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Multilingualism protects against accelerated aging in cross-sectional and longitudinal analyses of 27 European countries

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Aging trajectories are influenced by modifiable risk factors, and prior evidence has hinted that multilingualism may have protective potential. However, reliance on suboptimal health markers, small samples, inadequate confounder control and a focus on clinical cohorts led to mixed findings and limited applicability to healthy populations. Here, we developed biobehavioral age gaps, quantifying delayed or accelerated aging in 86,149 participants across 27 European countries. National surveys provided individual-level positive (functional ability, education, cognition) and adverse (cardiometabolic conditions, female sex, sensory impairments) factors, while country-level multilingualism served as an aggregate exposure. Biobehavioral factors predicted age (R^2 = 0.24, r = 0.49, root mean squared error = 8.61), with positive factors linked to delayed aging and adverse factors to accelerated aging. Multilingualism emerged as a protective factor in cross-sectional (odds ratio = 0.46) and longitudinal (relative risk = 0.70) analyses, whereas monolingualism increased risk of accelerated aging (odds ratio = 2.11; relative risk = 1.43). Effects persisted after adjusting for linguistic, physical, social and sociopolitical exposomes. These results underscore the protective role of multilingualism and its broad applicability for global health initiatives.

Population aging and its associated disorders represent the most pervasive demographic shift worldwide, making the identification of protective factors for healthy aging a critical public health priority[1–5]. Multilingualism—the regular use of more than one language—has emerged as a promising contributor to cognitive reserve[6]. Evidence suggests that multilingualism may delay dementia onset[7–10] and promote healthy aging by preserving brain structural integrity[11,12] and functional efficiency[13,14], thereby mitigating age-related cognitive decline.

However, critical gaps hinder a robust test of this hypothesis. Most evidence stems from clinical populations already exhibiting cognitive deficits (for example, Alzheimer's disease, mild cognitive impairment)[7–10]. At the same time, studies in healthy cohorts often rely on heterogeneous measures and modest sample sizes, undermining generalizability. Inconsistent findings[6,15,16] further reflect the absence of direct aging health-related markers capturing protective effects. Additionally, language-related confounders—such as immigration status[9],

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the number and typological distance between spoken languages[14] and patterns of institutional and community-based language usage[10]—are frequently overlooked, complicating the interpretation of results. Moreover, it is largely unknown whether macro-level exposomes[17]—cumulative lifelong exposures to physical (air quality)[18], social (gender inequality, structural socioeconomic inequality)[19,20] and sociopolitical (party freedom, inclusive suffrage, credible elections, local democracy)[21,22] factors—interact with multilingualism to shape aging trajectories. Finally, multilingual research lacks multicountry data and combined cross-sectional and longitudinal approaches, limiting scalable estimates of its cumulative impact at the population level. Addressing these limitations is essential to elucidate the mechanisms by which multilingualism may provide protection against age-related cognitive and functional decline.

Here, we apply our recent biobehavioral clocks framework[5]—a computational approach that quantifies accelerated or delayed healthy aging—to examine how multilingualism and related factors modulate aging trajectories. Our approach[5,23–26] leverages aggregate-level measures—such as multilingualism and exposome variables—as predictors and covariates of individual-level health outcomes[20,27,28], captured through biobehavioral age gaps (BAGs)[5]. BAGs—defined as the difference between an individual's chronological age and predicted age based on the interplay of positive and adverse risk factors[2,29]—offer a scalable, cost-effective estimate of (un)healthy aging. Inspired by biological aging clocks[28,30], our model[5] integrates positive (for example, preserved cognition, functional ability, education, physical activity) and adverse (for example, cardiometabolic conditions, female sex, sensory deficits) factors to predict age. By quantifying deviations from expected aging trajectories, BAGs provide a direct measure of health status, where BAG < 0 indicates delayed aging and BAG > 0 reflects accelerated aging[31].

This approach allowed us to measure the impact of multilingualism in delaying aging while adjusting for multiple exposome factors. Epidemiological cross-sectional and longitudinal designs included individuals from 27 European countries (n = 86,149). Multilingualism was analyzed as an aggregate-level exposure—defined by the country-level percentage of individuals speaking only their mother tongue (monolinguals) or one, two, three or more additional foreign languages—with individual-level BAGs serving as the primary outcome. Sensitivity analyses controlled for macro-level exposomes, including country-level linguistic, socioeconomic, environmental and sociopolitical factors. We hypothesized that multilingualism would be associated with current and future delayed aging (BAGs < 0), reflecting a protective effect against accelerated aging. We expected these effects to remain robust after controlling for macro-level exposomes supporting a sui generis contribution of multilingualism to healthy aging.

Results

Biobehavioral factors predict chronological age and influence aging trajectories

We analyzed 86,149 participants (45.31% female participants, mean age = 66.55 years, s.d. = 9.91, range = 51–90) from SHARE Europe[32–35] (Fig. 1 and Supplementary Table 1). Chronological age was successfully predicted using biobehavioral factors, including positive and adverse predictors (R^2 = 0.24, F^2 = 0.32, r = 0.49, RMSE = 8.61, mean directional error (MDE) = 0.03, mean absolute error (MAE) = 7.05). All performance metrics reported in Fig. 2a were calculated on the test sets during cross-validation, using only held-out data not seen during the training. The combination of a relatively high Pearson's r and a higher MAE is consistent with the broad age range in our sample (51–90 years). In this context, r reflects the model's ability to effectively preserve the rank ordering of participants by age, capturing age-related variance. Meanwhile, MAE reflects the average absolute deviation between predicted and chronological age in years, which tends to increase with age-related heterogeneity.

We performed multiple tests to further assess the robustness of our model. The predictor-based age-estimation model was validated using three complementary approaches. First, we reran the model using nested cross-validation for hyperparameter tuning. We performed a fivefold Bayesian search on the training set in each outer fold and then evaluated the optimized model on the held-out data. Compared to the base model (Fig. 3a), performance metrics remained consistent (R^2 = 0.24, F^2 = 0.32, r = 0.49, RMSE = 8.61, MDE = 0.03, MAE = 7.04; Fig. 3b), with differences on the order of 10^{-2}–10^{-3}, indicating reliable generalization estimates. Next, we implemented a leave-one-country-out (LOCO) cross-validation strategy by iteratively excluding each country from training and testing the model based on that country's data. These results (R^2 = 0.23; F^2 = 0.31; r = 0.48; RMSE = 8.65; MDE = 0.03; MAE = 7.09; Fig. 3c) matched those of the base multicountry model, demonstrating similar cross-national performance. Finally, we assessed the model on a fully independent, country-stratified hold-out dataset to ensure balanced representation. Results were similar (R^2 = 0.23; F^2 = 0.30; r = 0.48; RMSE = 8.65; MDE = 0.03; MAE = 7.08; Fig. 3d), and remained consistent across training, validation and test datasets (Supplementary Table 2), indicating no overfitting.

Across models, key positive factors were functional ability, education and preserved cognition, while major adverse factors included hearing impairment, hypertension and heart disease (Fig. 3a–d). These findings suggest positive and adverse biobehavioral risks substantially contribute to delayed or accelerated aging.

Multilingualism delays aging according to epidemiological findings

In the cross-sectional analysis, monolinguals (that is, those speaking only their mother tongue) were 2.11 times more likely to experience accelerated aging (odds ratio (OR) = 2.11, 95% confidence interval (CI): 1.98–2.24; Fig. 2b). Conversely, individuals speaking at least one additional foreign language were 2.17 times less likely (OR = 0.46, 95% CI: 0.43–0.49) to experience accelerated aging. Specifically, speaking one foreign language were 1.3 times less likely (OR = 0.77, 95% CI: 0.71–0.83), two foreign languages 1.96 times less likely (OR = 0.51, 95% CI: 0.47–0.55), and three or more foreign languages 1.56 times less likely (OR = 0.64, 95% CI: 0.59–0.69). These findings underscore the protective effect of multilingualism on aging trajectories.

The longitudinal analysis further supported this protective effect, as illustrated in Fig. 2c. Monolinguals were 1.4 times more likely to develop accelerated aging over time (relative risk (RR) = 1.43, 95% CI: 1.38–1.48). In contrast, multilinguals showed a lower risk, being 1.43 times less likely to develop accelerated aging (RR = 0.70, 95% CI: 0.68–0.72). Protective effects increased alongside the number of languages spoken. Individuals speaking one additional language were 1.11 times less likely to develop accelerated aging (RR = 0.90, 95% CI: 0.86–0.94), those speaking two additional languages were 1.25 times less likely (RR = 0.80, 95% CI: 0.77–0.82), and those speaking three or more additional languages were 1.41 times less likely (RR = 0·71, 95% CI: 0.68–0.75). These results suggest a cumulative protective effect of multilingualism, promoting delayed aging and preserving functional ability and cognition over time.

