiver operating characteristic (ROC) curves for random forest models under both 80/20 and 70/30 splits, and for XGBoost models under the 70/30 split used in robustness analyses.

4 | DISCUSSION

This study assessed the contribution of sociodemographic and knowledge-based factors to modifiable dementia risk. Lower SES and education were the strongest predictors of behavioral risk, while only SES predicted health-related risk. Younger age was modestly associated with higher behavioral risk. Sex, family history, and dementia knowledge were not associated with either risk index. Dementia knowledge correlated positively with education and negatively with age, and older age was modestly associated with reporting a family history. Overall, social disadvantage, reflected by SES and education, showed a stronger association with dementia risk than AD knowledge and should be prioritized in prevention efforts.

Our findings reinforce evidence that social disadvantage is a key contributor to dementia risk.[4,33] Although measured at the individual level, SES and education reflect broader structural conditions shaping access to resources, exposure to chronic stressors, and opportunities for health-promoting behaviors.[49,50] Individuals with lower SES or education face greater barriers to healthy lifestyles due to economic constraints, environmental disadvantage, stress, and limited health literacy.[50] Education may further support the understanding and application of health information, facilitating risk reduction.[33] The modest association between younger age and higher behavioral risk may reflect generational differences in norms or delayed engagement in health behaviors earlier in life.[51] These findings highlight the need for early, equity-oriented prevention strategies that address both individual behaviors and upstream social conditions across the life course, with age-sensitive interventions prioritizing socioeconomically disadvantaged populations.

Across univariate and multivariate models, accuracy and confidence in AD knowledge were not associated with lower risk. This suggests that improving dementia knowledge alone, although commonly proposed as a preventive strategy, may be insufficient, particularly in socially disadvantaged populations.[24,27–29] While informational campaigns can improve awareness, their population-level impact remains inconsistent.[22–25] Translating knowledge into preventive behavior requires cognitive, motivational, and contextual resources that are inequitably distributed.[24,52] Evidence from dementia and cardiovascular research shows a weak link between awareness and sustained behavior change,[27–29] underscoring the need for approaches that extend beyond knowledge dissemination.

Predictive performance was consistently stronger for the behavioral risk index across models and validation splits. Physical inactivity, low social engagement, and negative attitudes toward aging were associated with both SES and education, consistent with their reliance on daily opportunities, health literacy, and social participation.[53,54] The inverse association with age likely reflects life-course or generational differences in health behaviors.[55] Health-related risks were associated only with SES, suggesting cumulative socioeconomic exposures such as chronic stress, environmental adversity, neighborhood disadvantage, and health-care access.[19–21] Although higher education has been linked to lower risks of hypertension,[56] diabetes,[56] and depression,[57] these associations often attenuate after accounting for structural disadvantage,[58,59] consistent with our findings. Overall, behavioral and health-related risks capture partially distinct socioeconomic dimensions, supporting the prioritization of dementia risk reduction among socioeconomically disadvantaged populations.[11]

From a public health perspective, these findings underscore the limits of information-only strategies. While awareness is necessary, it is rarely sufficient to change socially embedded behaviors. Effective dementia prevention must also address structural barriers to healthy behavior, particularly among higher risk groups.[11,27] Tailored strategies grounded in lived realities and implemented through policy-level actions are essential to reduce disparities and promote brain health across the lifespan.

Several limitations should be noted. The cross-sectional design precludes causal inference. Self-reported data may be affected by social desirability bias. The predominantly female, self-selected, English-speaking app-based sample limits generalizability. Not all modifiable risk factors were assessed (e.g., hearing loss, head trauma, alcohol use). Model discrimination was modest (AUC at the lower acceptable range) and should be interpreted accordingly; additional variables may improve performance. Future research should use longitudinal designs to examine how knowledge and social factors interact over time and to identify psychological and contextual mediators of knowledge–behavior links. Equity-oriented interventions should be co-developed with vulnerable populations and combine educational and structural components.

In conclusion, SES and education were more strongly associated with behavioral than health-related dementia risk, while AD knowledge was not a significant predictor of either index. These findings underscore the limitations of awareness-based approaches and highlight the importance of addressing structural conditions that constrain healthy behaviors. Equity-focused, context-sensitive strategies are essential to reduce dementia risk and promote brain health across diverse populations.

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CONFLICT OF INTEREST STATEMENT

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ETHICAL APPROVAL

All participants gave their informed consent before participating in the study.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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