To assess potential age-related cohort effects, we performed a stratified analysis by age group (51–64 years, n = 38,670; 65–77 years, n = 31,289; 78–90 years, n = 14,168). The association between multilingualism and BAGs remained consistent across age cohorts (Extended Data Fig. 1) and statistically significant in both cross-sectional and longitudinal analyses (Supplementary Tables 3 and 4, respectively). The risk of accelerated brain aging among monolinguals was evident across all strata and increased with age. Speaking one additional language conferred a modest protective effect that diminished in older groups. In contrast, speaking two, three, or more additional languages was associated with a consistently protective effect that became more

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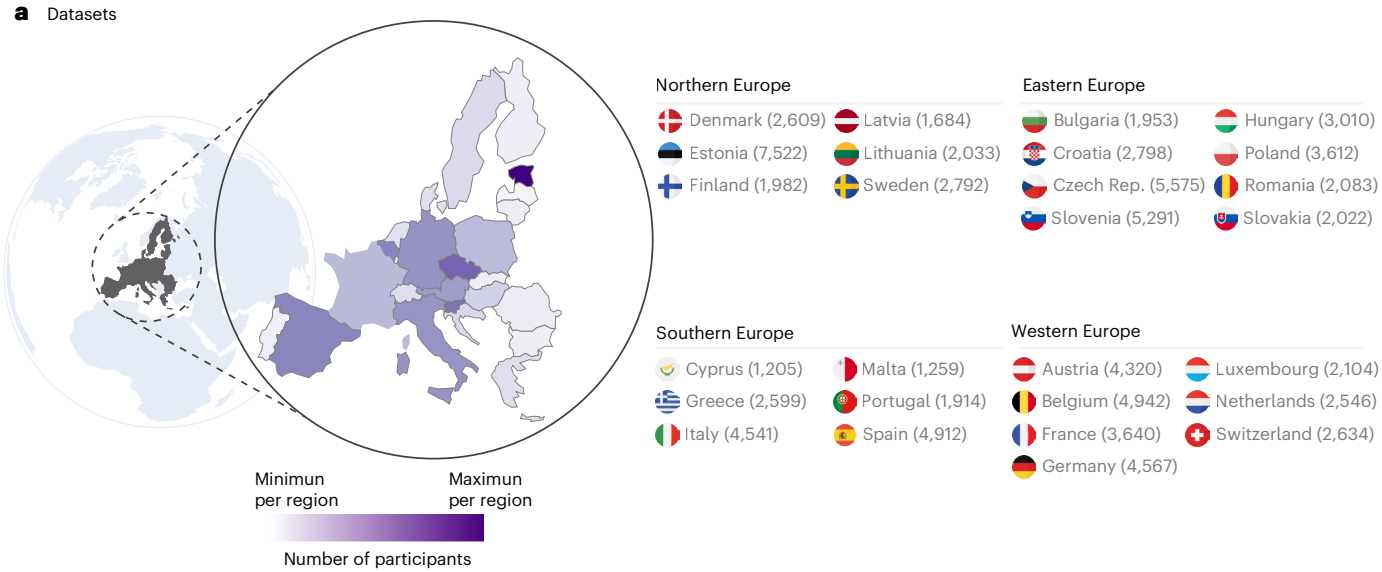

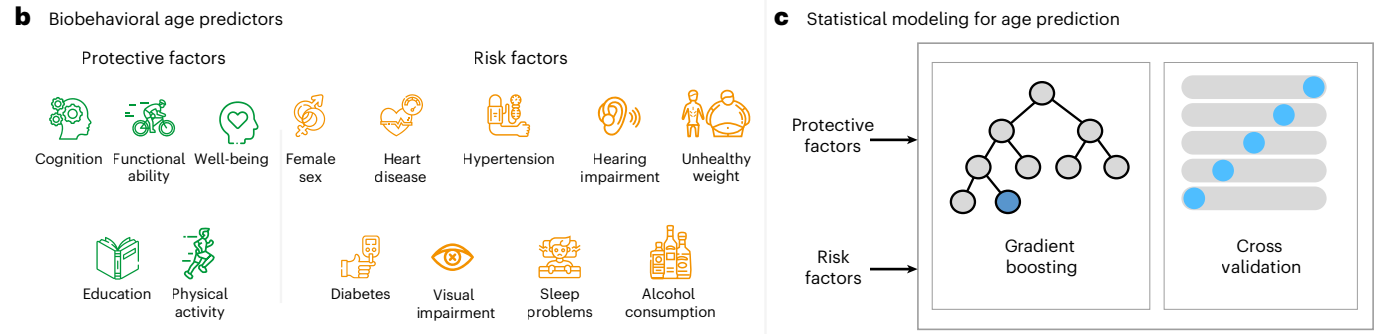

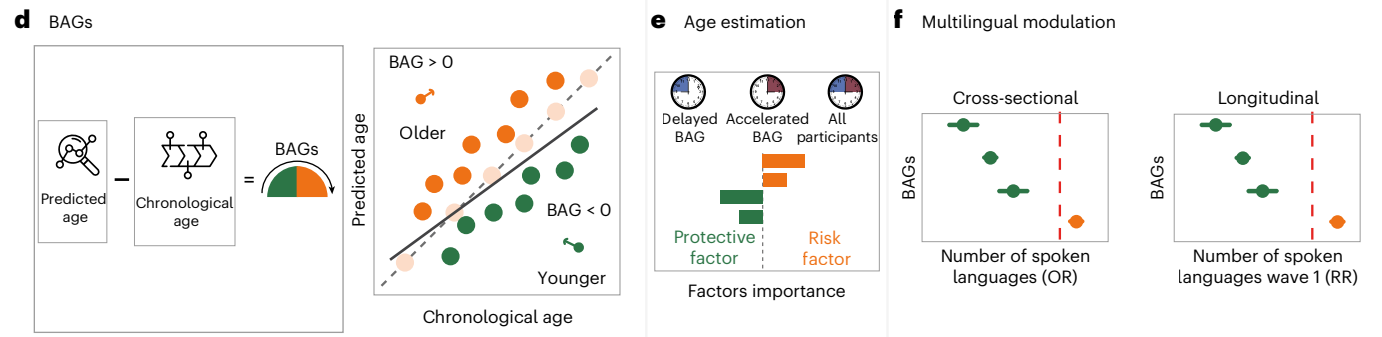

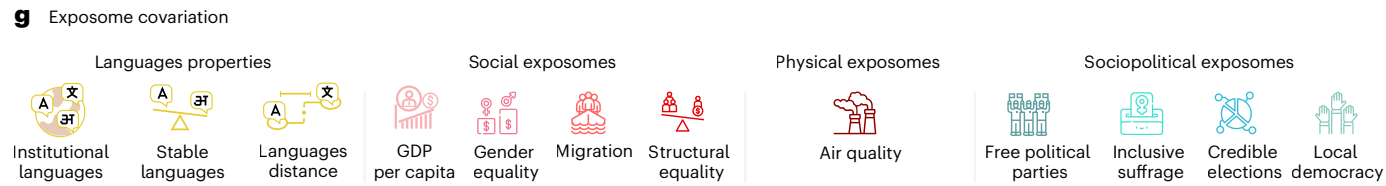

Fig. 1 | Study design and analytical workflow. a, The dataset includes 86,149 participants from European aging surveys, with sample sizes per country shown in parentheses. **b**, Chronological age was estimated based on harmonized biobehavioral protective and risk factors. **c**, A gradient-boosting regression model was trained on 90% of the dataset and tested on the remaining 10% using tenfold cross-validation to predict chronological age from biobehavioral data. **d**, BAGs were calculated as the difference between predicted and chronological age (BAG > 0 suggests an older biobehavioral profile, while BAG < 0 suggests a younger one). To mitigate regression-to-the-mean bias, chronological age was regressed from BAGs. **e**, Feature importance was evaluated using the mean decrease in impurity (MDI) metric. **f**, Multilingual analyses included both cross-sectional (OR) and longitudinal (RR) epidemiological assessments. **g**, A sensitivity analysis examined the influence of country-level factors, including language (migration status, number of institutional and stable languages, typological distance between most spoken languages), social (gender equality, structural equality), physical (air quality) and sociopolitical (democracy indices: free political parties, inclusive suffrage, credible elections, and local democracy) exposomes.

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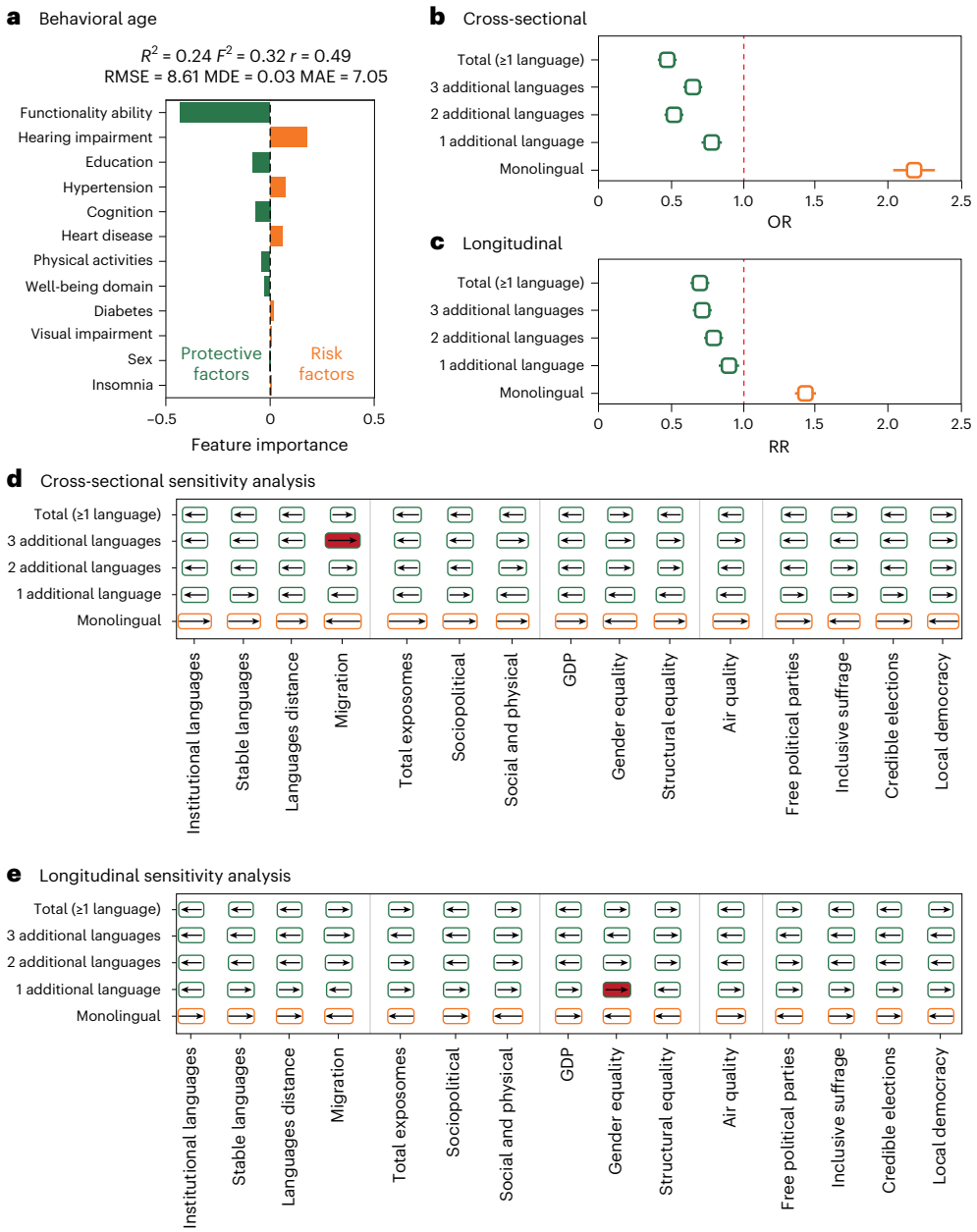

Fig. 2 | BAG results and epidemiological associations. a, Prediction of chronological age using biobehavioral factors (n = 86,149 participants), with goodness-of-fit metrics and feature importance provided. **b**, ORs from the cross-sectional analysis, estimated using logistic regression models. Two-sided Wald z-tests were used to derive exact P values and 95% CIs. Results indicate that multilingualism is significantly associated with delayed aging, whereas monolingualism is linked to accelerated aging. **c**, RRs from the longitudinal analysis, estimated using log-binomial generalized linear models. Two-sided Wald z-tests were used to derive exact P values and 95% CIs. The findings were consistent with the cross-sectional results, confirming multilingualism as a protective factor for healthy aging and monolingualism as a risk factor. In **b** and **c**, lines indicate the 95% CI, with the central tendency defined by the mean. **d**,**e**, Differences in OR and RR calculations using macro-level exposomes in cross-sectional and longitudinal analyses, respectively. Arrows indicate whether epidemiological metrics increased (rightward arrow) or decreased (leftward arrow). The box size reflects the difference's magnitude, while the red shading indicates a loss of statistical significance when adjusting for covariates. In the cross-sectional analysis, significance was lost for migration. In the longitudinal analysis, significance was lost for gender inequality.

pronounced with increasing age. These findings support a cumulative association between multilingualism and healthier brain aging across the lifespan.

Protective effects of multilingualism are robust across language-related confounders and exposomes

We adjusted the results using aggregate-level exposomes. Figure 2d,e summarizes the main difference and direction of the effect of each adjustment for the cross-sectional and longitudinal results, respectively. The protective effects of multilingualism remained statistically significant after all covariations, with only minor changes in magnitude (Fig. 4). Covariates included country-level language-related factors (for example, immigration status, typological distance between the two most spoken languages in each country) and macro-level physical (for example, air quality), social (for example, gender and socioeconomic inequality), and sociopolitical (for example, political representation, local democracy) exposomes. Risk effects associated with being monolingual exhibited the most significant change, with the risk increasing

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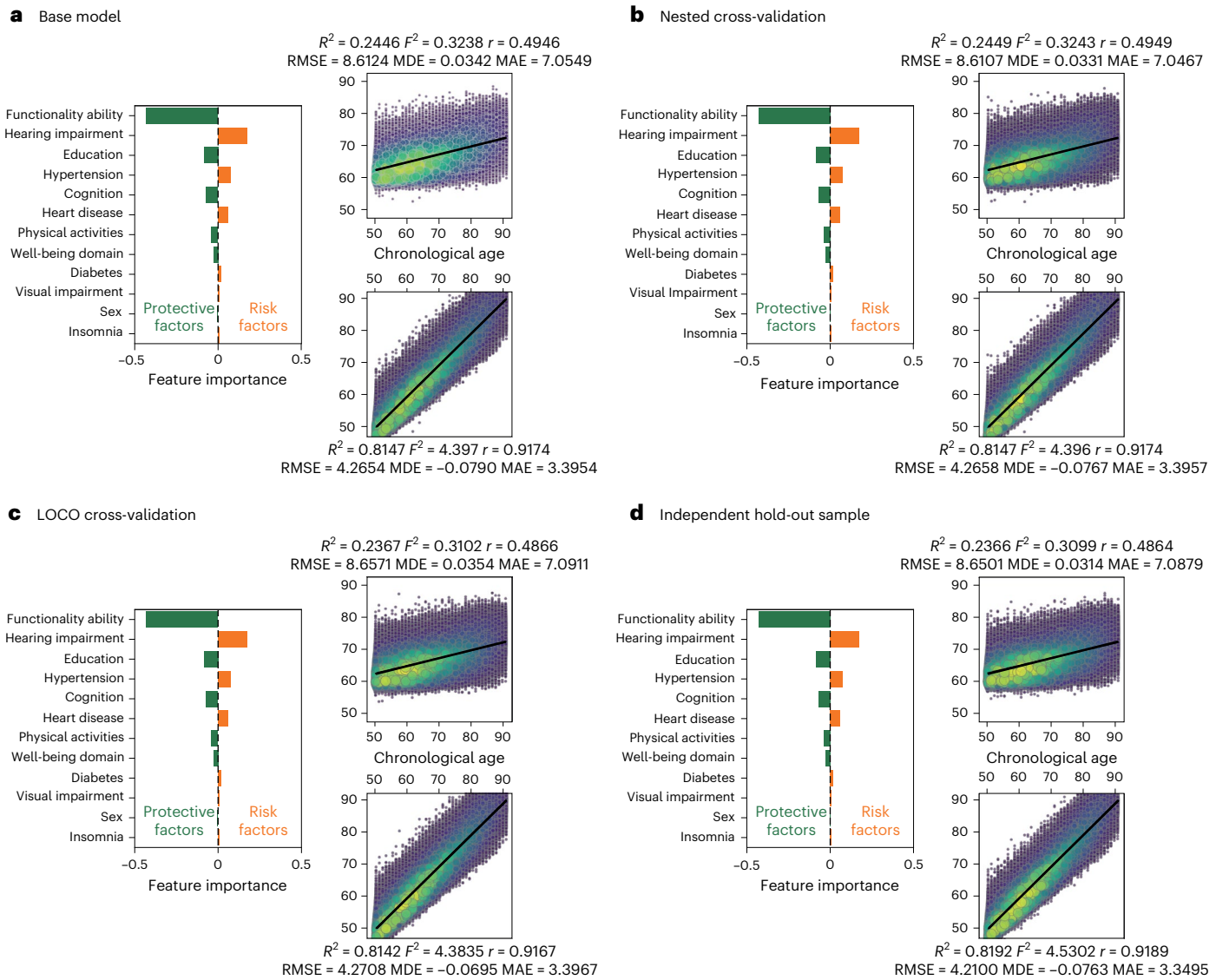

Fig. 3 | Validation of the biobehavioral age prediction model and derived BAGs. **a**–**d**, The figure summarizes model performance across four evaluation schemes: the base model (**a**), nested cross-validation (**b**), LOCO cross-validation (**c**) and an independent hold-out sample stratified by country (**d**). For each scheme, the left column displays feature-importance rankings, along goodness-of-fit statistics (R^2, RMSE, MAE, Pearson's r), and the right column shows scatterplots of predicted versus chronological age before (upper row) and after (lower row) bias correction.

in approximately 67% of cases in the cross-sectional analysis and about 53% of cases in the longitudinal analysis.

Two exceptions were observed. In the cross-sectional analysis, speaking three or more foreign languages lost the delayed aging effect after adjustments for immigration status. Similarly, in the longitudinal analysis, speaking one foreign language lost the reduced risk of developing accelerated aging when controlled for gender equality. Figure 4a,b displays the results for each adjustment in the cross-sectional and longitudinal analyses. Detailed results are provided in Tables 1 and 2, respectively.

Model calibration tests further confirmed the robustness of the estimated OR (Supplementary Table 5).

Discussion

We examined the impact of multilingualism on delaying aging across European countries. BAGs—estimated as the difference between chronological age and predicted age based on the interplay of positive and adverse biobehavioral factors—strongly predicted aging outcomes, with positive factors linked to delayed aging and adverse factors to accelerated aging. Multilingualism was consistently associated with lower BAGs—indicating a protective effect—and predicted a reduced risk of accelerated aging in longitudinal analyses. In contrast, monolingualism was associated with larger BAGs and an increased risk of accelerated aging. The long-lasting protective effects of multilingualism were dose dependent, rising with the number of languages spoken. Most associations remained significant after adjusting for various linguistic, physical, social and sociopolitical macro-level exposomes, and after stratifying by age groups. This supports the consistency of effects across the lifespan. Overall, these results underscore the independent protective role of multilingualism and the value of BAGs as key markers of (un)healthy aging trajectories.

Aging is linked to changes in brain structure and function, resulting in reduced functionality, cognitive decline and progressive neurodegeneration. However, positive factors—such as physical activity, education and prosociality—influence the quality of aging and the risk of age-related disorders[2,29]. Our findings show that these positive factors delay aging trajectories, as indicated by lower BAGs, replicating our previous main effects using this biobehavioral clock framework in a larger

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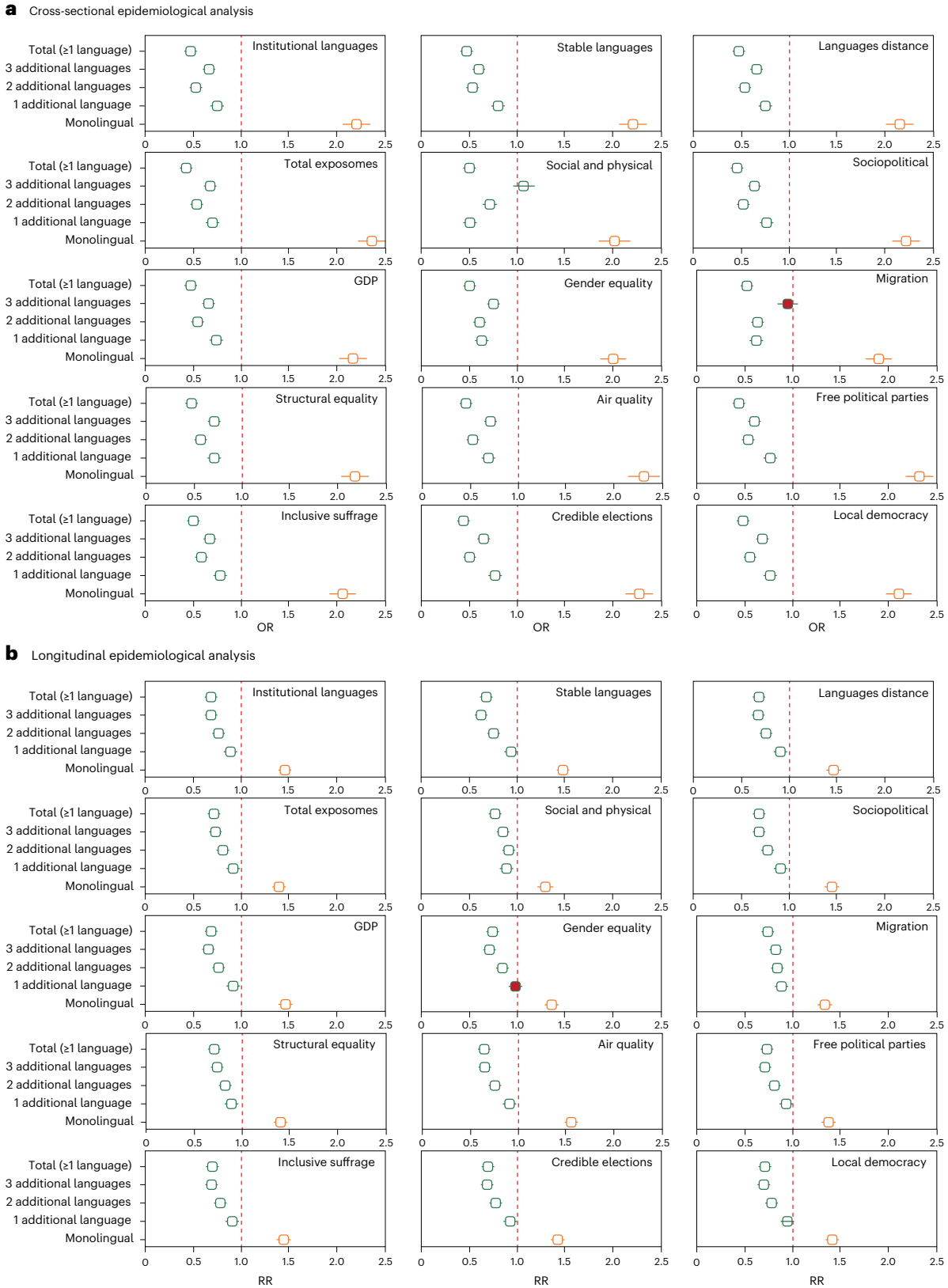

Fig. 4 | Epidemiological outcomes after covariate adjustments. a, ORs estimated using logistic regression models (n = 86,149 participants) adjusted for macro-social covariates. Two-sided Wald z-tests were used to derive P values and 95% CIs. When controlling for migration, the previously significant association between speaking three additional languages and aging no longer remained significant. Full numerical details are provided in Table 1. **b**, RRs estimated using log-binomial generalized linear models (binomial family), adjusted for macro-social covariates. Two-sided Wald z-tests were used to derive P values and 95% CIs. In **a** and **b**, lines indicate the 95% CI, with the central tendency defined by the mean. The association between speaking one additional language and aging lost significance after adjusting for gender equality. Refer to Table 2 for exact values.

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Table 1 | Results for the cross-sectional analysis using ORs, estimated with logistic regression models

Without co-variables	95% CI	OR	z	*P* value
Monolingual	(1.98, 2.24)	2.11	23.49	$<1\times10^{-15}$
1 additional language	(0.69, 0.81)	0.75	−7.24	4.41×10^{-13}
2 additional languages	(0.51, 0.59)	0.54	−16.01	$<1\times10^{-15}$
3 additional languages	(0.62, 0.72)	0.67	−10.62	$<1\times10^{-15}$
Total (≥1 language)	(0.45, 0.5)	0.47	−23.48	$<1\times10^{-15}$
Co-variable (total exposomes)				
Monolingual	(2.23, 2.56)	2.39	24.9	$<1\times10^{-15}$
1 additional language	(0.67, 0.78)	0.72	−7.95	$<1\times10^{-15}$
2 additional languages	(0.46, 0.54)	0.5	−16.6	$<1\times10^{-15}$
3 additional languages	(0.59, 0.69)	0.64	−10.77	$<1\times10^{-15}$
Total (≥1 language)	(0.39, 0.45)	0.42	−24.89	$<1\times10^{-15}$
Co-variable (sociopolitical exposomes)				
Monolingual	(2.09, 2.37)	2.23	24.94	$<1\times10^{-15}$
1 additional language	(0.7, 0.82)	0.76	−6.92	4.6×10^{-12}
2 additional languages	(0.49, 0.57)	0.53	−16.76	$<1\times10^{-15}$
3 additional languages	(0.59, 0.68)	0.63	−11.95	$<1\times10^{-15}$
Total (≥1 language)	(0.42, 0.48)	0.45	−24.94	$<1\times10^{-15}$
Co-variable (social and physical exposomes)				
Monolingual	(1.99, 2.31)	2.14	19.55	$<1\times10^{-15}$
1 additional language	(0.52, 0.61)	0.56	−13.35	$<1\times10^{-15}$
2 additional languages	(0.56, 0.68)	0.61	−10.12	$<1\times10^{-15}$
3 additional languages	(0.77, 0.92)	0.84	−3.86	9.06×10^{-13}
Total (≥1 language)	(0.43, 0.5)	0.47	−19.54	$<1\times10^{-15}$
Co-variable (GDP)				
Monolingual	(2.03, 2.3)	2.16	23.83	$<1\times10^{-15}$
1 additional language	(0.68, 0.8)	0.74	−7.52	5.38×10^{-14}
2 additional languages	(0.5, 0.58)	0.53	−16.22	$<1\times10^{-15}$
3 additional languages	(0.6, 0.7)	0.65	−10.98	$<1\times10^{-15}$
Total (≥1 language)	(0.43, 0.49)	0.46	−23.82	$<1\times10^{-15}$
Co-variable (institutional languages)				
Monolingual	(2.06, 2.34)	2.19	23.83	$<1\times10^{-15}$
1 additional language	(0.69, 0.81)	0.75	−6.97	3.09×10^{-12}
2 additional languages	(0.49, 0.57)	0.53	−16.13	$<1\times10^{-15}$
3 additional languages	(0.61, 0.71)	0.66	−10.96	$<1\times10^{-15}$
Total (≥1 language)	(0.43, 0.49)	0.46	−23.81	$<1\times10^{-15}$
Co-variable (stable languages)				
Monolingual	(2.06, 2.34)	2.2	24.6	$<1\times10^{-15}$
1 additional language	(0.73, 0.86)	0.8	−5.64	1.67×10^{-8}
2 additional languages	(0.49, 0.57)	0.53	−16.69	$<1\times10^{-15}$
3 additional languages	(0.55, 0.65)	0.6	−13.12	$<1\times10^{-15}$
Total (≥1 language)	(0.43, 0.48)	0.45	−24.59	$<1\times10^{-15}$
Co-variable (language distance)				
Monolingual	(2.01, 2.28)	2.14	23.81	$<1\times10^{-15}$
1 additional language	(0.69, 0.81)	0.75	−7.22	5.1×10^{-13}
2 additional languages	(0.49, 0.57)	0.53	−16.38	$<1\times10^{-15}$
3 additional languages	(0.61, 0.71)	0.65	−10.96	$<1\times10^{-15}$
Total (≥1 language)	(0.44, 0.5)	0.47	−23.8	$<1\times10^{-15}$
Co-variable (gender equality)				

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Table 1 (continued) | Results for the cross-sectional analysis using ORs, estimated with logistic regression models

Without co-variables	95% CI	OR	z	*P* value
Monolingual	(1.87, 2.13)	1.99	20.63	$<1\times10^{-15}$
1 additional language	(0.58, 0.68)	0.63	−11.25	$<1\times10^{-15}$
2 additional languages	(0.56, 0.66)	0.61	−11.92	$<1\times10^{-15}$
3 additional languages	(0.7, 0.82)	0.76	−7.03	2.1×10^{-12}
Total (≥1 language)	(0.47, 0.54)	0.5	−20.62	$<1\times10^{-15}$
Co-variable (migration)				
Monolingual	(1.76, 2.03)	1.89	17.61	$<1\times10^{-15}$
1 additional language	(0.57, 0.67)	0.62	−11.79	$<1\times10^{-15}$
2 additional languages	(0.58, 0.68)	0.63	−11.9	$<1\times10^{-15}$
3 additional languages	(0.86, 1.03)	0.94	−1.26	0.208779
Total (≥1 language)	(0.49, 0.57)	0.53	−17.59	$<1\times10^{-15}$
Co-variable (air quality)				
Monolingual	(2.14, 2.47)	2.3	23.07	$<1\times10^{-15}$
1 additional language	(0.62, 0.73)	0.68	−9.48	$<1\times10^{-15}$
2 additional languages	(0.47, 0.56)	0.51	−14.74	$<1\times10^{-15}$
3 additional languages	(0.64, 0.76)	0.7	−8.63	$<1\times10^{-15}$
Total (≥1 language)	(0.41, 0.47)	0.43	−23.06	$<1\times10^{-15}$
Co-variable (structural equality)				
Monolingual	(2.03, 2.32)	2.17	22.62	$<1\times10^{-15}$
1 additional language	(0.65, 0.76)	0.7	−8.82	$<1\times10^{-15}$
2 additional languages	(0.52, 0.6)	0.56	−14.78	$<1\times10^{-15}$
3 additional languages	(0.64, 0.76)	0.7	−8.65	$<1\times10^{-15}$
Total (≥1 language)	(0.43, 0.49)	0.46	−22.61	$<1\times10^{-15}$
Co-variable (free political parties)				
Monolingual	(2.17, 2.47)	2.32	25.83	$<1\times10^{-15}$
1 additional language	(0.71, 0.83)	0.77	−6.72	1.82×10^{-11}
2 additional languages	(0.5, 0.58)	0.54	−16.28	$<1\times10^{-15}$
3 additional languages	(0.55, 0.64)	0.6	−13.47	$<1\times10^{-15}$
Total (≥1 language)	(0.4, 0.46)	0.43	−25.82	$<1\times10^{-15}$
Co-variable (inclusive suffrage)				
Monolingual	(1.92, 2.18)	2.05	22.29	$<1\times10^{-15}$
1 additional language	(0.71, 0.83)	0.77	−6.75	1.43×10^{-11}
2 additional languages	(0.53, 0.62)	0.57	−14.32	$<1\times10^{-15}$
3 additional languages	(0.62, 0.72)	0.67	−10.68	$<1\times10^{-15}$
Total (≥1 language)	(0.46, 0.52)	0.49	−22.28	$<1\times10^{-15}$
Co-variable (credible elections)				
Monolingual	(2.12, 2.41)	2.26	24.94	$<1\times10^{-15}$
1 additional language	(0.7, 0.82)	0.76	−6.9	5.05×10^{-12}
2 additional languages	(0.46, 0.53)	0.49	−17.64	$<1\times10^{-15}$
3 additional languages	(0.6, 0.69)	0.64	−11.42	$<1\times10^{-15}$
Total (≥1 language)	(0.41, 0.47)	0.44	−24.93	$<1\times10^{-15}$
Co-variable (local democracy)				
Monolingual	(1.97, 2.24)	2.1	23.24	$<1\times10^{-15}$
1 additional language	(0.7, 0.82)	0.76	−6.93	4.34×10^{-12}
2 additional languages	(0.51, 0.59)	0.55	−15.82	$<1\times10^{-15}$
3 additional languages	(0.62, 0.72)	0.67	−10.58	$<1\times10^{-15}$
Total (≥1 language)	(0.45, 0.51)	0.48	−23.23	$<1\times10^{-15}$

Two-sided Wald *z*-tests were used to derive *P* values and 95% CIs. GDP, gross domestic product.

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Table 2 | Results for the longitudinal analysis using RRs, estimated with log-binomial regression models

Without co-variables	95% CI	RR	z	*P* value
Monolingual	(1.38, 1.48)	1.43	20.36	$<1\times10^{-15}$
1 additional language	(0.86, 0.94)	0.9	−4.87	1.14×10^{-6}
2 additional languages	(0.77, 0.82)	0.8	−12.28	$<1\times10^{-15}$
3 additional languages	(0.68, 0.75)	0.71	−13.11	$<1\times10^{-15}$
Total (≥1 language)	(0.68, 0.72)	0.7	−20.38	$<1\times10^{-15}$
Co-variable (total exposomes)				
Monolingual	(1.38, 1.48)	1.42	19.49	$<1\times10^{-15}$
1 additional language	(0.88, 0.97)	0.92	−3.42	0.000615
2 additional languages	(0.77, 0.83)	0.8	−11.88	$<1\times10^{-15}$
3 additional languages	(0.68, 0.75)	0.71	−12.9	$<1\times10^{-15}$
Total (≥1 language)	(0.68, 0.73)	0.7	−19.52	$<1\times10^{-15}$
Co-variable (sociopolitical exposomes)				
Monolingual	(1.39, 1.49)	1.44	21.11	$<1\times10^{-15}$
1 additional language	(0.87, 0.95)	0.91	−4.22	2.45×10^{-5}
2 additional languages	(0.75, 0.81)	0.78	−13.42	$<1\times10^{-15}$
3 additional languages	(0.66, 0.73)	0.69	−14.21	$<1\times10^{-15}$
Total (≥1 language)	(0.67, 0.72)	0.69	−21.14	$<1\times10^{-15}$
Co-variable (social and physical exposomes)				
Monolingual	(1.31, 1.41)	1.36	15.36	$<1\times10^{-15}$
1 additional language	(0.86, 0.95)	0.9	−4.41	1.05×10^{-5}
2 additional languages	(0.83, 0.9)	0.86	−7.05	1.81×10^{-12}
3 additional languages	(0.73, 0.81)	0.77	−9.59	$<1\times10^{-15}$
Total (≥1 language)	(0.71, 0.76)	0.73	−15.39	$<1\times10^{-15}$
Co-variable (GDP)				
Monolingual	(1.41, 1.51)	1.46	21.84	$<1\times10^{-15}$
1 additional language	(0.87, 0.95)	0.91	−4	6.42×10^{-5}
2 additional languages	(0.73, 0.79)	0.76	−14.21	$<1\times10^{-15}$
3 additional languages	(0.62, 0.69)	0.66	−15.37	$<1\times10^{-15}$
Total (≥1 language)	(0.66, 0.71)	0.69	−21.86	$<1\times10^{-15}$
Co-variable (institutional languages)				
Monolingual	(1.41, 1.51)	1.46	21.3	$<1\times10^{-15}$
1 additional language	(0.85, 0.93)	0.89	−4.87	1.13×10^{-6}
2 additional languages	(0.74, 0.8)	0.77	−13.73	$<1\times10^{-15}$
3 additional languages	(0.65, 0.72)	0.68	−14.45	$<1\times10^{-15}$
Total (≥1 language)	(0.66, 0.71)	0.69	−21.33	$<1\times10^{-15}$
Co-variable (stable languages)				
Monolingual	(1.42, 1.52)	1.47	23.02	$<1\times10^{-15}$
1 additional language	(0.91, 0.99)	0.95	−2.31	0.020912
2 additional languages	(0.73, 0.78)	0.75	−15.42	$<1\times10^{-15}$
3 additional languages	(0.59, 0.66)	0.63	−17.55	$<1\times10^{-15}$
Total (≥1 language)	(0.66, 0.7)	0.68	−23.02	$<1\times10^{-15}$
Co-variable (language distance)				
Monolingual	(1.41, 1.52)	1.46	21.5	$<1\times10^{-15}$
1 additional language	(0.86, 0.95)	0.9	−4.36	1.29×10^{-5}
2 additional languages	(0.73, 0.79)	0.76	−13.97	$<1\times10^{-15}$
3 additional languages	(0.65, 0.72)	0.68	−14.41	$<1\times10^{-15}$
Total (≥1 language)	(0.66, 0.71)	0.68	−21.52	$<1\times10^{-15}$
Co-variable (gender equality)				

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Table 2 (continued) | Results for the longitudinal analysis using RRs, estimated with log-binomial regression models

Without co-variables	95% CI	RR	z	*P* value
Monolingual	(1.31, 1.4)	1.35	17.22	$<1\times10^{-15}$
1 additional language	(0.93, 1.02)	0.97	−1.17	0.242085
2 additional languages	(0.81, 0.87)	0.84	−9.49	$<1\times10^{-15}$
3 additional languages	(0.67, 0.74)	0.7	−14.12	$<1\times10^{-15}$
Total (≥1 language)	(0.71, 0.77)	0.74	−17.26	$<1\times10^{-15}$
Co-variable (migration)				
Monolingual	(1.28, 1.39)	1.34	13.38	$<1\times10^{-15}$
1 additional language	(0.85, 0.93)	0.89	−5.05	4.5×10^{-7}
2 additional languages	(0.81, 0.87)	0.84	−8.84	$<1\times10^{-15}$
3 additional languages	(0.78, 0.88)	0.83	−6.1	1.04×10^{-9}
Total (≥1 language)	(0.72, 0.78)	0.75	−13.4	$<1\times10^{-15}$
Co-variable (air quality)				
Monolingual	(1.49, 1.6)	1.55	23.43	$<1\times10^{-15}$
1 additional language	(0.87, 0.95)	0.91	−4.11	4×10^{-5}
2 additional languages	(0.73, 0.79)	0.76	−14.19	$<1\times10^{-15}$
3 additional languages	(0.62, 0.7)	0.66	−14.98	$<1\times10_{-15}$
Total (≥1 language)	(0.62, 0.67)	0.65	−23.45	$<1\times10^{-15}$
Co-variable (structural equality)				
Monolingual	(1.35, 1.45)	1.4	18.09	$<1\times10^{-15}$
1 additional language	(0.84, 0.92)	0.88	−5.39	7.09×10^{-8}
2 additional languages	(0.79, 0.86)	0.82	−9.82	$<1\times10^{-15}$
3 additional languages	(0.7, 0.78)	0.74	−10.96	<1×10–15
Total (≥1 language)	(0.69, 0.74)	0.72	−18.12	$<1\times10^{-15}$
Co-variable (free political parties)				
Monolingual	(1.32, 1.42)	1.37	18.01	<1×10–15
1 additional language	(0.88, 0.97)	0.92	−3.4	0.000672
2 additional languages	(0.78, 0.84)	0.81	−11.51	$<1\times10^{-15}$
3 additional languages	(0.68, 0.75)	0.71	−13.31	$<1\times10^{-15}$
Total (≥1 language)	(0.71, 0.76)	0.73	−18.04	$<1\times10^{-15}$
Co-variable (inclusive suffrage)				
Monolingual	(1.39, 1.49)	1.44	21.05	$<1\times10^{-15}$
1 additional language	(0.87, 0.95)	0.91	−4.22	2.49×10^{-5}
2 additional languages	(0.75, 0.81)	0.78	−13.2	$<1\times10^{-15}$
3 additional languages	(0.66, 0.73)	0.69	−14.11	$<1\times10^{-15}$
Total (≥1 language)	(0.67, 0.72)	0.69	−21.07	$<1\times10^{-15}$
Co-variable (credible elections)				
Monolingual	(1.38, 1.48)	1.43	20.8	$<1\times10^{-15}$
1 additional language	(0.88, 0.97)	0.93	−3.29	0.000985
2 additional languages	(0.75, 0.8)	0.77	−13.94	$<1\times10^{-15}$
3 additional languages	(0.65, 0.72)	0.69	−14.46	$<1\times10^{-15}$
Total (≥1 language)	(0.68, 0.72)	0.7	−20.82	$<1\times10^{-15}$
Co-variable (local democracy)				
Monolingual	(1.36, 1.46)	1.41	19.81	$<1\times10^{-15}$
1 additional language	(0.91, 0.99)	0.95	−2.1	0.035451
2 additional languages	(0.76, 0.81)	0.78	−13.17	$<1\times10^{-15}$
3 additional languages	(0.67, 0.74)	0.7	−13.9	$<1\times10^{-15}$
Total (≥1 language)	(0.68, 0.73)	0.71	−19.83	$<1\times10^{-15}$

Two-sided Wald *z*-tests were used to derive *P* values and 95% CIs.

population sample[5]. As in this prior work, functional ability emerged as the strongest predictor of age, aligning with recent studies[2,29,36] emphasizing its role as a key protective factor, and echoing the World Health Organization's (WHO, 2015)[37] redefinition of healthy aging focused on maintaining optimal functionality. Three complementary validation strategies (nested cross-validation, LOCO and stratified hold-out) yielded similar performance metrics, supporting the stability of our model and confirming that its predictive power was not biased by data partitioning schemes or country-specific patterns. While prior studies have proposed multilingualism as a potential protective factor[6,8–10], findings remain mixed due to methodological limitations[16], including reliance on indirect proxies of healthy aging, unaddressed confounding factors, limited large-scale, multicountry data and a primary focus on clinical populations. Furthermore, meta-analyses[15,16] reveal weak or null effect sizes, wide CIs and low statistical power, preventing broader generalizability of prior evidence. Our framework represents a step forward, offering a scalable methodology inspired by biological clocks[28,30], directly assessing healthy and unhealthy aging through BAGs. We show that multilingualism is associated with reduced BAGs at the population level among healthy individuals and predicts a lower risk of future accelerated aging. These findings validate multilingualism as a population-wide protective factor, on par with other lifestyle factors highlighted in public health guidelines, laying the groundwork for tailored interventions on a global scale.

The protective effect of multilingualism was dose dependent suggesting that functional and cognitive benefits scale with the number of languages spoken. Because all languages remain active even when only one is in use[38,39], each additional language likely increases executive, attentional and memory demands—reinforcing cognitive reserve mechanisms in a cumulative way[40]. Insofar as multilingual benefits arise from continuous recruitment and reinforcement of these networks, protective effects should increase as more languages are simultaneously controlled. This interpretation is consistent with experience-dependent neuroplasticity models[41–44], positing that sustained multilingual engagement strengthens brain networks through ongoing cognitive challenge. Indeed, enhanced brain networks are those most vulnerable to age-related decline, mild cognitive impairment and dementia[40,45], highlighting the potential relevance of multilingualism as a protective factor.

Epidemiological outcomes were adjusted for various country-level exposomes, including linguistic, physical, social and sociopolitical conditions. Most findings remained statistically significant or exhibited an increased effect size, reinforcing the domain-independent protective effect of multilingualism in promoting healthy aging. However, some exceptions indicate that certain types of multilingualism may interact with macro-level linguistic and structural factors, potentially attenuating their protective benefits. For instance, migration—often linked to health risks such as psychosocial stress, increased alcohol consumption and sleep disruption—[46] can lead to stressful multilingualism, where individuals learn multiple languages out of necessity due to high mobility and socioeconomic pressures. In such cases, the benefits of multilingualism may be counteracted by the negative health consequences of such stressors. Likewise, in settings with greater institutional fragility, the risk of developing accelerated aging over time may be better explained by other structural factors—such as gender disparities—which exert a strong influence on health outcomes[19,20]. These results underscore the interplay between individual-level factors and broader country-level exposome influences in shaping life-course trajectories. Age-stratified analyses revealed that monolingual individuals face a higher risk of accelerated aging as they get older. For people who speak one extra language, the benefit in reducing this risk diminishes with age. However, those who speak two or more additional languages tend to experience stronger protective effects against accelerated aging in older age groups. This pattern further supports the cumulative impact of multilingualism across the lifespan.

The present study has multiple strengths. We leveraged large, diverse datasets from 27 European countries, enabling cross-sectional and longitudinal analyses in healthy individuals screened to exclude dementia diagnoses, thus ensuring broad generalizability. By incorporating country-level indices alongside macro-level exposome data for covariate adjustments, we show that multilingualism-related protection is detectable and robust at a population level. Although our measures were coarse, and participants likely represented mixed multilingual profiles, the strength and consistency of the effect suggests that it was not driven by any single phenotype but rather generalized across diverse multilingual experiences. Nevertheless, future research should incorporate individual-level measures of multilingualism to clarify underlying mechanisms and identify specific subprofiles linked to varying degrees of protection. While previous studies have yielded mixed findings[15,16], we advance the field by using BAGs[5] as direct markers of health outcomes, offering a more sensitive measure of delayed or accelerated aging than earlier approaches based on indirect proxies of health. Prior work using brain clock models[28] has shown a stepwise increase in neuroimaging-based BAGs from healthy controls through mild cognitive impairment to Alzheimer's disease. This suggests that BAGs capture cumulative, accelerated aging across the disease continuum. Similarly, cognitive-clock approaches[47,48] that model typical cognitive trajectories over time have shown to be superior to chronological age for predicting dementia, mild cognitive impairment and mortality. Although our biobehavioral clock framework[5] has yet to be validated in neurodegenerative populations, present results provide initial evidence that multilingualism is linked to reduced BAGs in healthy individuals. Future research should test whether multilingualism mitigates BAG increases in clinical cohorts.

Our analytical approach accounted for critical confounding factors, including immigration status, the number and typological distance between spoken languages, institutional and community-based usage patterns and macro-level physical, social and sociopolitical exposomes. Findings, validated with epidemiological metrics, were consistent across designs and showed robust effect sizes, highlighting a cumulative, domain-independent protective effect of multilingualism on healthy aging. Moreover, these insights were derived using BAGs as cost-effective and harmonized measures, enhancing their applicability for global health initiatives.

This study also has limitations. The heterogeneity of data sources and variability across datasets may constrain the generalizability of our findings. However, we mitigated this issue by using validated data harmonization pipelines shown to be effective in prior large-scale studies[2,5,27]. Our analysis was also limited to 27 European countries, potentially reducing its applicability to other regions. Still, this geographic scope covers diverse linguistic and sociopolitical contexts, and we leveraged nationally representative samples—successfully standardized in previous research[5]—to address this regional limitation. Our longitudinal analyses were based on a repeated-wave survey design. While this approach provides evidence of temporal precedence, it does not establish causality. Proper causal inference would require experimental, quasi-experimental or intervention-based designs. For instance, randomized controlled trials could explicitly manipulate multilingualism and directly assess its effects on aging clocks. Additionally, multilingualism was estimated from country-level data rather than individual-level language metrics, limiting our ability to link variability in specific experiential factors[49] (for example, age of acquisition, proficiency level, amount of code-switching) to aging outcomes. Recent systems-based frameworks of multilingualism[50] emphasize the importance of ecological and societal language dynamics, which can be quantified with census-based demographic statistics and country-level public indicators. Unlike individual circumstances, which are more variable over time, macro-level exposures evolve gradually, potentially exerting more stable and lasting influences on aging[27,51]. However, future research should expand to include individual-level

multilingual metrics. Migration patterns also pose challenges, as we did not distinguish between internal and external migration or whether it was voluntary or forced. Potential lag-time effects further complicate interpretation, as individuals may move between disadvantaged and enriched environments over time. Using only the current country of residence, without information on length of stay or migration history, makes it difficult to identify which specific aspects of migration most influence aging outcomes. Despite these sources of variability, our findings showed robust and systematic effect sizes. Future work would benefit from expanding to non-European populations and better-characterizing migration profiles. Integrating additional contributors such as genetic predispositions and neurobiological measures into predictive models is also recommended.

Our findings underscore the key role of multilingualism in fostering healthier aging trajectories. By showing that speaking multiple languages can serve as a population-wide protective factor against accelerated aging—despite varying linguistic, physical, social and sociopolitical factors—this study highlights an actionable avenue toward enhancing functional ability and cognitive resilience in aging populations. They also underscore the need for targeted educational initiatives and informed policy decisions that address modifiable risk factors, strengthen protective measures and reduce health disparities. Ultimately, embedding multilingualism into public health and educational frameworks holds promise for improving healthy aging on a global scale.

Methods

Dataset

We included 86,149 participants (45.31% female participants, mean age = 66.55 years, s.d. = 9.91, age range = 51–90) from SHARE Europe[32–35] (Fig. 1a and Supplementary Table 1). Data collection followed standardized procedures, face-to-face interviews and a probabilistic, clustered, stratified, multistage design. Only participants without a dementia diagnosis were included. As in previous studies[5,52], we excluded participants who self-reported a physician diagnosis of dementia, assessed in SHARE with item ph006d16: "Has a doctor ever told you that you have or have had Alzheimer's disease/dementia?". Individuals who answered 'Yes' were excluded from the analysis.

All methods adhered to the Declaration of Helsinki, with participant's written informed consent and ethics approvals obtained. The databases of national surveys from all countries are open and were obtained according to the established procedures for each country. Power calculations used G*Power 3.1.9.7. We adopted an OR of 1.8 as our reference effect size, based on meta-epidemiological reviews[53] indicating that ORs between 1.5 and 2.0 represent moderate, clinically meaningful associations in population studies. Detecting an OR of 1.8 with 99% power ($\alpha = 0.05$, one-sided test, normal distribution, $\mu = 0$, $\sigma = 1$) required 202 participants (critical $z = 1.65$); this threshold was exceeded by every country subsample in our dataset. A one-sided test was chosen because our hypothesis was explicitly directional, expecting the exposure to increase the odds of the outcome, thereby maximizing power in the predicted direction[54]. Nevertheless, our final sample sizes comfortably exceeded the requirement to detect even smaller effects using two-sided tests. For example, detecting an OR of 1.3 with 95% power ($\alpha = 0.05$, two-sided test) requires approximately 1,188 participants, a number exceeded even by our smallest country subsample (Malta, $n = 1,259$).

Predictors of age

As in prior biobehavioral clock findings[5], our model (Fig. 1b–e) integrated positive and risk factors from biological and behavioral domains, based on their well-established associations with healthy aging and dementia risk[1,2,29]. The 'bio' component included inherent biological factors—female sex, cardiometabolic conditions (hypertension, diabetes, heart disease), sensory–perceptual impairments (vision and hearing loss), unhealthy weight and sleep disturbances. While women in the European Union have a longer average lifespan[55], we included female sex as a biological risk factor due to their higher prevalence of age-related conditions such as dementia[56,57]. The behavioral component captured modifiable lifestyle and cognitive features, including functional ability, educational attainment, preserved cognition, subjective well-being, physical activity and alcohol consumption. All variables were selected for their documented relevance to aging and their consistent availability across SHARE datasets. Detailed descriptions of how each biobehavioral predictor was derived from SHARE data are provided in Supplementary Note 1.

Statistical analysis

Predictor-based age estimation. We used gradient-boosting regression models[58] to predict participants' chronological age (Fig. 1c) based on biobehavioral positive and adverse risk factors. The model was trained on 90% of the dataset and tested on an independent 10% subset using tenfold cross-validation. Model performance was assessed through R^2, MDE and root mean squared error (RMSE)[30]. Cohen's f^2 quantified effect sizes, while MDI determined feature importance. Bayesian optimization fine-tuned the hyperparameters, identifying the best configuration. As in prior work[2,5,59], we tuned hyperparameters with Bayesian optimization on an independent, randomly selected 80% subsample. The resulting configuration was then held fixed across all subsequent cross-validation folds. To ensure this fixed-split approach did not bias performance estimates, we repeated the analysis with a fully nested cross-validation scheme (fivefold Bayesian search within each outer fold). Performance remained virtually unchanged ($\Delta < 10^{-2}$–10^{-3}).

BAG estimation. We derived each participant's BAG as the difference between the gradient-boosting model's predicted age and their actual chronological age (BAG = predicted age − chronological age; Fig. 1d). Positive BAGs (BAG > 0) indicate accelerated aging. In other words, individuals whose biobehavioral profile appears older than expected for their chronological age. Negative values (BAG < 0) reflect delayed aging, suggesting a younger-than-expected profile. This metric captures the extent to which a person's biobehavioral profile aligns with, or deviates from, the normative aging trajectory for their chronological age[5]. BAGs were derived without including multilingualism in the prediction model, ensuring that subsequent analyses treat multilingualism as an external explanatory factor. To account for regression-to-the-mean bias, we regressed chronological age from estimated BAGs and used residuals for BAG correction[30]. Regression coefficients were obtained from the training data and applied to the test data.

Cross-sectional and longitudinal multilingual modulation of BAGs. In separate cross-sectional and longitudinal analyses, we treated multilingualism as an aggregate-level exposure and individual BAGs as the outcome, evaluating whether country-level multilingual profiles were associated with lower (that is, younger) BAG values. Multilingual status was defined as the country-level percentage of monolinguals (those speaking only their mother tongue), individuals speaking one, two, three or more additional languages, and the overall proportion of individuals speaking at least one additional language. Country-level percentages of self-reported language skills were obtained from the European Statistical Office (Eurostat) database (https://ec.europa.eu/eurostat/statistics-explained/index.php?/title=Foreign_language_skills_statistics/), covering four waves (2007, 2011, 2016 and 2022; Supplementary Table 6). BAGs were dichotomized, with values above zero indicating accelerated aging. We dichotomized BAGs because ORs and RRs require a binary outcome variable[53]. Cross-sectional and longitudinal analyses were conducted using ORs and RRs[60], respectively. In cross-sectional analyses, ORs assessed the associations between

BAGs at each participant's registration year[61] and multilingual status from the corresponding Eurostat wave. For cases where participants' registration years did not match available waves, missing data were imputed using linear interpolation, averaging the nearest Eurostat waves before and after the missing year. In longitudinal analyses, RRs quantified the predictive value of BAGs for changes over time, using multilingual status from 2007 (the earliest Eurostat wave) as baseline, and adjusting for the time difference between each participant's registration year and 2007.

Sensitivity analysis. We assessed the effects of cross-sectional and longitudinal analysis by incorporating aggregate country-level exposomes as covariates. These included language-related (migration[46]—international migration volumes as a percentage of the population; number of institutional languages—those used and sustained by formal institutions beyond the home; number of stable languages—maintained primarily within home and community settings; and typological distance between the two most spoken languages in each country—measured via the perplexity of *n*-gram models derived from text corpora[62]), social (gender inequality[20]—Gender Inequality Index (GII); structural inequality[19]—Gini index; and GDP per capita), physical (air quality—$PM_{2.5}$ exposure)[18] and sociopolitical (party freedom, inclusive suffrage, credible elections, local democracy)[21,22] exposomes (Fig. 1e,f). Data sources included Ethnologue (number of institutional and stable languages: https://www.ethnologue.com/), the WHO (GII: https://www.who.int/data/), the World Bank (Gini, migration, air quality: https://databank.worldbank.org/) and the Global State of Democracy Indices (sociopolitical exposomes: https://www.idea.int/democracytracker/dataset-resources/). As in previous reports, country-level exposomes were based on participants' years and country of residence at the time of the interview[61]. Exposomes were analyzed by normalizing each measure (0 to 1) and calculating a global score as the average of normalized values, with higher scores indicating better conditions. Missing macro-level exposome data were imputed by linearly interpolating the country's nearest years.

Finally, to assess the potential overfitting of ORs, we performed model calibration analyses, incorporating the Hosmer–Lemeshow goodness-of-fit test[63] and bootstrapped CIs to evaluate the reliability and robustness of the results. The calibration procedure involved 1,000 iterations, each with 500 participants, while adjusting the number of groups based on recommended guidelines. A good model fit is indicated by a *P*value > 0.05 (ref. 63).

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All databases used in this study are publicly accessible. Indicators of GDP, air quality, socioeconomic inequality (Gini index) and migration were obtained from the World Bank's platform (https://databank.worldbank.org/). Country-level gender inequality indexes (GII) are available on the WHO's website (https://www.who.int/data/nutrition/nlis/info/gender-inequality-index-(gii)/. Sociopolitical exposome indicators are available through the Global State of Democracy Indices (https://www.idea.int/democracytracker/dataset-resources/). Country-level percentages of foreign-speaking languages are sourced from the Eurostat database covering 2007, 2011, 2016 and 2022 waves (https://ec.europa.eu/eurostat/statistics-explained/index.php?/title=Foreign_language_skills_statistics/). Linguistic exposome indicators for the number of stable and institutional languages per European country are available from Ethnologue (https://www.ethnologue.com/). The two most spoken languages per country are sourced from the 'Europeans and their languages' Eurobarometer survey by the European Commission (https://languageknowledge.eu/countries-list/). The typological distance between languages was estimated using the Perplexity metric available at https://github.com/gamallo/Perplexity/.

Code availability

Analysis code (https://github.com/euroladbrainlat/Biobehavioral-age-gaps-Multilingualism/tree/main/scripts/) and preprocessed data containing individual BAG estimates (https://github.com/euroladbrainlat/Biobehavioral-age-gaps-Multilingualism/tree/main/scripts/main/data/) are freely available on GitHub.

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Author contributions

Research design: A.I., H.H. and L.A.; Data collection, curation and analysis: H.H. and L.A.; BAG methods: H.H., H.S.M., S.B. and A.I.; multilingualism methods: L.A. and A.M.G.; writing—original draft: L.A., H.H., A.M.G. and A.I.; writing—reviewing and editing: all authors; project administration and funding: A.I.; accessed and verified data: H.H., L.A., S.B. and H.S.M.

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All authors declare no competing interests.

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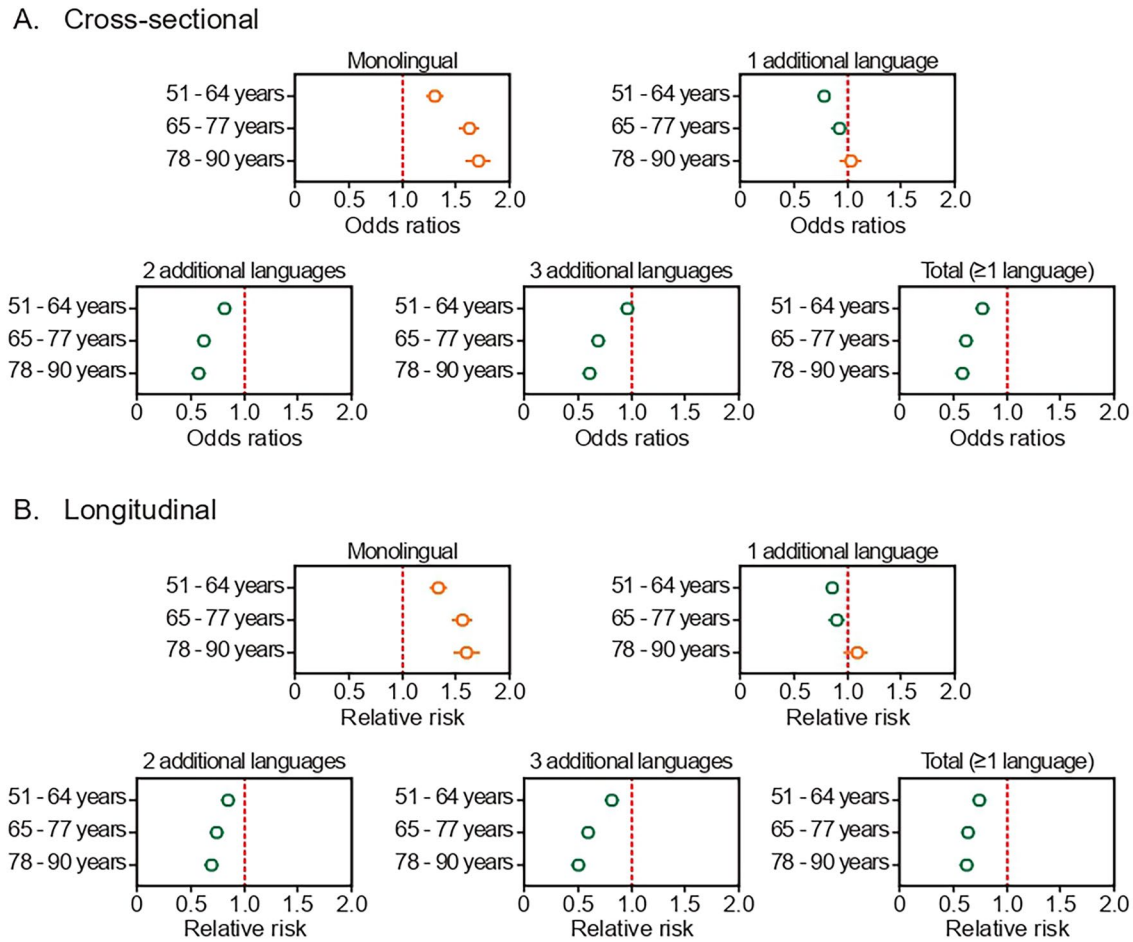

Extended Data Fig. 1 | Stratified analysis by age group. Associations between number of spoken languages and BAGs across age cohorts (n = 86,149 participants). **A**) Odds ratio (OR) estimates from the cross-sectional analysis and **B**) relative risk (RR) estimates from the longitudinal analysis, both stratified by age. Across designs, results show that risk of accelerated aging increases with age among monolinguals. For individuals speaking one additional language, the protective effect weakens with age. In contrast, speaking two or more additional languages is linked to progressively stronger protection with advancing age.

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Data analysis	Python (3.8.18); numpy (1.24.4); pandas (2.0.3); pingouin (0.5.5); scikit-learn (1.3.2); scikit-optimize (0.9.0); scipy (1.10.1); statsmodels (0.14.1); R version (4.4.2); G*Power (3.1.9.7)

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All databases used in this study are publicly accessible. Analysis codes and preprocessed data for BAGs are freely available on GitHub (https://github.com/

euroladbrainlat/Biobehavioral-age-gaps). Indicators of GDP, air quality, socioeconomic inequality (Gini index), and migration were obtained from the World Bank's platform (https://databank.worldbank.org/). Country-level gender inequality indexes (GII) are available on the World Health Organization's website (https://www.who.int/data/nutrition/nlis/info/gender-inequality-index-(gii)). Sociopolitical exposome indicators are available through the Global State of Democracy Indices (https://www.idea.int/democracytracker/dataset-resources).
Country-level percentage of foreign-speaking languages are sourced from the Eurostat database covering 2007, 2011, 2016, and 2022 waves (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Foreign_language_skills_statistics). Linguistic exposome indicators for the number of stable and institutional languages per European country are available from Ethnologue (https://www.ethnologue.com/). The two most spoken languages per country are sourced from the "Europeans and their languages" Eurobarometer survey by the European Commission (https://languageknowledge.eu/countries-list). The typological distance between languages was estimated using the Perplexity metric available at https://github.com/gamallo/Perplexity.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	We considered female sex as a risk factor for accelerated aging. The surveys utilized did not contain questions regarding gender. All methods adhered to the Declaration of Helsinki, with informed consent and ethics approvals. We included 86,149 participants (45.31% females).
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Population characteristics	We analyzed biobehavioral data consisting of protective factors (cognition, functional ability, education) and risk factors (cardiometabolic conditions: hypertension, diabetes, heart disease; female sex; sensory impairments: visual and hearing impairments) relevant to healthy aging and dementia risk.
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Data exclusions	Only participants without a dementia diagnosis were included.
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